Enhancing the Existing Microscopic Simulation Modeling Practice for Express Lane Facilities

Kelvin S. Machumu
University of North Florida, kelvinsimon05@gmail.com

ENHANCING THE EXISTING MICROSCOPIC SIMULATION MODELING PRACTICE FOR EXPRESS LANE FACILITIES

By

Kelvin Simon Machumu

A thesis submitted to the School Engineering

In partial fulfillment of the requirements for the degree of

Masters of Science in Civil Engineering

UNIVERSITY OF NORTH FLORIDA

COLLEGE OF COMPUTING, ENGINEERING, AND CONSTRUCTION

July 2017

The thesis “Enhancing the Existing Microscopic Simulation Modeling Practice for Express Lane Facilities” submitted by Kelvin S. Machumu in partial fulfillment of the requirements for the degree of Masters of Science in Civil Engineering has been

Approved by the thesis committee: **Date:**

______________________________ ____________________

Dr. Thobias Sando,
Thesis Advisor and Committee Chairperson

______________________________ ____________________

Dr. Christopher Brown,
Committee Member

______________________________ ____________________

Dr. Brian Kopp,
Committee Member

Accepted for the School of Engineering:

______________________________ ____________________

Dr. Murat Tiryakioglu,
Director

Accepted for the College of Computing, Engineering, and Construction:

______________________________ ____________________

Dr. Mark Tumeo,
Dean

Accepted for the University of North Florida:

______________________________ ____________________

Dr. John Kantner,
Dean of the Graduate School

DEDICATION

I would like to dedicate this thesis to my beloved parents Simon and Theopista; and to my four siblings.

ACKNOWLEDGEMENTS

First, I wish to thank the Almighty God for his endless blessings in my life. Through it all, Dr. Thobias Sando, my supervisor, committee chair, and extremely talented mentor, has been a tremendous source of accomplishment of this thesis. I thank him for his enthusiasm for the subject matter and for tireless support. I am grateful for the example he has set by his leadership, expertise, understanding, patience, and dedication, all of which molded me into the engineer and researcher I am. Special thanks also go to my committee members, Dr. Christopher Brown and Dr. Brian Kopp, who spent time reviewing my draft material and offering their creative ideas and guidance throughout my thesis preparation.

I am indebted to the UNF Transportation Lab members for the encouragement, endless support, and creative ideas.

Finally, A special word of thank also goes to my family for their continuous support and encouragement over these many years, I love you all.

TABLE OF CONTENT

Page

LIST OF TABLES

LIST FIGURES

Page

LIST OF ACRONYMS

ANOVA	Analysis of Variance
AASHTO	American Association of State Highway and Transportation Officials
CI	Confidence Interval
COM	Component Object Model
DCP	Data Collection Point
DOT	Department of Transportation
DSL	Dynamic Shoulder Lane
EL	Express Toll Lane
EVMLE	Existing VISSIM Managed Lane Evaluation
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
GPL	General Purpose Lane
HCM	Highway Capacity Manual
HOV	High Occupancy Vehicle
HOT	High Occupancy Toll
LOS	Level of Service
ML	Managed Lane
MLE	Managed Lane Evaluation

MLRD	Managed Lane Routing Decision
MOE	Measures of Effectiveness
MUTCD	Manual of Uniform Transportation Device
OD	Origin Destination
PMLE	Proposed Managed Lane Evaluation
PTV	Planug Transport Verkehr (German)
RDD	Routing Decision Distance
RBC	Ring Barrier Control
RITIS	Regional Integrated Transportation System
SR	State Road
TSM&O	Transportation System Management and Operation
TTS	Travel Time Savings
U.S	United Sates
USDOT	United States Department of Transportation
VB	Visual Basic
VISSIM	**V**erkehr **I**n **S**tädten – **SIM**ulationsmodell (German)

ABSTRACT

The implementation of managed lanes (MLs), also known as dynamically priced express lanes, to improve freeway traffic flow and personal throughput is on the rise. Congestion pricing is increasingly becoming a common strategy for congestion management, often requiring microscopic simulation during both planning and operational stages. VISSIM is a recognized microscopic simulation software used for analyzing the performance of managed lanes (MLs). This thesis addressed two important microscopic simulation issues that affect the evaluation results of MLs.

One of the microscopic simulation issues that has not yet been addressed by previous studies is the required minimum managed lane routing decision (MLRD) distance upstream of the ingress point of MLs. Decision distance is an optimal upstream distance prior to the ingress at which drivers decide to use MLs and change lanes to orient on a side of MLs ingress. To answer this question, this study used a VISSIM model simulating I-295 proposed MLs in Jacksonville, Florida, United States (U.S), varying the MLRD point at regular intervals from 500 feet to 7,000 feet for different levels of service (LOS) input. Three measures of effectiveness (MOEs) - speed, the number of vehicles changing lanes, and following distance - were used for the analysis. These MOEs were measured in the 500 feet zone prior to the ingress. The results indicate that as the LOS deteriorates, speed decreases, the number of vehicles changing lanes increases, and the following distance decreases. When the LOS is constant, the increase in the MLRD distance from the ingress point was associated with the increase in the speed at the 500 feet zone prior to the ingress, less number of lane changes, and the increase in following vehicle gap. However, the MOEs approached constant values after reaching a certain MLRD distance. LOS D was used to determine the minimum MLRD distance to the ingress of the MLs. The determined minimum MLRD distances were 4,000 and 3,000 feet for 6 and 3 lane segments prior to the ingress point, respectively.

Another issue addressed in this thesis is the managed lane evaluation (MLE) outputs, which include speed, travel time, density, and tolls. In computing the performance measures, the existing VISSIM managed lane evaluation (EVMLE) tool is designed to use the section starting at the point when vehicles are assigned to use MLs, also known as the MLRD point, which is located upstream of the ingress. The longer the MLRD distance from the ingress, the more the EVMLE tool uses the traffic conditions of the MLs traffic before entering the ML in its computations. This study evaluates the impact of the MLRD distance on the EVMLE outputs and presents a proposed algorithm that addresses the EVMLE shortcomings. In order to examine the influence of the MLRD distance on the outputs of the above-mentioned two algorithms, simulation scenarios of varying MLRD distances from 500 ft to 7,000 feet from the ingress were created. For demonstration purposes, only the speed was used to represent other performance measures. The analysis of variance (ANOVA) test was performed to determine whether there was a significant difference in the speed results with the change in the MLRD distance. According to the ANOVA results, the EVMLE tool produced ML speeds that are MLRD dependent, yielding lower speeds with an increased MLRD distance. On the other hand, the ML speed results from the proposed algorithm were fairly constant, regardless of the MLRD distance.

Keywords: VISSIM, Manages lanes, Managed lane routing decision, Existing VISSIM managed lane routing decision, Proposed managed lane routing decision.

CHAPTER 1: INTRODUCTION

Background

The Florida Department of Transportation (FDOT) has increasingly considered express lanes, also known as managed lanes (MLs), as a way to improve mobility for urban freeways. An ML is a "freeway within a freeway" where lanes are separated from a general-purpose lane (GPL) and its operation actively responds to demand while achieving an optimal condition such as free flow speeds (FHWA, 2008). The Federal Highway Administration (FHWA) defines MLs as a set of lanes where operational strategies are proactively implemented and managed in response to changing conditions. According to the FDOT (CS, 2014), a ML is a highway facility within an existing highway where operational strategies are proactively implemented and managed in response to changing conditions with a combination of tools. For the sake of this study, ML represents only one type of ML facilities, dynamically priced express lanes.

In Florida, the success of the I-95 express lane in Miami Dade County (Figure 1.1) led to implementation of other ML facilities including on I-595, I-75, and Palmetto Expressway. More ML implementation is underway in other Florida metropolitan areas including in Tampa, Jacksonville, and Orlando. Figure 1.2 shows a list of ongoing ML projects in Florida.

Figure 1.1. The first ML facility in Florida (I-95 in Miami-Dade, South Florida).

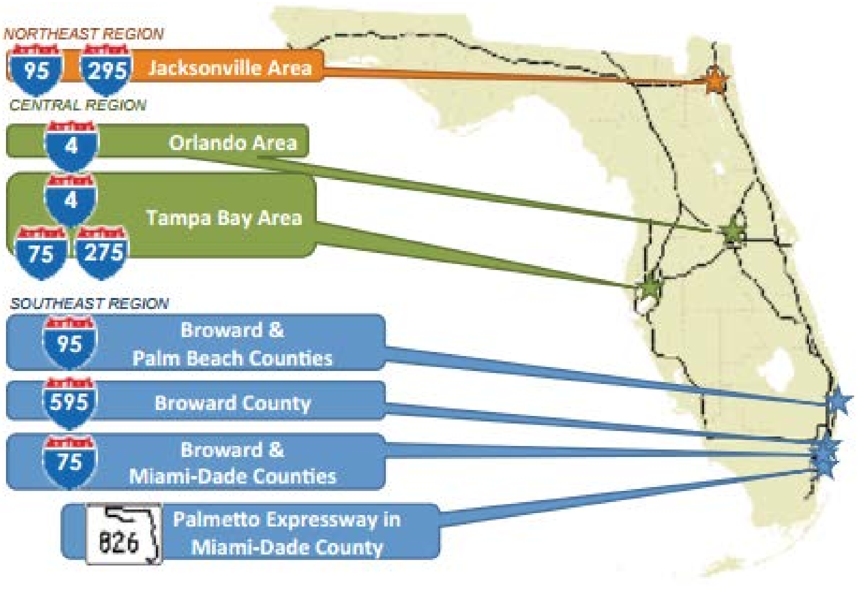


Figure 1.2. Map of potential express lane project (Source: FDOT, 2013).

Study Objectives

The analysis of ML facilities involves traffic simulation studies. There is an increased work on ML microscopic and macroscopic simulations as a result of many ML projects in the state. This thesis has two overarching goals;

1) To determine the optimal MLRD distance which allows drivers to initiate lane change maneuvers and access the express lane ingress with little disruption of traffic conditions.
2) To develop an improved ML performance measures output tool using the Component Object Model (COM) environment.

Potential Study Benefits

Currently, there is no guidance on the MLRD distance that analysts should use when modeling ML facilities. With the same model inputs, VISSIM, a software used to analyze ML facilities in Florida, would produce significantly different performance measures depending on the used MLRD distance. The findings of this study could potentially provide guidance to

transportation agencies on the optimum MLRD distance for site conditions. Also, the tool developed in this study would reveal issues associated with the existing VISSIM MLs evaluation tool and potentially prompt the software vendor to redesign the way the software performs the ML evaluation.

Thesis organization

This thesis is comprised of four chapters. Chapter 1 provides the general overview of the research problem, the description of the research objectives, and possible contributions of the study to the academic and industrial realm at large. The next two chapters of the thesis are comprised of two research articles. Hence, Chapter 2 is a stand-alone journal paper that addresses the first objective of this thesis and has already been accepted for publication. Chapter 3 focuses on the second objective. It is another journal article that is about to be submitted for publication consideration. Chapters 4 provides the overall conclusion of the studies.

CHAPTER 2: PAPER 1

Establishing the Minimum Routing Decision Distance for Managed Lanes

Paper 1 has been accepted for publication in the 2017 *Advances in Transportation Studies (ATS)*. The same paper was also presented during the 96th TRB annual meeting in January 2017 in Washington, D.C.

Introduction

In the United States (U.S), nearly ninety percent (90%) of people drive to work (Winston, 2013), with a considerable proportion of commuters using freeways. Urban freeways are characterized by congestion (CPCS, 2015) due to recurring incidents, mainly caused by peak hour traffic and non-recurring incidents. Every year, traffic congestion costs billions of dollars. For example, time lost due to congestion is about 91 million hours, which is worth $2.4 billion annually (CPCS, 2015). Congestion also leads to a loss of 35 million gallons of fuel per year, pollutes the environment by adding 740 million pounds of CO_2, and leads to 9,800 crashes (CPCS, 2015). A recently released report by the USDOT, "Beyond Traffic" (USDOT, 2015), indicates that America's population will grow by 79 million by 2045, and by 2050, emerging mega regions could absorb 75% of the U.S. population, as rural populations continue to decline. Subsequently, this will increase traffic demand on urban freeways, resulting in more congestion. Increased congestion in urban highway facilities has caused transportation agencies to implement congestion-pricing initiatives across the country. Florida is no exception. One of the Transportation Systems Operations and Management (TSMO) strategies used by several states is dynamic tolling facilities, also known as MLs. Under the new Florida Department of Transportation (FDOT) policy (FDOT, 2013), all additional capacity on the interstate shall be MLs.

Any freeway facility whose operational strategies are implemented and managed in response to changing conditions (e.g., increased freeway efficiency, maximized capacity, and management of demand), falls under the broad rubric of ‘managed lanes’ (AASHTO, 2011). Managed lanes include high occupancy toll lanes (HOT), ELs, truck lanes, bus lanes, and other special use lanes. MLs are examined in this study.

As MLs are becoming more pronounced, more studies are done to mimic their operation. The advantages of MLs, such as increasing freeway efficiency by providing predictable trips with little to no congestion, have been well documented by previous studies including a Texas study by Fisher et al., 2005. The operation of MLs can be bi-directional or reversible with reduced number of entry and exit to ensure better flow. The establishment of MLs have proven to be successful. A good example of successful MLs is documented in the Florida I-95 ML annual report (FDOT, 2013) which shows improvements in the overall performance. According to the report, travel speeds of MLs have increased by 20 mph and are about 63 mph and 56 mph for southbound and northbound, respectively. Whereas for the GPLs, 20 mph average speed increase for northbound and 15 mph for southbound, resulting in average speeds of 50 mph and 42 mph for southbound and northbound, respectively.

Since MLs are gaining popularity, more work on microscopic simulation of proposed and existing corridors is being conducted. One of the issues that has neither been addressed nor modeled is the determination of minimum MLRD distance to ML ingress. Decision distance is an optimal upstream distance prior to the ingress at which drivers decide to use MLs and change lanes to orient on a side of MLs ingress. This distance allow drivers to initiate lane change maneuvers and reach MLs ingress with minimal or no conflicts. Drivers are supposed to make an early decision to use MLs so that they can easily access the lanes. This helps to avoid last minute rush which can lead to conflicts. The decision to change lanes and align on the lane to MLs ingress comes wherever the signs are placed. A cursory review of developed simulation

models for Florida dynamic tolling facilities by various consulting firms shows inconsistency in coding the MLRD distance. To the authors' knowledge, no research has been done focusing on the influence of decision distance upstream the ingress point on operational characteristics of dynamic tolling facilities. Therefore, this study intends to establish decision distance thresholds necessary for a smooth traffic operation at the proximity of the ML ingress points.

Literature Review

Traffic microscopic simulation modeling has long been recognized as a useful and important tool for planning and operational analysis of transportation infrastructure. There are several traffic simulation models including VISSIM, Paramics, Intergration, CORSIM, and SimTraffic. These models differ in simulation capabilities and limitations. In the U.S, for MLs in particular, the two most commonly used models are CORSIM and VISSIM (Steven et al., 2004; Gomes et al., 2004; FDOT, 2014; PTV AG, 2015). A dynamic tolling module was added in version 5.30 of VISSIM and, since then, most agencies have been using it for modeling MLs with dynamic tolling. In the current model, the decision to use MLs in lieu of GPLs is determined by the tolling algorithm that uses base, cost, and time coefficients as user inputs. A pricing algorithm plays a key role in the analysis of ELs. Since MLs are dynamically managed, a dynamic toll algorithm that reacts to real-time traffic change conditions (Fu et al., 2013), computes the new toll price based on real-time information. Specifically, these computations are calculated at a given time interval, typically 15 minutes.

Dynamic tolling algorithms have been a focus of many studies for the last decade. The study by Zhang et al. (2009) developed a dynamic tolling algorithm for HOT lane operations in VISSIM because at that time VISSIM could only simulate static tolling conditions. Michalaka et al. (2013) developed three sets of modeling components to demonstrate HOT lane operation. The first component implements responsive pricing. While the second component mimics drivers' change behavior in the presence of tolls, the third represents toll structure for

multi-segment HOT facilities. The existing dynamic tolling algorithm in VISSIM is not without limitations. It uses only speed as the congestion performance measure to vary tolling cost and likelihood of drivers using the managed lanes (Gomez et al., 2004). In an effort to improve the existing model, PTV America, a vendor for VISSIM software, was contracted by the Florida Turnpike Enterprise to develop a script that incorporates density in the existing module. The aforementioned script was used in a recent study (Velasquez et al., 2016) that developed a verification tool for dynamic traffic assignments on I-95 MLs. The tool compares the theoretical number of drivers who decide to use MLs based on the logit dynamic assignment model and the VISSIM output.

At the time when this study was being undertaken, there was no literature on minimum decision distance prior to managed lane ingress. This distance relates to MLRD distance on MLs in VISSIM. Perhaps the closest scenario to decision distance from the ingress point is the minimum weaving distance to the MLs, i.e., distance from the closest on-ramp upstream of the ingress point. For the decision distance scenario, drivers using the inside lanes that do not intend to utilize MLs have to move to the outside lanes to avoid entering the MLs. On the other hand, drivers who are in the outside lanes and need to use the MLs would need to change lanes to access the MLs (Figure 2.1 illustrates).

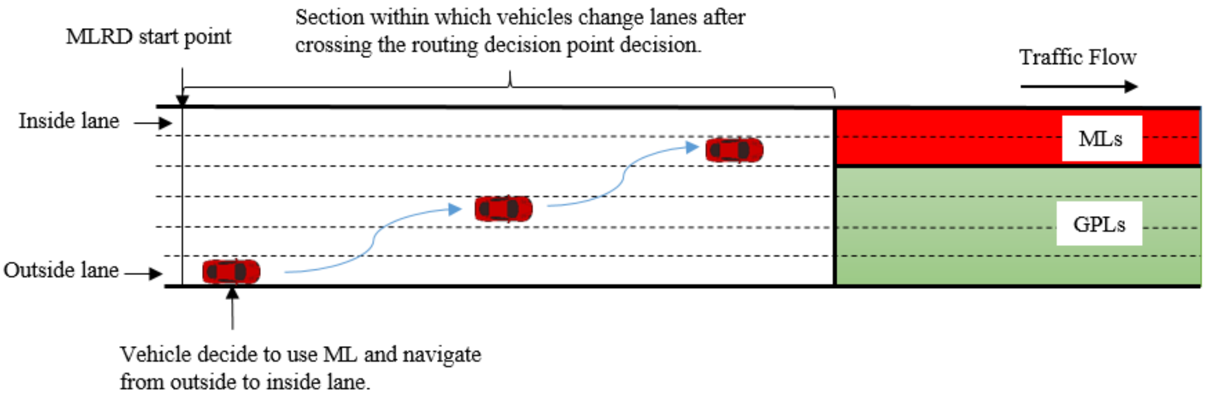


Figure 2.1. Vehicles changing lanes and from outside lane to inside lane to access MLs.

For the weaving maneuver that starts from the on-ramp upstream of the ingress point, drivers would need to change several lanes to access the MLs located adjacent to the median.

For weaving sections, the State of California guidelines (Caltrans, 2003) allow a minimum distance of 800 feet per lane change on an intermediate opening of managed lanes and an opening of an intermediate access that is not less than 2,000 feet.

Another scenario that is similar to the MLRD distance is the placement of notification signage prior to the managed lane ingress. Here, the assumption is that drivers will start taking action after they read the sign, similar to the assumption made in simulation, i.e., drivers will decide whether or not to use MLs at the predefined decision distance from the ingress. According to Chrysler et al. (2014), advanced signs should be placed at a distance of at least 800 meters (2,625 feet) prior to the ingress. On the other hand, the Manual on Uniform Traffic Control Devices (MUTCD) (FHWA, 2009) requires MLs guidance signs to be placed approximately 2,640, 5,280, and 10,560 ft in advance of entry point from a GPL. The Washington State guidelines (Burgess, 2006) have minimum weaving distance requirements based on different traffic composition (truck percentages) and desired LOS, with a minimum recommended weaving distance of 500 feet per lane. Table 2.1 shows the minimum distances reviewed from different sources.

Table 2.1. Minimum Distance Scenarios Related to Minimum MLRD

Scenarios	**Distance, feet**	**Source**
Weaving distance	500	Burgess, 2006
Advanced sign placement	2,625	Chrysler et al. 2014
	2,640 – 10,560	FHWA, 2009

Methodology

This section summarizes the information on project site, data source, and modeling process of the simulated scenarios. Specifically, these scenarios are decision distance from 500 to 7,000 feet (10 scenarios) with variable volume inputs giving different LOS from LOS A to E (5 scenarios). These scenarios are simulated with 10 variable random seeds (from 35 to 53 at an increment of 2) in the VISSIM software (10 Scenarios). This makes 10*10*5 = 500

scenarios. Three measures of effectiveness - number of lane changes, following or trailing distance, and speed - were used to compare the aforementioned scenarios.

Project Site

The project site includes 4.3 and 3.1-miles stretches for the northbound and the southbound respectively, of I-295 proposed managed lanes in Jacksonville, Florida. This section extends from San Jose Boulevard (SR 13) to I-95 (Figure 2.2). It is part of an interstate beltway around the city of Jacksonville that serves as an important route for moving people and goods to different parts of Jacksonville. The ML segment of I-295 within Duval County is a closed access facility with barrier separation. It was proposed for the purpose of adding capacity and improving travel time on I-295 from west of SR 13 to the I-95/I-295 south system to system interchange. The MLs will use dynamic tolling, which will vary with traffic volume to maintain the optimum number of vehicles so that the usage cannot compromise speed and travel times.

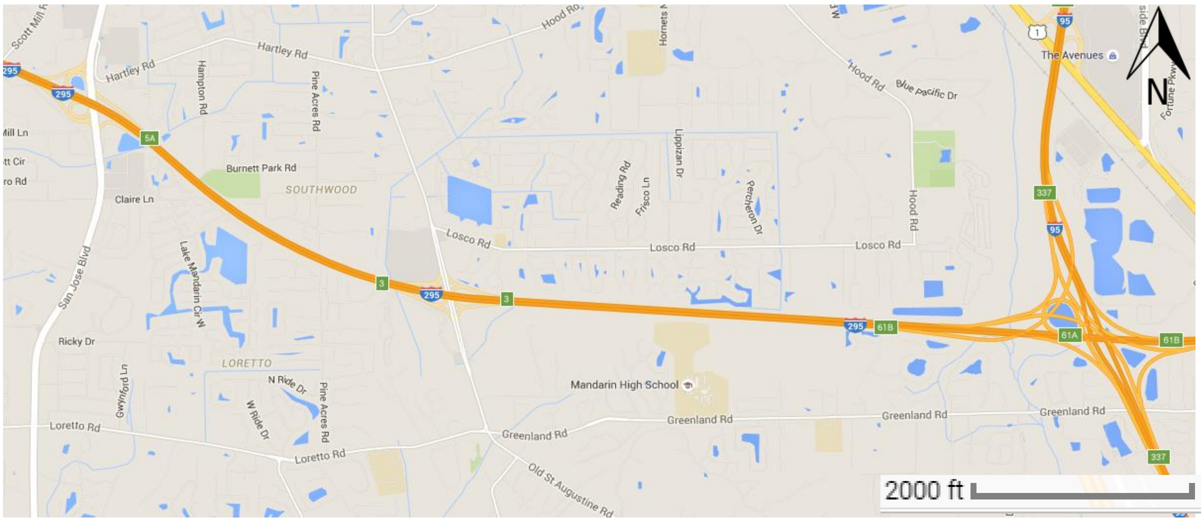


Figure 2.2. Location of the I-295 ML project (Source: Google Earth 2016).

Data Source

Simulation models require accurate and detailed data in order to replicate the actual traffic condition and operation. In the I-295 MLs project, models were developed to reflect the actual

site condition and features including alignments, weaving sections, and number of lanes. A microscopic traffic simulation model, VISSIM, is used in this study. A simulation period of two (2) hours with 30 minutes seeding time and 30 minutes dissipating time, specifically an AM eastbound peak hour from 8:00 to 10:00 AM is used. One-year weekly traffic data were used to create a model. Traffic data input is varied to obtain different LOS. Speed profiles (Table 2.2), which plays a significant role in network setting in VISSIM, are used in modeling.

Table 2.2. Speed Percentiles for MLs and GPLs

Percentiles, %	0	10	20	30	40	50	60	70	80	90	100
GPLs (mph)	9	32	52.5	58.8	61.1	62.3	63.4	64.7	66.4	70	77.4
ML (mph)	40.6	63.8	65.2	66.3	67.4	68.6	70.8	75	76.8	78.3	89

Modeling Process

Figure 2.2 shows a flowchart of the modeling process. The Visual Basic (VB) dynamic tolling script developed by PTV and described by Velasquez et al. (2016) was customized to reflect the site characteristics. Traffic distribution for the project site was adopted from the Reynolds, Smith, and Hills Inc. (RS&H, 2015) model that had been vetted and used for the design of the managed lanes. An origin-destination (OD) matrix was created by distributing traffic volumes and assigning the inputs to a specific lane. RS&H, a consulting company, created a model for the design year 2040. The model was customized to obtain research goals; traffic demand matrix was modified at different LOS, for conducting the sensitivity analysis. The VB script to implement dynamic tolling was also developed then incorporated in the model.

The model was calibrated by adjusting lane change and car-following behaviors based on the Wiedemann car-following model type (Wiedemann 74 for terminal intersections and Wiedemann 99 – for freeway links). Calibration was done in accordance to the FDOT protocol (FDOT, 2014) and Sajjadi et al. (2017) for calibrating microscopic simulation models. Parameters such as drivers' behaviors were adjusted (Table 2.3) to make the output practically

represent the actual field condition. Prior to adjusting drivers' behaviors, input data were checked if coded correctly. Since field data are vital to a successful calibration process, actual speed data were used to verify the calibrated model (Figure 2.4). Lastly, a spreadsheet that was created by URS as a user guideline was used to verify the ML outputs against the toll-pricing model (Table 2.3).

Table 2.3. Calibration Parameters

Parameters	Default	EL
CC0 (feet)	4.92	4.92
CC1 (s)	0.90	1.90
CC2 (feet)	13.12	39.37
CC4	-0.35	-0.70
CC5	0.35	0.70

CC0 standstill distance

CC1 headway time

CC2 following variation

CC3 threshold for entering following

CC4 & CC5 Positive and Negative following threshold respectively

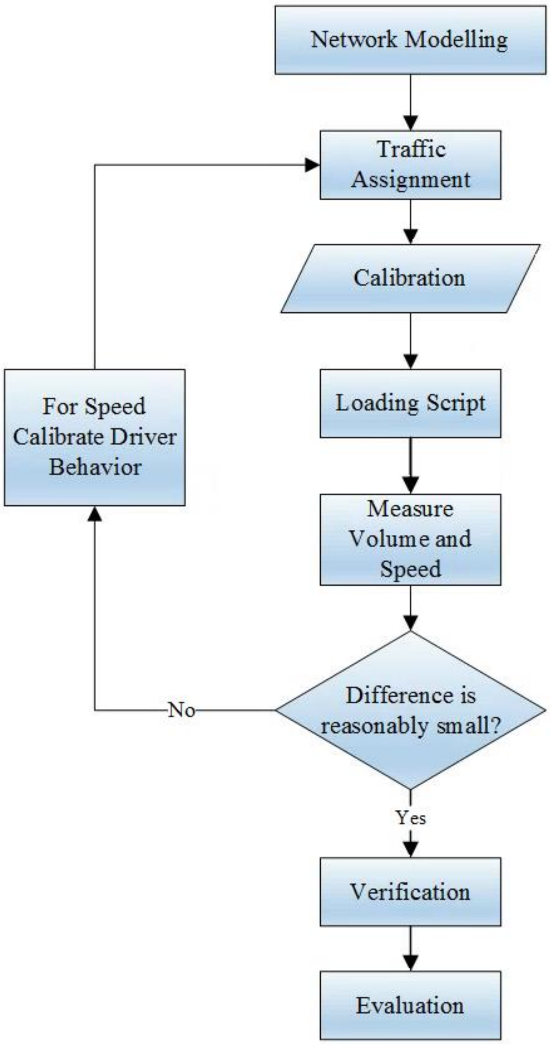


Figure 2.3. VISSIM microscopic simulation modeling flowchart.

Figure 2.4 shows plots of calibrated data and actual data. The regression (R^2) of the data used to calibrate the model was above 0.85, which means the more the value approaches 1 (from a scale of 0 to 1), the better are the data model used for analysis.

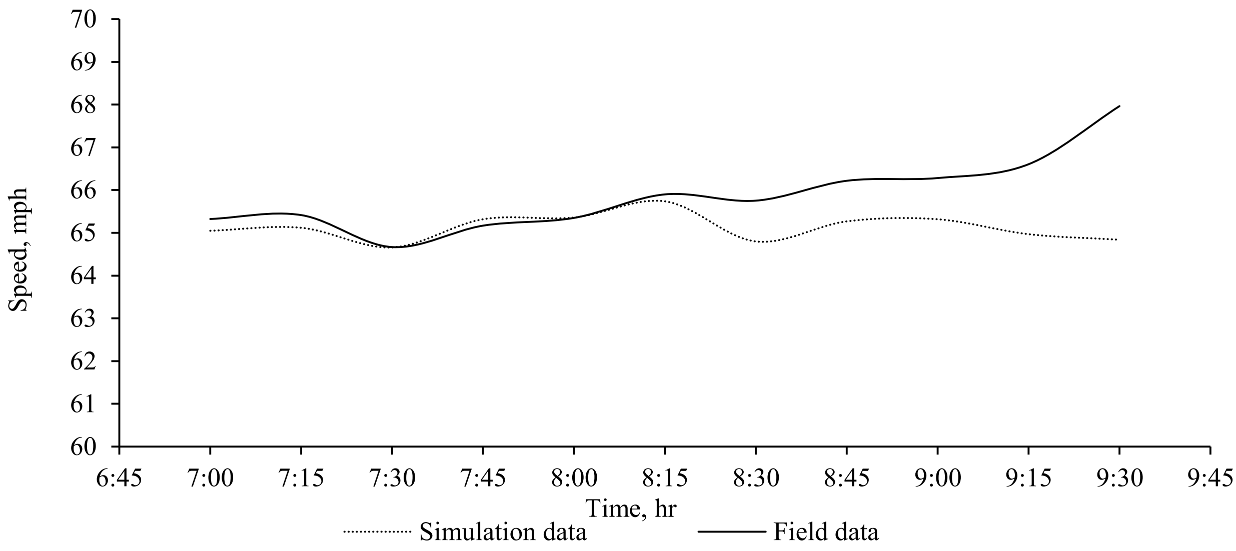


Figure 2.4. Traffic speed comparison between field data and simulation output.

Pricing Model Development

Since the basic toll-pricing model in VISSIM is limited in its application, a script, developed in Visual Basic (VB) was used to model dynamic tolling on MLs in order to replicate a robust pricing algorithm. In response to current traffic conditions, the algorithm calculates and updates the toll structure after every 900 seconds (15 minutes) as it is done in actual operations. The price updates in 15 minutes. Traffic conditions are determined by data collection points (detectors), which were located at about 1,500 feet interval along the MLs, similar to the field installations. The data collection points are used to determine operating speed that enables to compute flow rate and density. The traffic density is then obtained from flow rate and speed that is used to determine toll needed to control traffic. The current toll is based on rates established by FDOT for the I-295 project. The change in traffic density enables one to obtain toll adjustment rates from the Delta table. A Delta table is a chart that relates a change in traffic density with a variation in toll rates. If the new toll exceeds the maximum

value, the maximum value in a Delta table is used and if the new toll is lower than the minimum value, the minimum value in a Delta table is used. Table 2.4 shows a Delta table of the minimum and maximum toll thresholds used in the script.

Table 2.4. Minimum and Maximum Tolls Used in the Script.

LOS	Traffic Density, Vehicle/mile/lane		Toll rate per Mile, $/mile	
	Min	Max	Min	Max
A	0	11	0.25	0.25
B	12	18	0.25	0.25
C	19	26	0.25	0.5
D	27	35	0.5	1.25
E	36	45	1.25	3.25
F	46	50	3.25	5.00

The price is distance-based because there are several MLs with different distances. In this study the northbound is 4.3 miles whereas the southbound is 3.1 miles, and tolls are calculated based on the distance. When there is low demand, users are charged a minimum rate of $0.25 per section.

Discrete Choice Model

The decision to use the MLs depends on the current utility model (Equation 2.1 & 2.2) which is determined by the probabilistic model shown in Equation 2.3 (PTV AG, 2015). The utility for GPLs is always zero since there is no toll involved, whereas in the ML the utility varies depending on the coefficients, toll rate, and time-gain. The toll rates per mile are multiplied by the distance of a specific ML to obtain toll rates, which is used in Equation 1.

$$U_{(Toll)} = (\text{Cost coefficient} \times \text{Toll rate}) + (\text{Value of time} \times \text{travel time}) + \text{Base utility} \quad (2.1)$$

$$U_{(general\ purpose)} = 0 \quad (2.2)$$

Where $U_{(toll)}$ = Utility function on the toll system

$U_{(general\ purpose)}$ = Utility function of GPL

Toll rate is a function of traffic density

Travel time is a function of traffic density in the ML

The likelihood of motorists choosing to use the ML is computed by the binary logit model given in Equation 2.3. To minimize the impact of stochastic nature of the model on results, simulation models were run multiple times with different number of random seeds. Random seed values in VISSIM alter value sequence and the traffic flow changes. This allows one to simulate stochastic variation of vehicle arrivals in the network. Ten (10) simulation runs with different random seeds of an increment of 1 were undertaken.

$$P_{(Toll)} = 1 - \frac{e^{a*U_{Toll-free}}}{e^{a*U_{Toll-free}} + e^{a*U_{Toll}}} = 1 - \frac{1}{1+e^{a*U_{Toll}}} \quad (2.3)$$

Where

$P_{(toll)}$ = Probability of choosing the MLs

a = Logit alpha value

$U_{(toll)}$ = Utility function of MLs

The coefficients of the choice model (Table 2.5) from South Florida ML (I-95) are used in this model. Table 2.5 shows the coefficients that were changed in VISSIM from the default values.

Table 2.5. Coefficients of Choice Model Used in the Simulation Used on the I-95 ML model

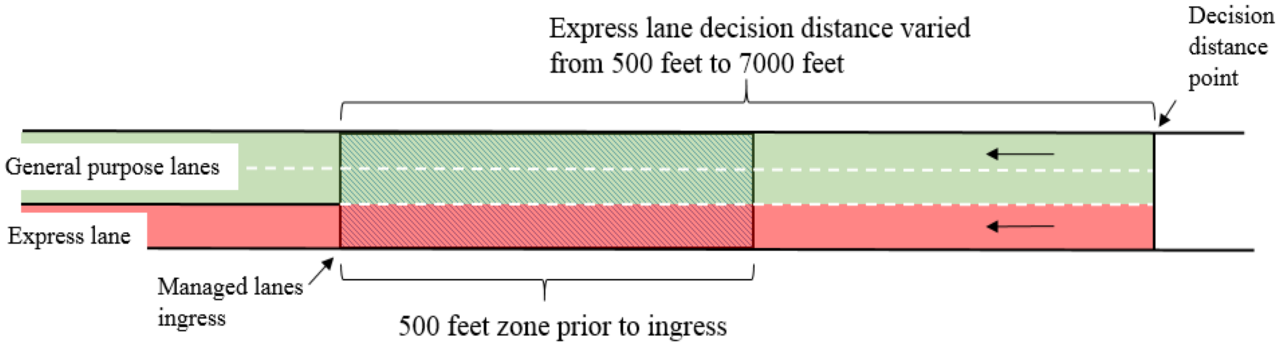
VISSIM Decision Model Parameters	VISSIM Defaults	Express-way values
Logit alpha value	0.05	1.00
Cost coefficient	-1.00	0.61
Time coefficient	0.40	0.39
Intercept	0.00	-0.80

Model Scenarios and Approaches

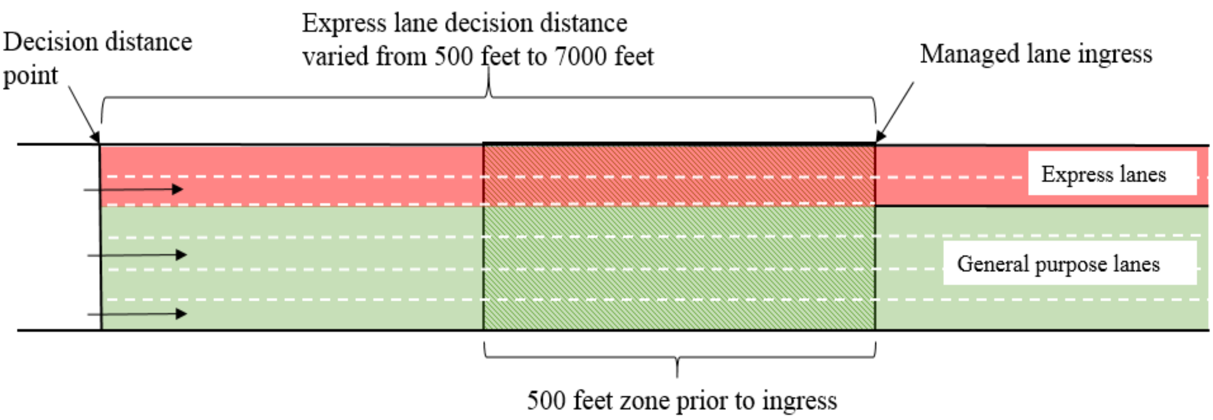
Three traffic indicators – speed, number of lane changes, and trailing/following distance – were used for analysis. In this study, these three variables were measured on the segment that starts from the ingress point and goes 500 feet upstream, as illustrated in Figure 2.5.

Simulation is done for one peak hour for the westbound direction, which is off peak in the eastbound direction. Volume for the peak hour is varied to obtain the five LOS. Ten models, each with a specific MLRD distance upstream the ingress, varying from 500 to 7,000 feet were

created and altered for different simulation runs. A 500 feet distance is used as a minimum MLRD distance. This is to take into consideration that the same distance is used as the minimum weaving distance (WSDOT, 2006). In addition, 7,000 feet is used as a maximum MLRD distance because there is an interchange in the westbound direction after 7,000 feet from ML ingress. After the base condition, the one with prevailing traffic conditions, is simulated, traffic volumes are varied to analyze the effects of MLRD distance given different LOS in both directions. LOS thresholds shown in Exhibit 11-6 of the Highway Capacity Manual (HCM) (TRB, 2010) for basic freeway segments is used for varying the volume inputs.



(a)



(b)

Figure 2.5. Layout of the site modeled in Vissim; (a) Westbound (b) Eastbound.

Model Verification

The VB script is incorporated in the VISSIM software to make the dynamic tolling model more robust and it updates the toll price after every 15 minutes (900 seconds). The script is verified to ensure appropriate functioning. To verify the methodology, a verification tool (Velasquez et al., 2016), developed in Microsoft Excel, was used to compare the empirical results based on the Logit probability function, Equation 2.3, manual computations and the simulation output. The percentage of vehicles using the MLs based on the simulation results was computed using Equation 2.4. Table 2.6 shows verification results for three (3) scenarios: speed, lane change, and following/trailing distance. The difference between the simulated and empirical percentages is small, with the highest difference being just above 1% (-1.13%). The results are better than similar studies, such as Velasquez et al. (2016), most likely because of the small model size, only 3.3 miles of MLs. Verification results indicate that the algorithm used in this study is appropriate for dynamic pricing.

$$Simulation\ share = \frac{ML\ traffic}{ML\ traffic + GPL\ traffic} \times 100 \tag{2.4}$$

Table 2.6. Verification/Validation of Model

MLRD distance, ft	ML Facility	ML Traffic, Vehicles	GPL Traffic, Vehicles	% ML Traffic		Difference %
				Simulation share	Logit Eqn.	
1,000	1	4922	12497	28	27	-1.13
	2	649	2141	23	23	-0.06
1,500	1	4538	12945	26	26	-0.29
	2	630	2124	23	23	0.40
2,000	1	4455	13042	25	25	-0.14
	2	628	2128	23	23	0.01

Statistical Analysis

Simulations of different scenarios were done and the evaluation results obtained are used for the analysis. The paired t-test was used to check if the data of consecutive MLRD distance points are significantly different from each other (Equation 2.5). This test assumes that the two distributions have the same variance.

$$t = \frac{\overline{X}_d - 0}{s_d/\sqrt{n_d}} \tag{2.5}$$

Where $\overline{X_d}$ = Sample mean difference

s_d = Sample standard deviation of differences

n_d = Number of pairs

A p-value is used to determine the significance of a hypothesis test. In this study, all values are tested at a 0.05 level of significance.

Simulation Results and Discussion

Table 2.7 summarizes the modeling results for each decision distance scenario (from 500 feet to 7,000 feet) and five LOS scenarios (LOS A to E). The values shown in Table 2.7 are the averages of ten simulation runs, with different random seeds for each scenario. The standard deviation of the average speeds range from 0.2 to 3.3 for speed, 3 to 9 for number of vehicles changing lanes, and 1.2 to 4.4 feet for following distances. The rest of section 4 provides a detailed discussion of the results shown in Table 2.7.

Table 2.7. Summary of the MOEs for Different LOS for Westbound and Eastbound Direction

D.D, feet	Eastbound, No. of vehicles changing lanes					Westbound, No. of vehicles changing lanes					Eastbound Speed, mph					Westbound Speed, mph				
	A	B	C	D	E	A	B	C	D	E	A	B	C	D	E	A	B	C	D	E
500	161	617	934	920	944	73	250	612	644	640	52.7	27.9	13.1	13.3	13.2	46.9	37.6	16.3	16.0	15.0
750	107	475	883	900	916	43	165	394	473	512	54.7	36.2	15.3	14.4	13.9	51.2	43.5	22.5	19.4	17.0
1,000	81	385	819	852	892	26	122	270	367	393	55.4	40.3	19.7	15.5	15.1	53.5	47.2	28.8	21.9	19.1
1,500	71	303	670	797	852	20	84	167	227	250	56.2	44.7	29.8	19.9	17.6	55.3	50.1	35.5	24.9	22.9
2,000	66	256	570	752	815	18	75	126	164	181	56.8	47.4	34.5	23.3	19.0	56.0	50.9	40.0	26.5	24.6
3,000	58	216	457	705	778	20	77	108	133	148	57.4	49.4	38.5	27.1	21.4	57.0	51.2	44.2	27.4	25.6
4,000	60	212	430	694	763	20	72	109	128	146	57.4	50.0	39.6	28.0	22.3	57.4	51.1	47.1	27.2	25.5
5,000	58	217	431	697	762	19	70	113	130	148	57.6	50.0	39.8	28.3	22.5	57.3	51.4	47.8	27.6	25.5
6,000	54	218	432	696	767	19	72	114	126	143	57.9	50.0	39.7	28.3	22.8	57.6	51.3	47.6	27.8	25.8
7,000	53	216	437	695	765	19	71	117	127	145	58.7	50.1	39.7	28.3	23.2	57.6	51.5	47.7	27.8	25.7

D.D is decision distance

A, B, C, D, E are LOS

No. of vehicles changing lanes is in vehicle per hour per lane.

.

D.D, feet	Eastbound following distance , feet					Westbound Following distance, feet				
	A	B	C	D	E	A	B	C	D	E
500	84.5	46.4	7.1	7.1	6.9	97.8	50.6	15.0	15.3	13.9
750	87.6	60.3	9.7	7.5	7.7	109.8	54.6	21.1	17.4	14.4
1,000	88.5	63.6	15.2	8.3	8.0	122.5	54.9	29.3	19.7	17.4
1,500	94.2	70.2	39.7	9.5	9.4	150.9	69.4	42.3	20.2	20.3
2,000	93.8	68.0	43.7	15.3	10.8	132.9	69.1	46.5	25.7	24.3
3,000	96.4	73.6	53.2	31.0	14.5	131.9	74.3	58.2	23.4	26.3
4,000	96.2	72.0	51.7	27.9	14.0	135.6	76.6	53.9	24.2	23.4
5,000	98.0	73.2	52.6	30.4	15.5	143.3	76.7	55.2	27.3	21.9
6,000	92.5	71.3	51.6	32.2	20.0	156.8	74.9	58.3	24.4	23.4
7,000	88.3	73.8	53.2	31.4	16.5	151.7	74.6	58.0	22.6	23.5

Measures of Effectiveness

As discussed earlier, determination of the minimum MLRD distance was based on three traffic measures–travel speed, following/tailing distance, and number of lane changes– within 500 feet upstream the MLs ingress point.

Travel Speed

VISSIM has an existing evaluation tool that gives travel speed as one of the performance functions for a selected section of a highway. In this case, a section of interest is the 500 feet upstream of the ingress point. The average travel speed for each scenario is shown in Table 2.7. Figure 2.6 presents the graphical presentation, of the same results in Table 2.7, for travel speed. There is a clear, discernible pattern, which indicates that speed decreases as the LOS deteriorates (from LOS A to E), as expected. Interestingly, as the MLRD distance is increased, for each LOS, the average speed also increases and approaches an asymptotic value after a certain distance. According to Figure 2.6(a), which represents results for the westbound direction, for LOS A and B, the travel speed is observed to remain constant after a decision distance of 1,500 feet whereas, for LOS C the speed remains constant after a decision distance of 4,000 feet. For LOS D and E, the travel speed appears to be constant from a decision distance of 3,000 feet. The speed curves for the eastbound direction (Figure 2.6(b)) have the same pattern as the westbound direction and appear to remain constant after 3,000 feet (for LOS A and B) and 4,000 feet (for LOS C, D, and E).

It should be noted that the eastbound has six lanes prior to ingress unlike the westbound, which has three lanes. The difference in the number of lanes (between the two bounds) explains the variation of the minimum decision distance. This suggests that the guidance for the minimum decision distance should also take into consideration the number of lanes.

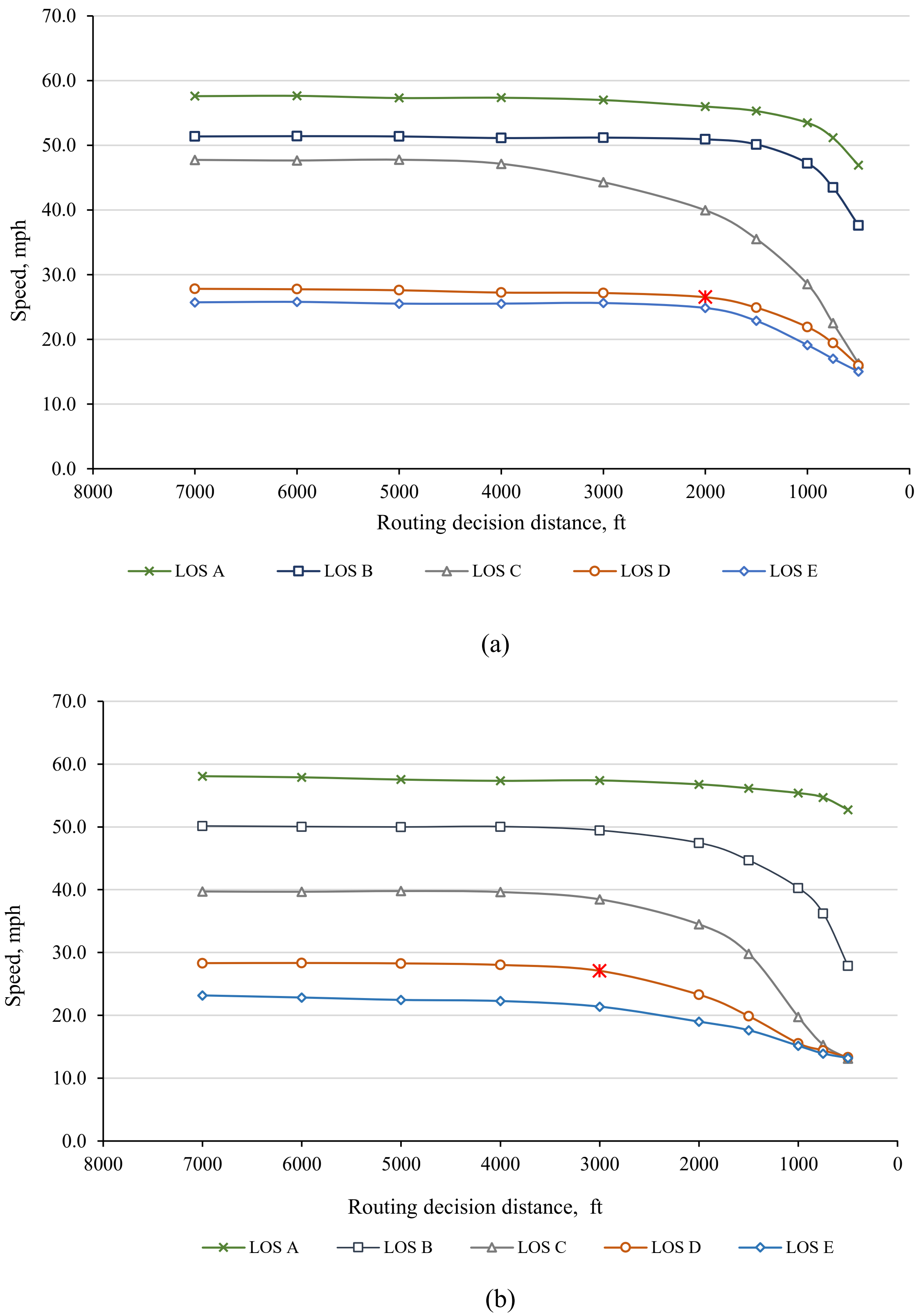


Figure 2.6: MLRD distance against Speed for (a) Westbound (3 lanes) (b) Eastbound (6 lanes).

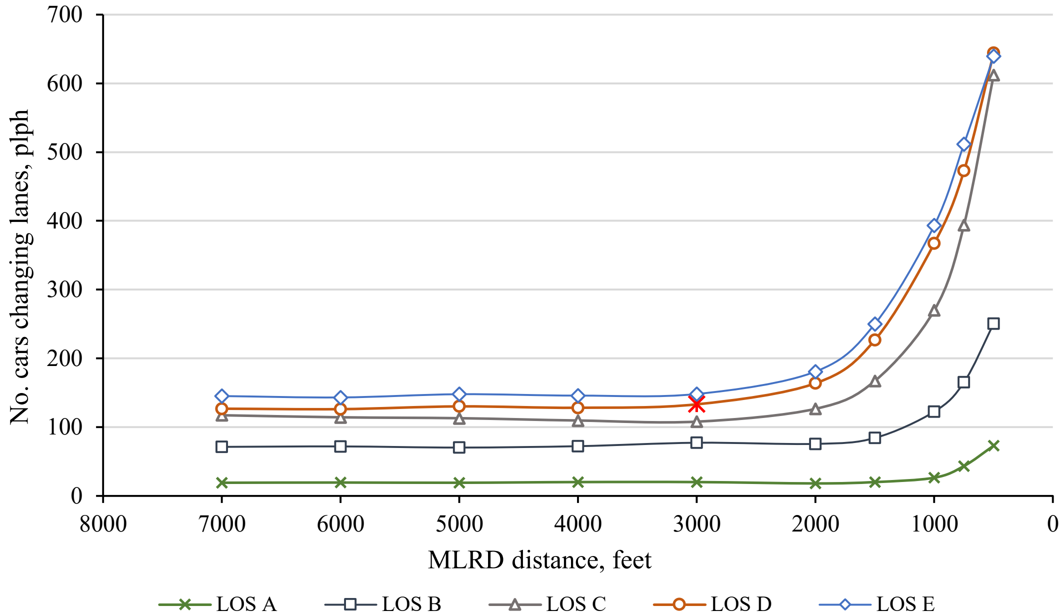
LOS D is used as the design LOS (TRB, 2010) to determine the optimum decision distance. A t-test is performed to check the significant difference between different points from 500 to 7,000 feet. The results indicate no significant difference between the decision distances from 2,000 and 3,000 feet for westbound and eastbound decision distance respectively. Therefore, considering speed, the minimum MLRD distance for the eastbound direction is 3,000 feet whereas for the westbound is 2,000 feet.

Number of Vehicles Changing Lanes

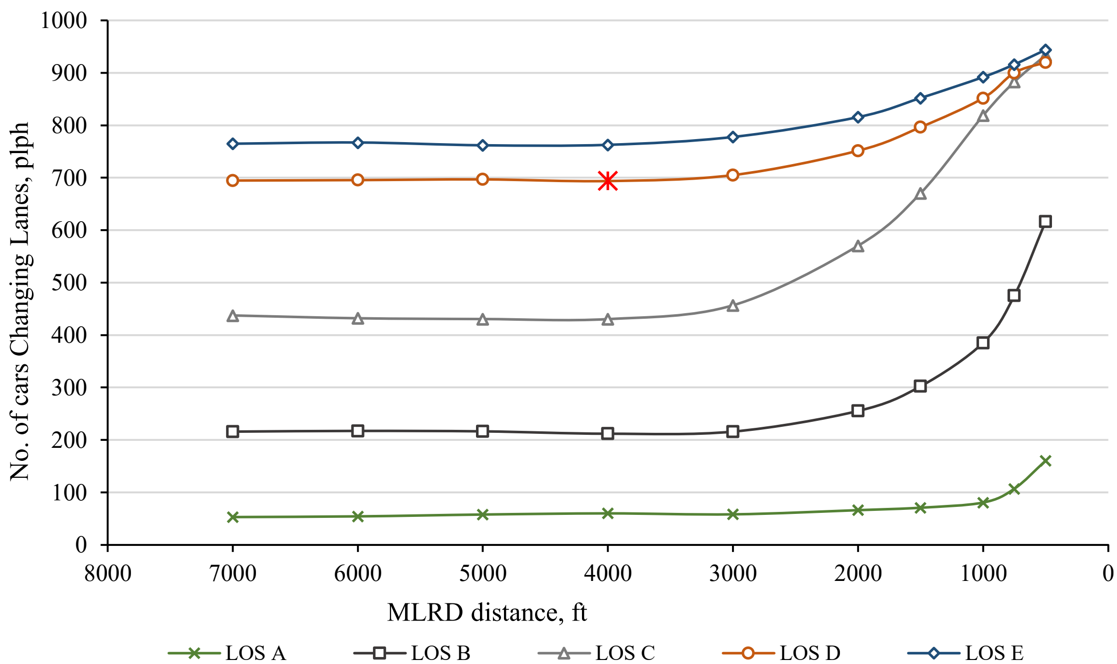
Generally, the area just upstream of the ingress point experiences a high activity of lane changing maneuvers as drivers that need to enter the MLs shift to the median lane(s) and those who do not want to use MLs move away from median lane(s). The evaluation tool in VISSIM also provides the number of vehicles that make lane changing maneuvers for a selected section, in this case the 500 feet zone before the ingress. The lane changing results are shown in Table 2.7 and graphed in Figure 2.7. It is important to note that this variable was normalized and reported as the number of lane changes per hour per lane, in order to appropriately compare the two directions, six lane section and three lane section, for eastbound and westbound, respectively.

As Figure 2.7 depicts, the number of lane changes increases with deterioration of LOS. This is to be expected as traffic volume is lower at high LOS, hence fewer number of vehicles changing lanes, and vice versa. Also, the results in Figure 2.7 indicate that the number of lane changes increases as the decision distance is reduced. This can be explained by the fact that the shorter the decision distance the closer to the ingress the decision to use or not use the ML is made, hence the later the lane changing maneuver. According to Figure 2.7(a), it appears that the number of lane changes per lane per hour starts to be constant at the decision distance of 3,000 feet or

longer for the westbound (3 lanes) directions. For the eastbound (6 lanes) direction (Figure 2.7(b)), the curves for all LOS are asymptotic after the decision distance of 4,000 feet.



(a)



(b)

Figure 2.7. Decision distance against number of cars changing lanes; (a) Westbound (b) Eastbound.

LOS D is used as the design LOS (TRB, 2010) to determine the optimum decision distance. A t-test is performed to check the significant difference between different points from 500 to 7,000 feet. The results indicate no significant difference between the decision distances from 3,000 and 4,000 feet for westbound and eastbound decision distance respectively. Therefore, considering number of vehicles changing lane, the minimum MLRD distance for the westbound direction is 4,000 feet whereas for the eastbound is 3,000 feet.

Following Distance

The bottleneck caused by weaving maneuvers just before the ingress point generally results in short following distances for vehicles near the ingress compared to vehicles further upstream. The average following/tailing distance in the 500 feet zone just before the ingress is shown in Table 2-6. The following/tailing distance is the distance between the preceding and the following vehicle. The results for this variable were not graphed but they show the same trend as that of the average speed. According to the following distance results shown in Table 2.7, as the decision distance increases, the following distance is decreased, and starts to remain constant after the decision distance of 2,000 to 3,000 feet depending on the LOS, for both directions.

LOS D is used as the design LOS (TRB, 2010) to determine the optimum decision distance. A t-test is performed to check the significant difference between different points from 500 to 7,000 feet. The results indicate no significant difference between the decision distances from 3,000 and 2,000 feet for westbound and eastbound decision distance respectively. Therefore, by considering the following distance, the minimum MLRD distance for the westbound direction is 2,000 feet whereas for the eastbound is 3,000 feet.

Concluding Remarks

This study has documented a complete methodology for simulation-based determination of the MLRD distance. The procedure included creating a VISSIM model the proposed roadway geometrics and the actual field data that were used to analyze the upcoming I-295 MLs in Jacksonville, Florida. Since the LOS D is widely used as the design LOS for freeways in both urban and suburban areas (AASHTO, 2011), the minimum MLRD distance values obtained at LOS D are adopted to inform the recommendations for the minimum MLRD distance. Table 2.7 shows a summary of the minimum MLRD distances, obtained graphically using Figures 2-5 and 2-6 (see solid symbols in Figures 2-5 and 2-6 for LOS D curves), and Table 2-6, based on each of the three traffic indicators: travel speed, number of vehicles changing lanes, and the following distance, for LOS D.

Table 2.8. Summary of Minimum MLRD Distance for LOS D

Direction Criteria	**Lanes**	**Minimum MLRD Distance for MOEs**			**Adopted Distance**
		Speed	**Following Distance**	**Lane Change**	
Eastbound	6	3,000	3,000	4,000	4,000
Westbound	3	2,000	2,000	3,000	3,000

NOTE: The distances are in feet

The values shown in Table 2.7 represent the minimum MLRD distance values after which the traffic indicators remained constant. It can be seen, from Table 2.7, that the minimum MLRD distance obtained was not the same for each of the three traffic indicators. Also, they were different for each direction – eastbound and westbound. For each direction, the largest value of the three was adopted as the recommended minimum decision distance, 4,000 feet for sections with six lanes prior to the ingress point and 3,000 feet for segments with three lanes prior to the ingress point. It should be noted that the obtained minimum MLRD distance of 3,000 feet for three lane

segments is slightly higher but comparable to the recommended minimum advanced sign placement of 2,625 feet (Chrysler, 2014).

The findings of this study can have policy implications and may be used twofold. First, transportation agencies can include this guidance in their traffic analysis and simulation guidelines, for example, in the state of Florida, the FDOT Traffic analysis handbook (FDOT, 2014). Engineering firms and researchers could therefore adopt this guidance, as there is currently none. Second, the suggested minimum MLRD distance can be used to inform transportation agencies on the minimum distance prior to ingress to place toll-pricing information, assuming that some drivers might decide whether to use MLs based on the price.

In light of new innovative initiatives such as connected and automated transportation systems, the optimum routing decision distance obtained in this study can also be used to provide a threshold for lane changes and maneuverability upstream the ML ingress point. This can be achieved by setting the maximum and minimum MLRD value for lane changes to reduce conflicts and improve traffic flow in the proximity of ML ingress.

Limitations and Opportunities

The study presented herein is the first step in addressing the required minimum MLRD distance issue for microscopic simulation models. In this study, the ML segment was only 3.3 miles. Since previous research (FDOT, 2013) has indicated that more drivers prefer to use MLs for longer commutes, the same procedure could be applied to a longer ML project to determine the influence of the length of the MLs on the minimum routing decision distance. Also, the study analyzed the total number of cars changing lanes and the mean speed on the section that is 500 feet prior to the ingress, but did not indicate the distance and speed distribution which shows the exact

position and speed respectively where each vehicle change lanes. This may show where a vehicle is making decision more clearly. Therefore, this provides a basis for future study.

The findings of this study suggest that the minimum MLRD distance should be different for sections with different numbers of lanes. In this study, only two segments, one with three (3) lanes and another with six (6) prior to the ingress, were studied. This study should be extended for sections with different numbers of lanes prior to ingress.

Lastly, in the Highway Capacity Manual, the LOS of MLs is determined by assuming that the ML is a basic freeway segment. In reality, managed lanes do not operate as basic freeway segments. Comprehensive research to investigate how the existing procedure for a basic freeway segment can be modified to evaluate LOS for MLs is warranted.

CHAPTER 3: PAPER 2

Improving Simulation Assessment of Express Lanes through Managed Lane Evaluation Output in VISSIM.

Paper 2 has been submitted to the *Journal of Transportation Research Board* (TRB) for consideration of presentation and publication in January 2018 in Washington, D.C.

Introduction

Most urban freeway corridors are characterized by recurrent congestion due to unmet demand, especially during the peak hours and non-recurrent congestion due to traffic incidents. Each year, traffic congestion costs billions of dollars. For example, time lost due to congestion is about 91 million hours, which is worth $2.4 billion annually (CPCS, 2015). Transportation agencies across the country are increasingly embarking on the use of managed lanes (MLs) as a way to reduce congestion. There are a handful of states, including Texas, Utah, California, Minnesota, and Florida, that have documented literature on ML (Baker et al., 2016; DKS, 2014; Sajjadi, 2017; Schultz et al., 2016; Velasquez et al., 2016). ML are lanes that are separated from GPLs, meant to provide higher level of mobility and improve trip time reliability. To use MLS, users have to pay tolls that vary based on the congestion level, a strategy referred to as congestion pricing.

Currently, in the U.S, most agencies use VISSIM-a microscopic-simulation software-for analyzing the effectiveness of MLs (PTV AG, 2015). Customarily, the in-built Managed Lanes Evaluation (MLE) outputs are used to assess the effectiveness of MLs, which include travel time, delay, speed, and revenue. The MLE output tool provides a simultaneous comparison of MLS and

GPLs at a selected regular time interval, 15 minutes interval for Florida, which allows for the evaluation of the benefits of using MLs in lieu of GPL.

The EVMLE tool computes performance measures starting at the beginning of the managed lane routing decision (MLRD) distance. Since there is no guidance on where to place the MLRD starting point, analysts are left to decide on the distance of the MLRD starting point from the ingress. There are several issues related to the EVMLE tool. First, since VISSIM considers performance measures of the ML to be from the beginning of the MLRD point, the results would vary depending on where the starting point is placed. The further it is from the ML ingress, the more the operational characteristics of the GPL would be weighted in the ML performance measures. Second, it is common to see an increased number of lanes upstream just before the ML ingress point. During congestion periods, speeds are lower on sections with fewer lanes, usually upstream the ML ingress. If the MLRD point extends further to sections with the fewest number of lanes, the reported MLE outputs would greatly underestimate the benefits of ML. Undoubtedly, operational benefits of MLs should be measured from the ingress to the egress of the MLs.

Study Objectives

The objectives of this study are twofold. First, the study demonstrates the effects of a MLRD distance to the performance measures reported using the Existing VISSIM Managed Lane Evaluation (EVMLE) tool. In order to accomplish this objective, several simulation scenarios are created, with varying MLRD distance from the ingress point, starting from 500 feet to 7,000 feet. The second objective is to develop a MLs performance evaluation tool that compares the performance of the MLs versus GPLs, starting at the ingress to the egress point, hence addressing limitations of the EVMLE tool. A computer algorithm is created in the Component Object Model (COM) interface, using a Visual Basic (VB) script. For demonstration purposes, only the operating

speed is used as a performance measure. To take into account variability of speeds on the network, space mean speed is used. Space mean speed is obtained by calculating harmonic speed in the study section.

Literature Synthesis

Currently, the state of Florida has several ML facilities in operation including I-95 (Miami), I-595 (Fort Lauderdale), and Veterans Expressway (Tampa). Dynamic toll lanes on other facilities such as I-75 (Tampa), I-4 (Orlando), and I-295 (Jacksonville) are on different stages of development, some in construction, and others in the planning and design phases. In fact, the Florida Department of Transportation (FDOT) requires MLs to be considered for all additional capacity on the interstates (FDOT, 2015).

The evaluation of MLs during planning and operational phases employ simulation – both macroscopic and microscopic. Several microscopic simulation packages including PARAMICS, CORSIM, VISSIM, and AISUM can be used for modeling freeway operations (Baykal-Gursoy et al., 2009). Each of these packages has its own strengths and limitations (PTV AG, 2015; Siemens, 2012; Steven et al., 2004). The first ML in Florida, I-95 in South Florida, was modeled using CORSIM during the planning stage (FDOT, 2010). After its completion, a follow-up empirical research study that evaluated the adjusted time-of-day pricing versus near-real time dynamic pricing also used CORSIM (Michalaka et al., 2010). Since then, VISSIM has been a prefered tool for modeling MLs due to its flexibility, in-built MLE module, and ease of customization through the COM environment. Some of the most recent studies that used VISSIM in evaluating MLs in Florida include Velasquez et al. (2015) and Machumu et al. (2016). Both studies used the EVMLE output tool for examining the benefits of MLs. As mentioned earlier, the EVMLE tool computes

the performance of ML from the beginning of the MLRD, which might be miles away upstream of the ingress of MLs.

Perhaps, the limitations of the MLE tool stems from the fact that the tool was not specifically developed for dynamically tolled ML facilities but rather for conventional MLs such as high occupancy vehicle (HOV) lanes. It should be noted that any freeway facility whose operational strategies are implemented and managed in response to changing conditions to increase freeway efficiency, maximize capacity, and manage demand, falls under the broad rubric of MLs (AASHTO, 2011). ML facilities include HOV lanes, dynamically tolled MLs, truck lanes, bus lanes, and other special use lanes. Most of the literature on modeling MLs using VISSIM focus on either HOV lanes (Gomes et al., 2004; Siuhi, 2006; Stamos et al., 2005; Zhang et al., 2009) or dynamically tolled MLs (DKS, 2014; Machumu et al., 2016 Sajjadi, 2017; Schultz et al., 2016; Velasquez et al., 2016). Although these two types of facilities are both considered as MLs, their operations are different in nature. For example;

- HOV lanes typically operate during peak hours only, mainly 7:00 AM to 9:00 AM and 4 PM to 6 PM, and during normal hours they become part of the GPLs. On the other hand, dynamically tolled MLs operate around the clock, with the price varying based on congestion level, regardless of the time-of-day.
- With an exception of a few cases where HOV lanes are separated from GPLs by vertical barrier, in most cases, for Florida in all cases, drivers can get in and out of the HOV lanes at any point because they are normally separated from the GPLs by two solid white lines.
- In Florida, HOV lanes are currently located on I-95 in Miami-Dade, Broward, and Palm Beach Counties. While in most cases there are no additional lanes at the beginning of these HOV lanes, there are a few cases with lane addition at the beginning of the HOV lanes. On

the other hand, in all cases, there is a gradual increase in number of lanes towards the ingress. As an illustration, considering Figures 3.1 through 3.3, in some cases like in Figure 3.1, the beginning of HOV lanes is not associated with lane increase (Figure 3.1) but in some cases there is a lane increase (Figure 3.2). Figure 3.3 illustrates a gradual lane increase for I-295 ML 0.4 miles from the ingress (from 4 to 5 total lanes) and 0.2 miles from the ingress (increase from 5 to 6 total lanes).

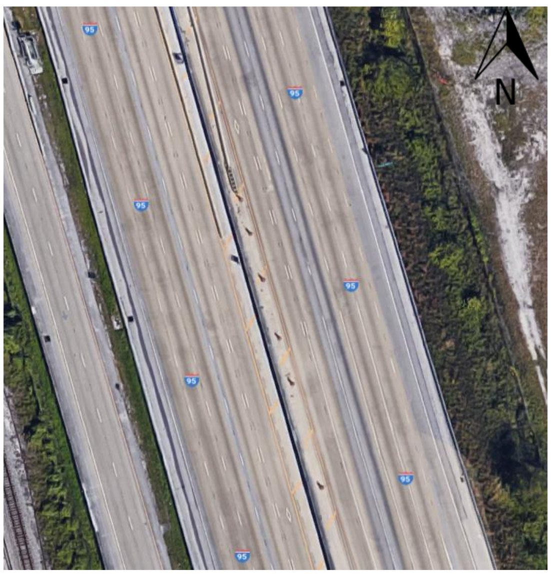


Figure 3.1. HOV ingress point along I-95 in Miami, Florida, northbound direction (Source: Google Earth).

Figure 3.2. HOV ingress point along I-95 in Miami, Florida southbound direction (Source: Google Earth).

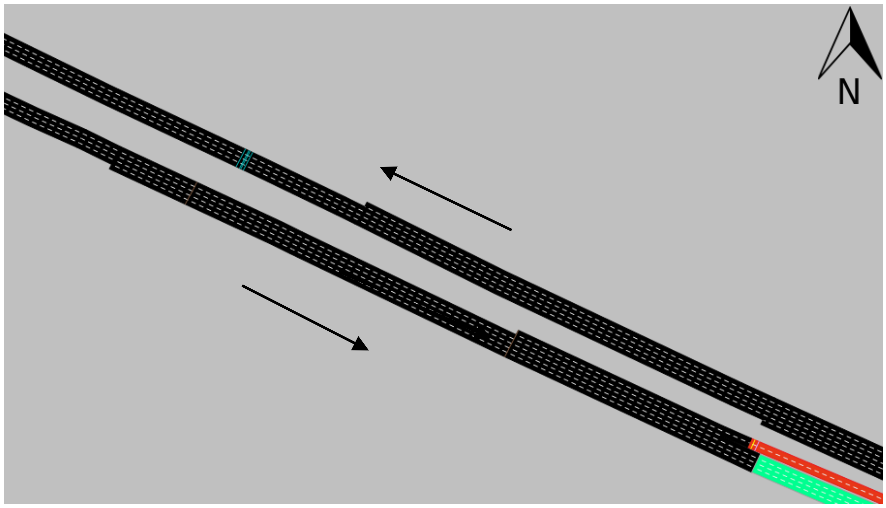


Figure 3.3. ML ingress setup on I-295 (VISSIM Model).

Bus lanes or truck restriction lanes are other types of MLs whereby some vehicle types are restricted from using lanes designated for trucks or buses. VISSIM has been used in several truck-lane restriction studies (Gomez et al., 2004; Siuhi, 2006; Venglar et al., 2002). In VISSIM, the truck restriction policy is emulated by filtering vehicles using the vehicle restriction object (PTV AG, 2015).

In the VISSIM software, when modeling MLs that are adjacent to GPLs, a MLRD has to be placed in the space between the static vehicle route and the ML ingress point. A MLRD point is the location were a decision whether to use the MLs or GPLs is made. As mentioned earlier, the MLRD starting point has to be placed downstream of the static route and upstream of the ingress point (gantry). The performance report by the EVMLE tool derives the performance measures of MLs and GPLs from the beginning of the MLRD. If the MLRD distance is extremely long, operational characteristics of the MLs maybe over weighted by operational characteristics before entering ML. The findings of this study are expected to provide insight on how different MLRD distances upstream the ingress of MLs affect the EVMLE output and propose a method that would address the limitations of the EVMLE.

Site Description

The objectives of this study were implemented using the 4.3 miles ML section on the I-295 beltway in Jacksonville, Florida. Specifically, the site starts at the State Road 13 (SR 13) interchange (Western end) to the I-295/I-95 system to system interchange on the East side of the study site. Figure 3.4 shows the location and proposed area of influence for the study. Since the same algorithm is to be implemented on both bounds of the ML, only the eastbound direction was taken into consideration and used in the analysis.

Figure 3.4. Location of the I-295 project in Duval County, Jacksonville. (Source: RS&H, 2015).

Methodology

Model Development

A freeway VISSIM model with GPLs and MLs was developed, including the five influencing arterials as shown in Figure 3.4. Each link was given a specific input volume based on the data that were collected by Reynold, Smith & Hills Inc., a consulting firm that conducted the feasibility study for the MLs. SYNCHRO was used for optimizing traffic signal timings for intersections that feed traffic on the freeway. The Ring Barrier Controller (RBC) files from

SYNCHRO were then loaded in VISSIM. Intersections along San Jose Boulevard, Old Saint Augustine Road, and Phillips Highway were taken into consideration since they had impacts on traffic along I-295. As mentioned earlier, only the eastbound direction was used for analysis; therefore, Table 3.1 depicts the vehicle input of the eastbound direction. Throughout the simulation process, demand is modified every 15 minutes, referred to as time segment/interval.

Table 3.1. Simulation Demand for Different Time Segment (Source; RS&H, 2015)

Time Segment	1	2	3	4	5	6	7	8	9	10	11
Time (Seconds)	0	900	1800	2700	3600	4500	5400	6300	7200	8100	9000
Demand (vph)	10189	9955	9825	9742	8966	8430	8350	8836	8446	7983	7810

vph – Vehicles per hour

The desired speed distributions along the section that are used in the VISSIM model development were obtained from the RITIS data, a database storing real-time data from microwave vehicle detectors. Speed distributions shown in Table 3.2 were derived from raw speed data reported in the RITIS database.

Table 3.2. Speed Percentiles for MLs and GPLs (Source; RITIS)

Percentiles, %	0	10	20	30	40	50	60	70	80	90	100
GPL (mph)	9	32	52.5	58.8	61.1	62.3	63.4	64.7	66.4	70	77.4
ML (mph)	40.6	63.8	65.2	66.3	67.4	68.6	70.8	75	76.8	78.3	89

mph – miles per hour

Figure 3.5 illustrates various components of the developed model. Construction of the network involves building of the roadway geometry and importing signal-timing data for signals in the influence area. Traffic volume input involves assigning origin-destination matrices to various routes. Lastly, various car-following parameters have to be adjusted until the calibration requirements are met. Once the model is complete, simulation involves visual observation and results extraction.

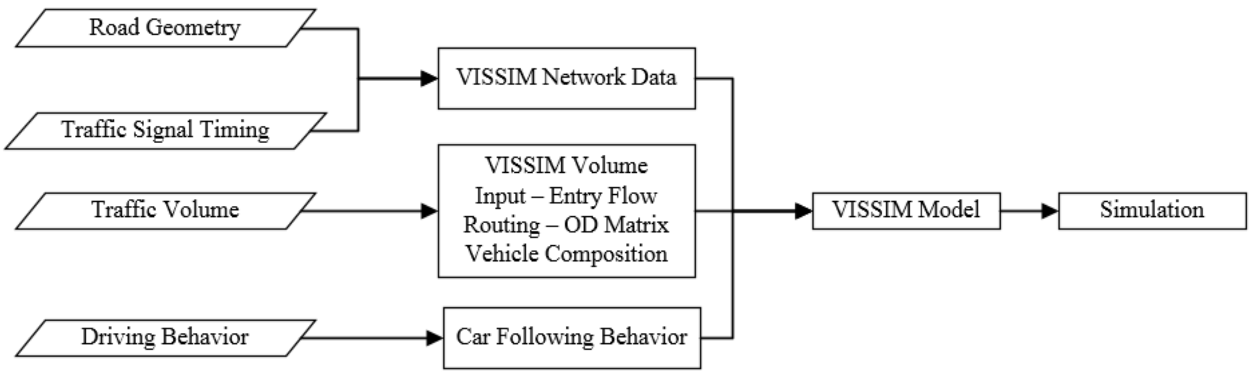


Figure 3.5. Experimental setup of VISSIM model development.

Car-Following Behavior

The VISSIM Software uses two Wiedemann car-following models: Wiedemann 74 for arterials and Wiedemann 99 for freeways. In this study, only the Wiedemann 99 model was used because it is designated for modeling freeways. In VISSIM, the Wiedemann 99 car-following model includes 10 tunable parameters. Table 3.3 below shows the car-following parameters modified from their default values. The parameters were adjusted according to the Traffic Analysis Handbook (FDOT, 2014) and a study by Sajjadi et al. (2017).

Table 3.3. Calibration Parameters

Parameters	Default	ML
CC0 (feet)	4.92	4.92
CC1 (s)	0.90	1.90
CC2 (feet)	13.12	39.37
CC4	-0.35	-0.70
CC5	0.35	0.70

CC0 standstill distance

CC1 headway time

CC2 following variation

CC3 threshold for entering following

CC4 & CC5 Positive and Negative following threshold respectively

Managed Lane Routing Decision, MLRD

In VISSIM, vehicles are required to follow a specific route. The MLRD that assigns vehicles to use MLs has to be set upstream of the ML. As illustrated in Figure 3.6, at the point of the MLRD, two routes are created: ML and GPL (PTV AG, 2015). A MLRD has to start at a point where drivers who want to use MLs would be able to make a decision and move to the inside lanes before reaching the ingress of the MLs. Vehicles in the outside lanes (see Figure 3.6) would need more room to change lanes and access the MLs.

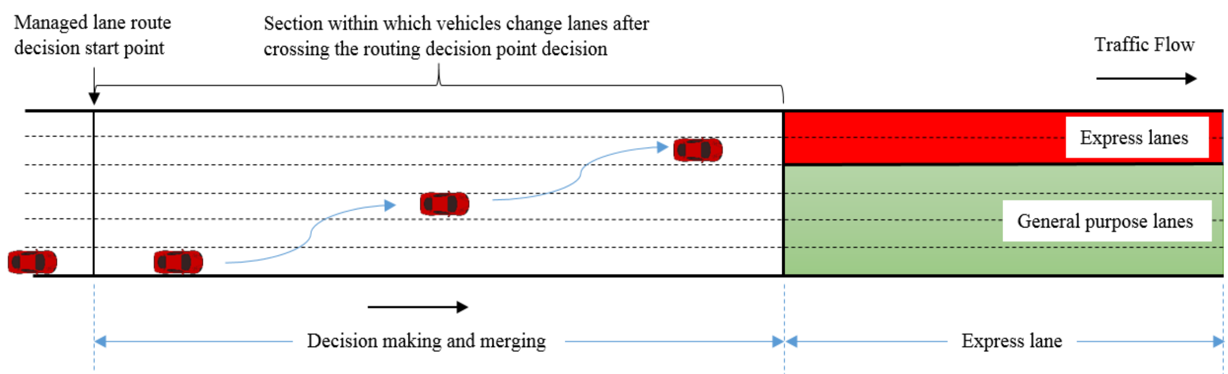


Figure 3.6. Modeling of MLs.

Data Collection Process

In this study, several performance measures, including travel time, speed, and density were collected. Travel time was computed by setting data collection points (DCPs) at the beginning and the end of the MLs. The time difference between the vehicle being detected at the beginning and the end of the MLs was considered the travel time. DCPs were also added at an interval of 1,500 feet on MLs to replicate the actual field conditions. These detectors continuously collect speeds of vehicles on MLs and after every 15 minutes (900 seconds), the speed measurements are averaged and used for density estimation. The estimated density is used to determine the toll amount for the next 15 minutes (the toll price is updated every 15 minutes); the same practice is performed in the actual toll computations.

ML Output Approaches

This study compares two approaches for determining the ML performance measures. As it has been alluded earlier, the first approach i.e., the EVMLE output tool, considers the section beginning at the MLRD starting point to the end of the ML route in calculating the performance measures. Thus, with the same traffic conditions on the MLs, the results would vary based on the upstream characteristics such as the location of the beginning of the MLRD, number of lanes upstream of the ingress and the congestion level before the beginning of the ML. In order to address shortcomings of the EVMLE tool, a new approach, referred to here as the proposed managed lane evaluation (PMLE) algorithm is discussed next.

Proposed Algorithm

The PMLE tool was implemented in VISSIM via the COM environment using a VB script. Figure 3.7 is a graphical depiction of the proposed approach. The PMLE uses two simultaneous algorithms, one for determining the measures of performance (left side of Figure 3.7) and another for toll computations (right side of Figure 3.7). More details of each algorithm are discussed next.

MLE script: The managed lane evaluation (MLE) script accesses several VISSIM containers, data collection measurements, vehicle travel-time measurements, and ML facilities. This script calculates the same attributes available in the EVMLE tool. The attributes include total travel-time savings, harmonic speeds, vehicle counts, and displayed tolls. The script is set to run from the start of the simulation with a period of 9,000 seconds at a resolution of one-tenth (1/10) of a second, i.e., ten (10) time step per simulation second. The performance measures are reported at 15-minute intervals (900 seconds) at which time the performance measures from this script are sent to the tolling script to update the toll price.

Tolling script: This script performs dynamic tolling calculations, similar to the in-built VISSIM dynamic tolling module but uses speeds obtained from MLE script. The tolling script uses density estimations based on speeds obtained from the MLE script. The Florida Turnpike toll-pricing table (Table 3.4) is to determine the toll price for the next 15 minutes. Table 3.4 shows the maximum and minimum tolls for different LOS and density. If the current toll is below the minimum or above the maximum rates for corresponding density, the minimum or maximum rates are applied respectively. If the current toll falls within the minimum or maximum toll range, then the current toll is applied.

Table 3.4. Toll Price Thresholds

LOS	**Traffic Density, V/m/l**		**Rate per Mile, $/Mile**	
	Min	**Max**	**Min**	**Max**
A	0	11	0.25	0.25
B	12	18	0.25	0.25
C	19	26	0.25	0.5
D	27	35	0.5	1.25
E	36	45	1.25	3.25
F	46	50	3.25	5.0

Min – Minimum
Max – Maximum
v/m/l – Vehicle per mile per lane
$/mile – dollar per mile

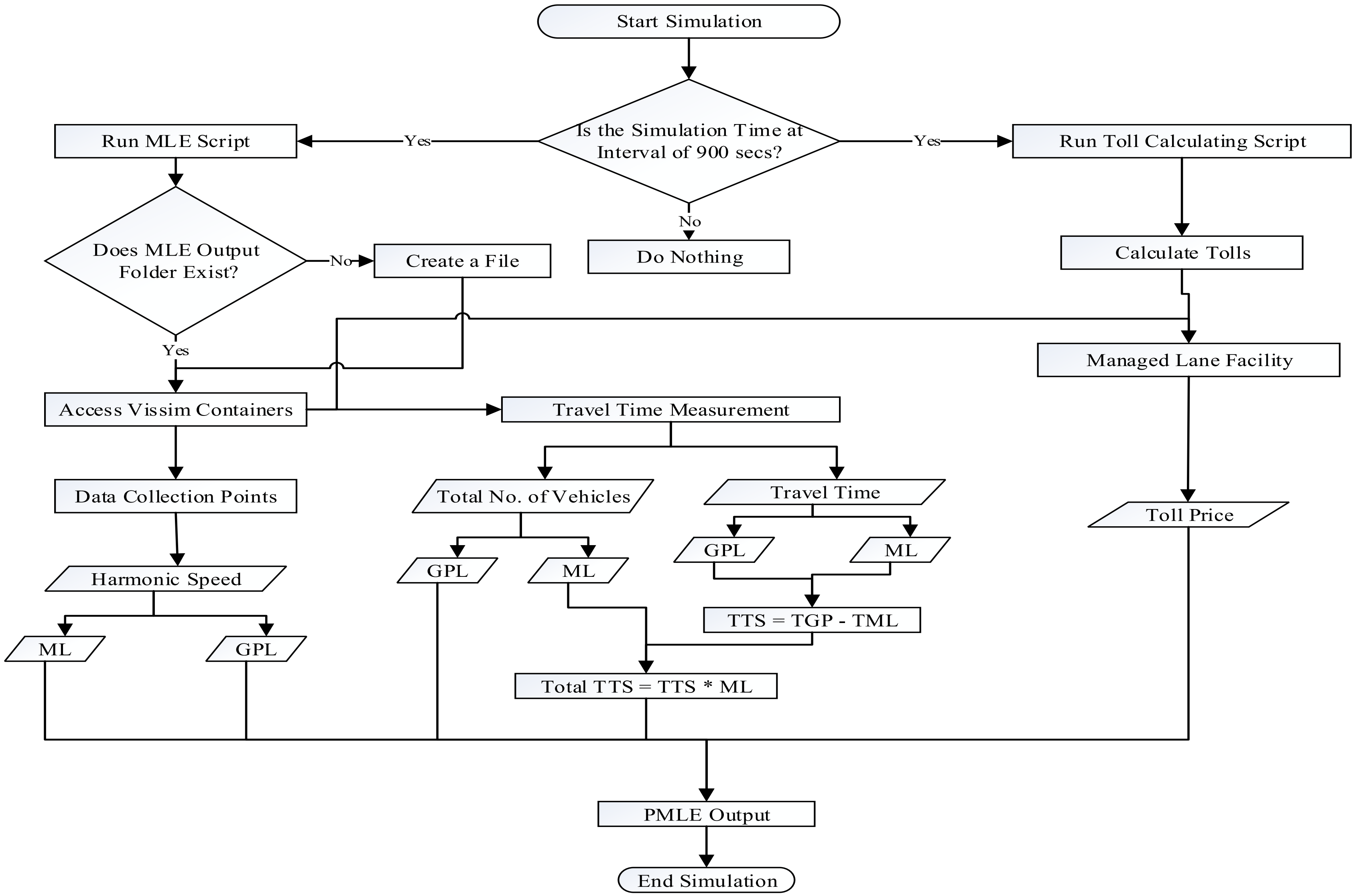


Figure 3.7. Operation of PMLE Algorithm (MLE & Toll Script).

Simulation Results

This section provides a detailed discussion of the analysis done in this study. First, the section shows the comparison of the two approaches based on the number of vehicles using MLs and GPLs. Second, the effects of the MLRD distance on the number of vehicles using the MLs and speed are discussed. Then, the drawbacks of using the EVMLE tool are illustrated. The last part of this section presents the results based on the PMLE algorithm. Figure 3.8 illustrates the lane configuration of the section of the highway where analysis was done.

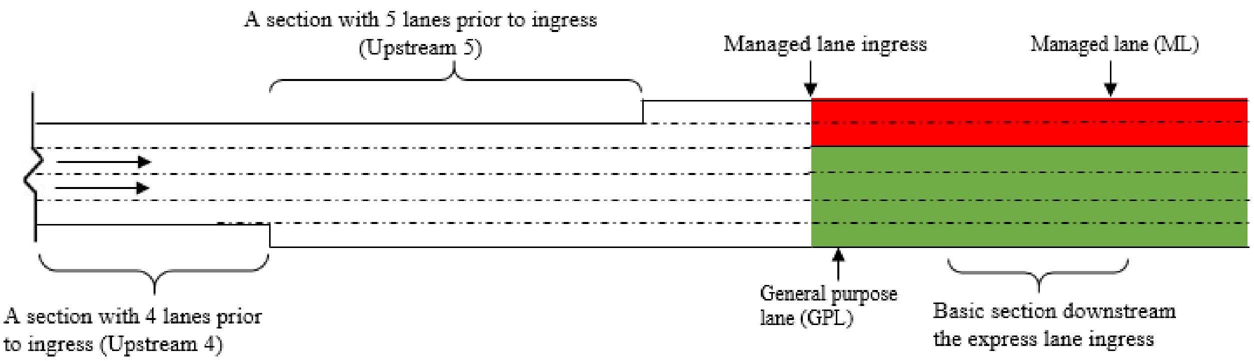


Figure 3.8. Section of the highway where analysis was done.

Normality Test for Speed Data

Since the statistical methods used in this study assume normally distributed data, it was imperative to test the data for normality. The speed results obtained from the EVMLE tool and the PMLE algorithm were tested for normality using the Anderson-Darling (AD) test. The AD test is known to be a more powerful normality test than other tests including the Kolomogrov-Smirnov, Kuiper, and Shaipiro-Wilk tests, which are based on a single distribution (Arshad et al., 2003; Shin et al., 2011). The AD test uses the AD value to determine which distribution best fits the data. The distribution with the lowest AD value is considered the best for the tested dataset. A *P*-value obtained from the AD test provides valuable information as to whether the sample data significantly differ from the empirical cumulative distribution function (Thas and Ottoy, 2003). Figures 3.9 and 3.10 show the plots of the AD tests for the speeds produced by

the EVMLE tool and the PMLE algorithm, respectively. Based on the results, the data appear to be normally distributed (Normal distribution has the smallest AD). Also, the normal distribution yielded the highest *p*-value and greater than 0.05, suggesting the non-rejection of the null hypothesis (null hypothesis: Data are normally distributed).

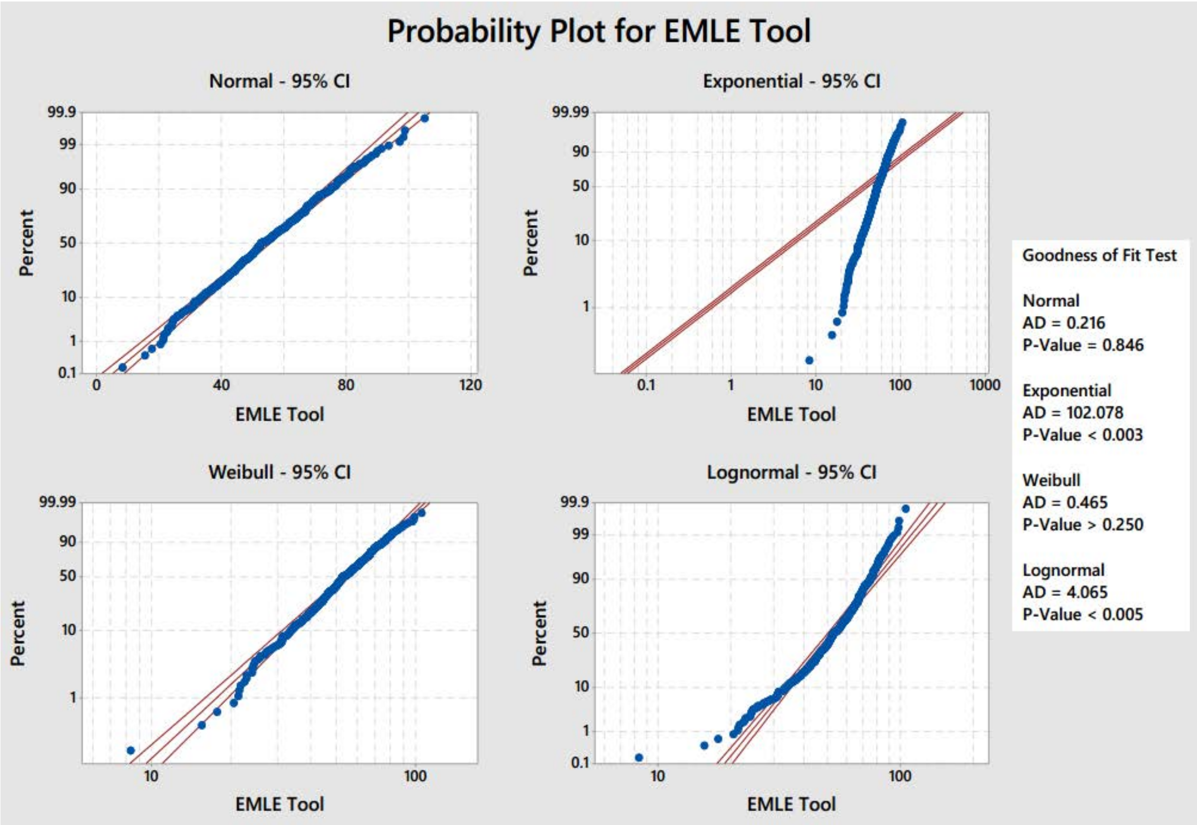


Figure 3.9. Distribution test of data obtained from EVMLE output.

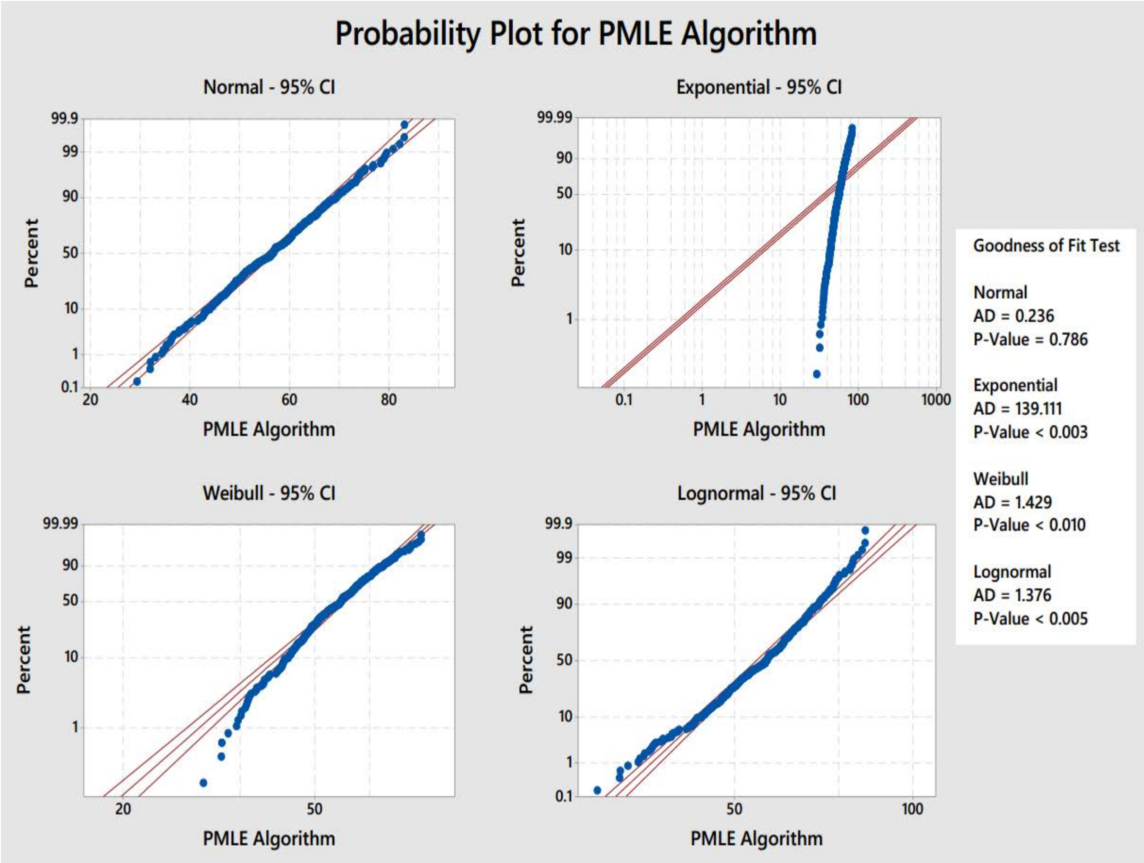


Figure 3.10. Distribution test of data obtained from PMLE output.

Model Verification

Both the EVMLE tool and the PMLE algorithms use the same discrete choice model that applies the logistic function based on cost and time-savings (Velasquez et al., 2016). Since the model inputs are the same, the number of vehicles using the MLs and GPLs determined by each of the two methods should be comparable. It is important to verify that the number of vehicles reported by the PMLE algorithm is not different from that recorded by the EVMLE tool. Table 3.5 shows a comparison of the outputs from the two MLE methods. The percentage difference of the two methods is small, less than 5%, for each MLRD scenario. A paired t-test was performed to evaluate whether the two methods cause a significant difference in the number of vehicles using the MLs and GPLs. According to the results shown in the bottom on Table 3.5, there is no significant difference between the usage of MLs and GPLs, at 95% confidence level (*p*-values of 0.239 and 0.980 for MLs and GPLs, respectively). The results also indicate that there is no significant difference between numbers of vehicles obtained using a script to those obtained using EVMLE output at the 95% CI. Therefore, the proposed algorithm computes the ML outputs by using a relatively similar number of vehicles.

Table 3.5. Average Number of Vehicles Using MLs and GPLs after every 15 minutes

MLRD Distance, feet	**ML, Vehicles PMLE**	**ML, Vehicles EVMLE**	**Difference**	**%**	**GPL, Vehicles PMLE**	**GPL, Vehicles EVMLE**	**Difference**	**%**
500	212	215	3	1.4	594	591	-3	-0.5
1,000	279	283	4	1.4	778	746	-32	-4.3
2,000	444	443	-1	-0.2	841	847	6	0.7
3,000	423	425	2	0.4	847	844	-3	-0.4
4,000	449	448	-1	3.8	866	871	5	0.6
5,000	430	433	3	1.9	894	903	9	1.0
6,000	453	455	2	2.1	837	846	9	1.1
7,000	473	470	-3	1.3	853	861	7	0.8
Paired t-test	n = 8 S = 93.8 SE = 33.7	n = 8 Sd = 95.7 SE = 33.2	t-value = -1.29 *p*-value = 0.239		n = 8 Sd =94.6 SE=33.5	n = 8 Sd =100.5 SE = 35.5	t-value = 0.03 *p*-value = 0.980	

Relationship between MLRD Distance and ML Usage

It is important to point out the effects of the MLRD distance on vehicle usage of MLs. The number of vehicles using the ML can be affected by the location at which drivers make a decision to use or not use the MLs. If the decision is made too close to the ingress during high traffic conditions, drivers in the outside lanes might not find enough gap to allow safe lane changing maneuvers to access the MLs before the ingress. Figure 3.11 shows the 15-minute average number of vehicle using the MLs for various MLRD distances. There is a difference between numbers of vehicles with models that have a MLRD below 2,000 feet (500 and 1,000 feet) to that having MLRD distance of above 2,000 feet. There are vehicles that are destined to use MLs but with a short MLRD distance, they are not able to change lanes to access the ingress of the MLs. Since there is variation of number of vehicles using MLs for MLRD distance less than 2,000 feet compared to the MLRD distance of 2,000 feet or longer, the MLRD distance of above 2,000 feet is used in the analysis for the rest of this manuscript.

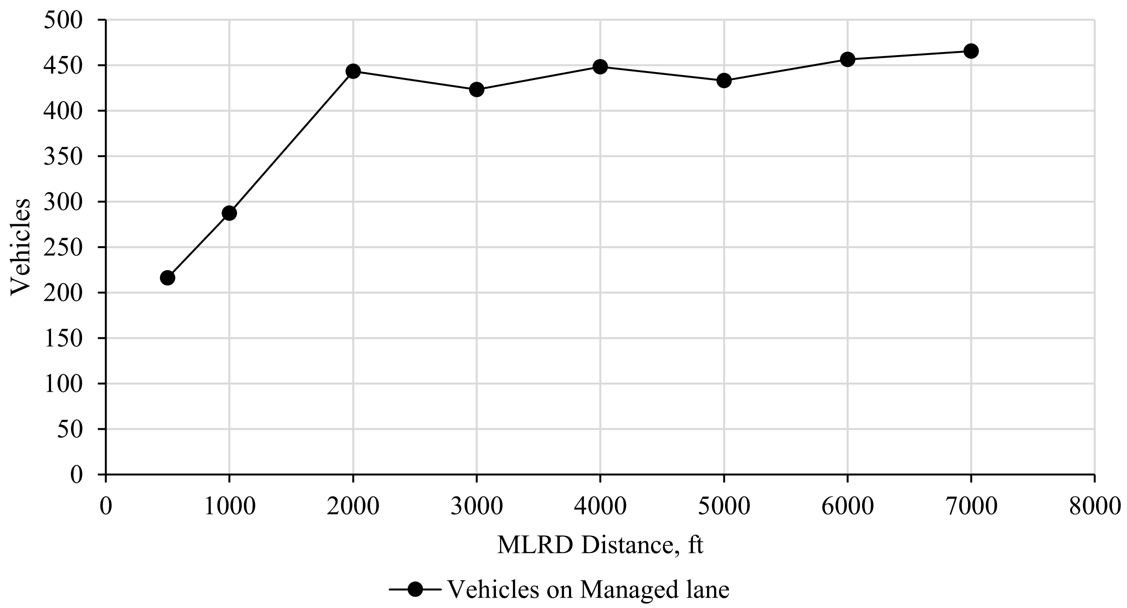


Figure 3.11. Average number of vehicles on ML after every 15 minutes.

Relationship between MLRD Distance and Speed

Table 3.6 shows speed measurements collected using different methods and how the results vary with the MLRD distance. The results obtained from the PMLE algorithm are shown in the second and third column while columns four and five show a list of average speeds reported by the EVMLE tool. The last three columns show the speeds collected using DCPs that were placed at respective locations as shown in Figure 3.11. By using speed-data collected using DCPs, the results in Table 3.6 (columns six and seven) indicate that the MLRD distance influences speed upstream of the ML ingress. Bottlenecks were observed upstream just prior to the ingress due to late decisions to use the MLs.

Table 3.6. Results of Speed Obtained Using EVMLE Tool and PMLE Algorithm

MLRD Distance, feet	**PMLE**		**EVMLE**		**Upstream 4 lanes**	**Upstream 5 lanes**	**Basic segment**
	ML	GPL	ML	GPL			
2,000	57.5	47.4	53.9	40.4	25.0	43.7	44.5
3,000	57.0	41.1	51.0	40.3	25.3	46.9	43.2
4,000	57.3	41.0	49.3	39.7	29.0	47.4	46.4
5,000	59.4	44.1	49.1	40.6	27.5	49.2	46.1
6,000	56.4	39.8	44.7	36.3	29.3	44.3	44.1
7,000	58.6	42.0	43.0	36.9	30.0	44.7	43.2

Speeds are in mph (miles per hour)

A graphical depiction of data in Table 3.7, which is shown in Figure 3.12 illustrates the effects of the MLRD distance on average speeds upstream of the ingress of the ML (dashed line), averaged for several four lane sections, and the GPL (solid line) parallel to the ML. In this case, also, in line with Figure 3.11, the MLRD distance of 2,000 feet appears to be a threshold after which speeds are asymptotic. These findings reinforce the importance of using a reasonable decision distance in modeling, as the simulation results can significantly vary if a short MLRD distance is adopted.

Table 3.7. Average Speed of Upstream Section and Basic Section

Decision Distance, ft	500	1,000	2,000	3,000	4,000	5,000	6,000	7,000
Upstream Sections, mph	9.7	18.1	24.1	25.2	26.2	27.5	29.3	29.5
Basic Segment, mph	60.8	57.5	44.5	43.2	46.4	46.1	44.1	43.2

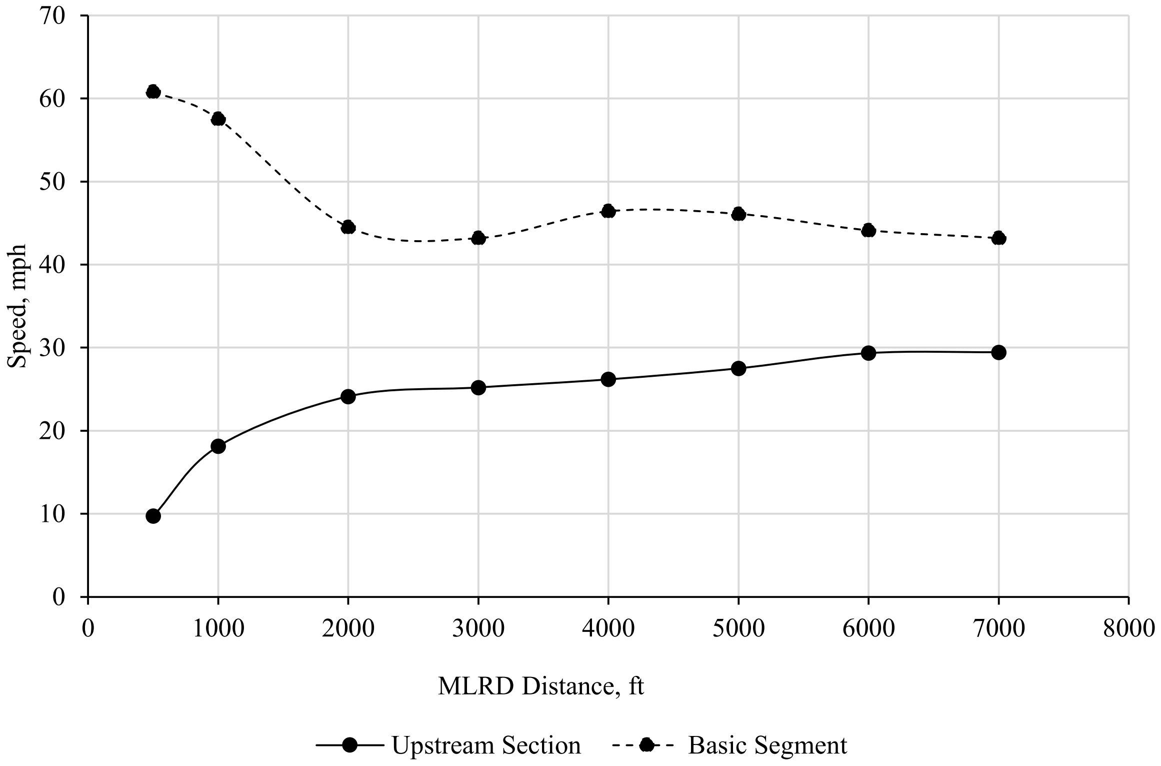


Figure 3.12. Vehicle speeds on the upstream section and basic freeway segment.

Speed Comparison between Various Sections Upstream Section and on the ML

Since the study site has a section with four lanes and increases to five lanes upstream of the ML ingress (see Figure 3.13), the two sections are considered separately in this comparative analysis. Also, the ML section and the GPL that run parallel are analyzed separately. The four lines shown in Figure 3.13 depict the speed differences observed for the above-mentioned four sections. According to the results shown in Figure 3.13, as expected, the highest average speed is obtained on ML (solid line with circular points). The second highest average speed is observed on the five-lane section. As expected, the section with the fewest total number of lanes (4 lanes) experienced the lowest average speed. Clearly, given the same

input, the five-lane section would be expected to have higher speeds due to density per lane reduction. Also, expectedly, the GPLs parallel to MLs had lower speeds than the MLs. This shows that if the MLRD is placed beyond the four-lane section, with the EVMLE, lower than actual average speeds will be reported for the MLs because the EVMLE computes the performance measures from the beginning of the MLRD. In this case, the reported ML speeds would consist of the weighted average of the four-lane, five-lane, and the ML section.

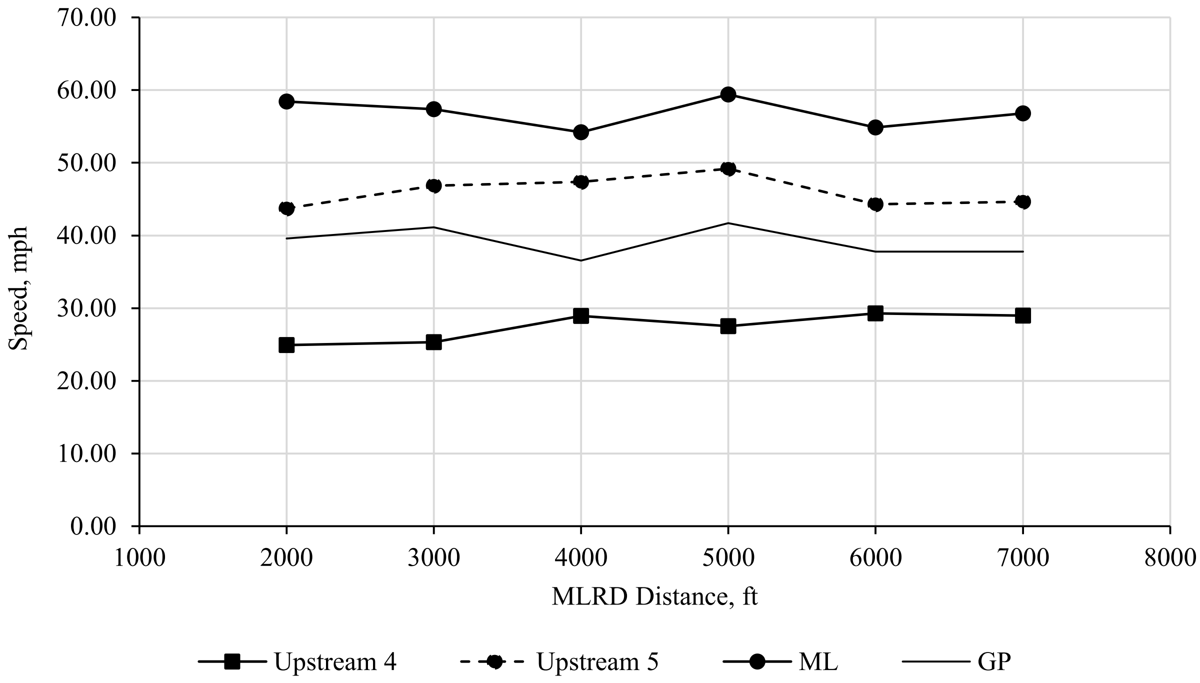


Figure 3.13. Speed of vehicles on lanes with different roadway section (with different geometric features) collected by the DCPs.

Comparison of EVMLE Tool and PMLE Algorithm

This section examines the differences in average speed outputs for ML using the EVMLE tool and PMLE algorithms. The comparison of the results from the EVMLE tool and the PMLE algorithm show an interesting discernible trend (Figure 3.14, data from Table 3.6, columns 2 and 3). The minimum MLRD distance of 2,000 feet was used based on the results presented in the aforementioned sections. While the average speeds for MLs for different MLRD distances obtained from the PMLE algorithm are relatively constant, for the same traffic

input, the average speeds reported by the EVMLE tool decrease with an increased MLRD distance. This trend is due to the fact that VISSIM computes the MLE outputs from the point when a vehicle is assigned a MLRD. Therefore, for shorter MLRD distances, only a small section of the upstream segment would be used for MLE measurements. For longer MLRD distances, say 7,000 feet, the MLE measurements would start upstream, for this case, more than a mile away. Hence, the measurements would potentially report lower speeds because of the inclusion of the upstream speeds, which are normally more congested. For this case, 7,000 feet upstream includes a four-lane section and a five-lane section. As collaborated by the results shown in Figure 3.13, a four-lane section has the lowest average speed of the entire study site, hence with the EVMLE output, the weighted average would significantly reduce the reported MLs speed, hence present unrealistic results. The PMLE algorithm, however, only considers the section from the ingress to the egress, hence results in little variations with the change in the MLRD distance.

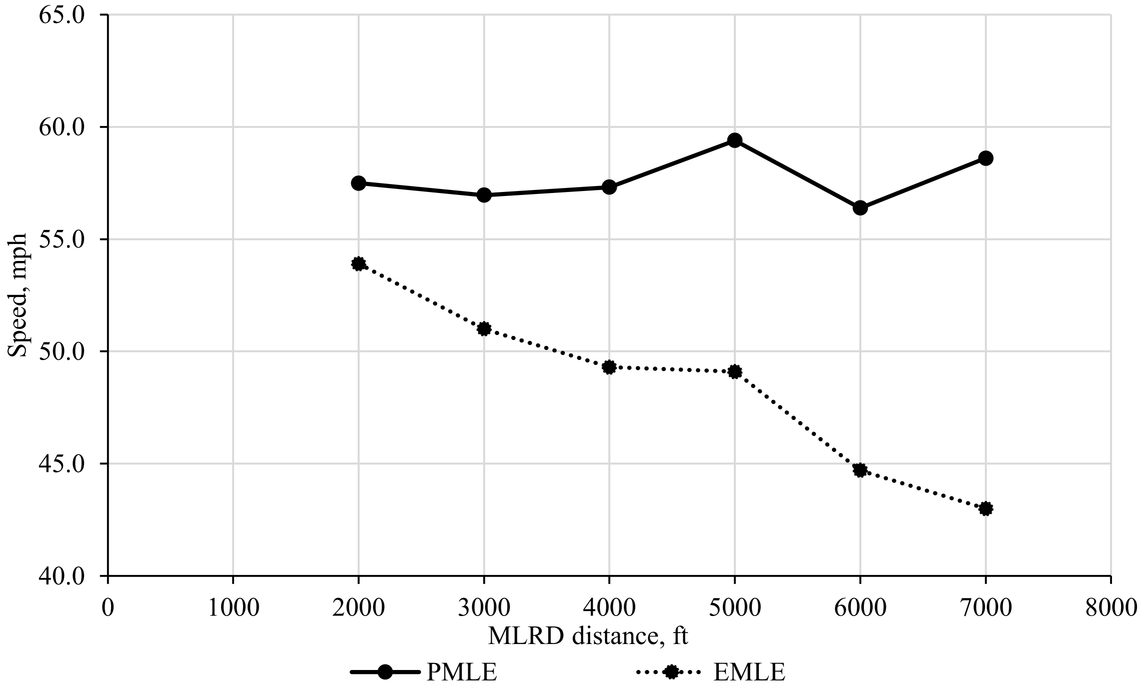


Figure 3.14. Variability of speed with MLRD distance.

Analysis of Variance (ANOVA) for Speeds using EVMLE tool Versus PMLE Algorithm

Table 3.8, a subset of Table 3.6, shows the speed values obtained using the PMLE and EVMLE methods for MLs and GPLs. The analysis of variance (ANOVA) was used to evaluate the difference in speeds reported by the two methods. The ANOVA compares the means of the response variables for various groups, also known as treatments. In this case, the two methods – EVMLE tool and PMLE algorithm – were the considered treatments. The speeds were evaluated for various scenarios of MLRD distances, also referred to as blocks in the ANOVA test. ANOVA uses the F value as a test statistic to determine the significance of the difference between means. The test was conducted at 95% confidence interval.

Table 3.8. Speed of MLs and GPLs for both EVMLE tool and PMLE Algorithm

MLRD Distance, feet	**MLs Speed**		**GPLs Speed**	
	PMLE	EVMLE	PMLE	EVMLE
2,000	57.5	53.9	47.4	40.4
3,000	57.0	51.0	41.1	40.3
4,000	57.3	49.3	41.0	39.7
5,000	59.4	49.1	44.1	40.6
6,000	56.4	44.7	39.8	36.3
7,000	58.6	43.0	42.0	36.9

Speeds are in mph (miles per hour)

Table 3.9 shows a summary of the ANOVA results. For ML, the F-value (27.73) is greater than the $F_{critical}$ (6.606) and the p-value is less than 0.05, therefore, there is a significant difference of speed between EVMLE tool and PMLE algorithm. As for the blocks (p-value = 0.542), which represent the MLRD distance, data does not suggest any effect of the MLRD distance on the speed outputs for the two methods.

Similar findings were obtained for the GPLs (see lower part of Table 3.9). For GPLs, the F-value (13.90) is greater than the $F_{critical}$ (6.608), and the p-value is 0.014, which is less than α of 0.05. Therefore, there is a significant difference between EVMLE and PMLE algorithms for both MLs and GPLs. The MLRD distance for both EVMLE and PMLE did not

show any significant difference, since the speed of EVMLE tool and PMLE algorithm are comparable for every decision distance (p-value = 0.113).

Table 3.9. ANOVA Analysis of Speeds between EVMLE Tool and PMLE Algorithm

MLs

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
MLRD Distances	41.450	5	8.290	0.906	0.542	5.050
EVMLE tool & PMLE Algorithm	253.920	1	253.920	27.763	0.003	6.608
Error	45.730	5	9.146			
Total	341.1	11				

GPLs

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
MLRD Distances	43.220	5	8.644	3.209	0.113	5.050
EVMLE tool & PMLE Algorithm	37.453	1	37.453	13.906	0.014	6.608
Error	13.467	5	2.693			
Total	94.140	11				

ANOVA Analysis of Speed among MLRD Distances

A separate ANOVA test was performed to evaluate the significance of the difference in speed values obtained at various MLRD distances for the two ML output methods – EVMLE tool and PMLE algorithm. In this case, the type of facility – MLs versus GPLs – were considered as blocks of the ANOVA test. The results of this test are summarized in Table 3-10. According to the results, for EVMLE tool, the F-value (5.375) for the decision distance is greater than the $F_{critical}$ (5.050) and the p-value is less than 0.05, suggesting a significant difference in speeds between MLRD distances. There is a significant difference in speeds between the MLs and GPLs facilities as well (p-value = 0.044). The results indicate that the speed results reported by the EVMLE tool vary significantly with the MLRD distance, both for MLs and GPLs. The ANOVA results are in line with the trend depicted in Figure 3.14 (see the dotted line), with speeds showing a discernible decreasing trend with the increase in the MLRD distance. On the other hand, the ANOVA test does not suggest any significant difference with varying MLRD distances when using the PMLE algorithm (p-value = 0.266). Consistent with

data plotted in Figure 3.10, findings suggest that when using the PMLE algorithm, the speed results for the ML are independent to the MLRD distance.

Table 3.10. ANOVA Analysis of Speeds between Decision Distances

ANOVA EVMLE tool

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
MLRD Distance	83.887	5	16.777	5.375	0.044	5.050
MLs and GPLs	268.853	1	268.853	86.134	0.000	6.608
Error	15.607	5	3.121			
Total	368.347	11				

ANOVA PMLE Algorithm

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
MLRD Distance	28.567	5	5.713	1.807	0.266	5.050
MLs and GPLs	687.053	1	687.053	217.330	0.000	6.608
Error	15.807	5	3.161			
Total	731.427	11				

Conclusions and Recommendations for Future Research

Dynamically priced toll lanes, also referred to as managed lanes (MLs), are increasingly recognized as a viable strategy to curb traffic congestion. Microscopic simulation models are used to analyze the performance of MLs during the planning phase and after deployment when they are in operation. In Florida and many other states, VISSIM is a preferred microscopic model for MLs due to the built-in modules for dynamic pricing and managed lane evaluation (MLE). The evaluation of ML performance is normally done using the VISSIM in-built MLE tool (EVMLE). In its computations, the EVMLE tool tracks vehicles from the beginning of the MLRD, upstream of the ingress, a location that differs depending on the analyst. This paper demonstrates the limitations of the EVMLE tool in reporting the MLs performance measures. The paper uses speed for demonstration purposes as the results implications can be easily expanded to other performance measures such as density, travel time, and delay.

Using speed to represent other performance measures, the results show that the longer the MLRD distance, the less accurate the results reported by the EVMLE tool. This is due to the inclusion of the segments prior to the ingress when computing the speed of the MLs vehicles. The study site consists of a four-lane section upstream of the MLs, which is widened to five lanes prior to the ingress. According to the results, when comparing speeds of different sections – four-lane, five-lane, GPLs, and MLs segments – using DCPs along those sections, the four-lane section had the lowest speed. If the MLRD distance is extended to or beyond the four lane section, the ML speed reported by the EVMLE tool would be the weighted average of the entire section (four-lane, five-lane, and ML section), hence lower than the actual speed of the ML section. Therefore, this paper proposes a modified algorithm that addresses the limitations of the EVMLE tool.

The PMLE algorithm is a stand-alone tool implemented in VISSIM by the use of the VB script via the COM environment. This tool computes the performance measures of the MLs

based on vehicles traversing from the ingress to the egress point. The (ANOVA) results suggest that the speeds reported by the PMLE algorithm are independent of the MLRD distance.

The methodology used for developing the PMLE algorithm is a standout and can be applied to similar simulation study. Variation of basic inputs such as position and length of MLs have to be changed. Although the PMLE algorithm produces reliable results, further improvements of lane changing behavior in VISSIM are desired for future applications through strengthening simulation models.

CHAPTER 4: OVERALL CONCLUSIONS AND RECOMMENDATIONS

The ML facilities have been increasingly recognized and accepted as a measure to combat traffic congestion. Many transportation agencies use VISSIM for traffic analysis of MLs. For accurate analysis of MLs, several simulations issues needs to be addressed. Using I-295 in Jacksonville as the case study, this thesis addressed two critical ML microscopic simulation issues – managed lane routing distance (MLRD) and managed lane evaluation (MLE). This chapter lists the main findings of this study, mentions limitations of the study, and provides recommendations for future work.

Managed Lane Routing Distance

Since I-295 Westbound has three lanes prior to the ingress of the managed lanes and the Eastbound has six lanes, this study established only the minimum MLRD thresholds for three and six lane scenarios. The thresholds were determined based on three performance measures – speed, number of lane changes, and the car following distance. Based on the results, for a three-lane section, a minimum MLRD of 3,000 feet was recommended. A minimum MLRD threshold of 4,000 feet was recommended for a 6-lane section.

Managed Lane Evaluation

This study has elaborated in great detail the limitations of the existing VISSIM Managed Lane Evaluation (EVMLE) tool. In short, for each vehicle that is assigned to use the MLs, the EVMLE tool starts to compute the measures of effectiveness the moment the decision to use the ML is made. This could be miles before the ingress of the MLs hence the tool tends to underestimate the performance measures of the MLs because the traffic conditions on the MLs are typically better than non-MLs. Because there is no guidance on what should be used as a MLRD, the managed lane evaluation results obtained by different analysts would differ based on the MLRD used. Another major contribution of this study was the development of

the algorithm that addresses the EVMLE limitations, the algorithm referred to as the proposed managed lane evaluation (PMLE) algorithm. Based on the results of this study, using speed to represent other performance measures, while the speeds reported by the EVMLE varied with the MLRD, the PMLE outputs were not dependent on the MLRD distance. The analysis of variance (ANOVA) results showed a significant difference between the evaluation results of the two approaches, the EVMLE tool and the PMLE algorithm, at 95% confidence level for various MLRD distance.

Limitations of the Study and Recommendations for Future Work

The case study used in this study is only 4.3 miles long. It would be interesting to conduct a similar study on a much longer ML facility. Also, the MLRD thresholds proposed by this study are limited to three-lane and six-lane sections only. Future work on sections with different number of lanes would provide clue to whether the findings of this study could be interpolated and extrapolated to facilities of different sizes. It should be noted that the PMLE tool is script-based. Knowledge of scripting is needed for one to use it as it would require minor adjustments for application to a different ML facility.

References for Chapter 1: Introduction

Cambridge Systematics Inc. (2014). 2014 I-95 Managed Lanes Monitoring Report. Fort Lauderdale.

Federal Highway Adminstration. (2004). Managed Lanes: A primer. Public Roads (Vol. 68). Washington, D.C.

Florida Department of Transportation. (2013). 95 Express Annual Report Project Status for Urban Partnership Agreement (Phase 1 Complete). Miami.

References for Chapter 2: Paper 1

AASHTO. (2011). A Policy on Geometric Design of Highways and Streets. Washington, D.C: Transportation Research Board of the National Academies.

Burgess, C. (2006). HOT Lane Buffer and Mid-Point Access. Washington State Department of Transportation, Report no. WA-RD 651.1, USA. Seattle.

California Department of Transportation (Caltrans) Division of Traffic Operations. (2003). High-Occupancy Vehicle Guidline for Planning, Design and Operations. Sacramento.

Certified Provider Credentialing Specialist. (2015). Unclogging America 's Arteries 2015 Prescriptions for Healthier Highways.

Chrysler, S. T., Williams, A., Schrock, S. D., & Llman, G. (2004). Traffic Control Devices for Managed Lanes.

FDOT Systems Planning Office. (2014). Traffic Analysis Handbook. Florida Department of Transportaion. Tallahassee.

Federal Highway Administration. (2009). Manual on Uniform Traffic Control Devices for Streets and Highways.

Fisher, G., & Goodin, G. (2005). Decision Framework for Selection of Managed Lanes Strategies.

Flolrida Department of Transportation. (2013). Florida Department of Transportation District Six. 95 Express Annual Report (Covering July 1, 2011 through June 30, 2012). Miami.

Florida Department of Transportation. (2010). SunGuide ® Disseminator (Vol. 450). Miami.

Florida Department ofTransportation. (2015). Express Lanes Handbook. Tallahassee.

Fu, L., & Kulkarni, R. (2013). Model-Based Dynamic Pricing Algorithm for Managed Lanes. *Transportation Research Record: Journal of the Transportation Research Board*, 2333, 74–79.

Gomes, G., May, A., & Horowitz, R. (2004). Congested Freeway Microsimulation Model

Using VISSIM. *Transportation Research Record: Journal of the Transportation Research Board*, 1876, 71–81.

Michalaka, D., Yin, Y., & Hale, D. (2013). Simulating High-Occupancy Toll Lane Operations. *Transportation Research Record: Journal of the Transportation Research Board*, 2396, 123–132.

PTV AG. (2015). PTV VISSIM 8 User Manual. Retrieved from

Reynolds Smith and Hills. (2015). System Intechange Modification Report. Jacksonville.

Sajjadi, S. (2017). Macroscopic and microscopic analyses of managed lanes on freeway facilities in South Florida. *Journal of Traffic and Transportation Engineering* (English Edition), 4(1), 61–70.

Siemens. (2012). Microscopic Traffic Simulation with V ISSIM. Munich.

Steven Jones, B. L., Sullivan, A. J., Naveen Cheekoti, P., Anderson, M. D., & Dillip Malave, P. (2004). Traffic Simulation Software Comparison Study.

Transportation Research Boards. (2010). Highway Capacity Manual 2010 (HCM2010). Washington, D.C.

United States Department of Transportation. (2015). Beyond Traffic 2045: Trends and Choices.

Velasquez, A., Mulandi, J., & Emam, E. (2016). An Application of Microscopic Dynamic Lane Choice Assignment for Express Lanes. In *Transportation Research Record: Journal of the Transportation Research Board*. Washington D.C.

Winston, C. (2013). On the Performance of the U.S. Transportation System: Caution Ahead. *Journal of Economic Literature*, 51(3), 773–824.

Zhang, G., Yan, S., & Wang, Y. (2009). Simulation-Based Investigation on High-Occupancy Toll Lane Operations for Washington State Route 167. *Journal of Transportation Engineering*, 135(10), 677–686.

References for Chapter 3: Paper 2

AASHTO. (2011). A Policy on Geometric Design of Highways and Streets. Washington, D.C: Transportation Research Board of the National Academies.

Arshad, M., Rasool, M. T., & Ahmad, M. I. (2003). Anderson Darling and Modified Anderson Darling Tests for Generalized Pareto Distribution. *Journal of Applied Sciences*, *3*(2), 85–88.

Baker, T., Moran, M., Pritchard, G., Lomax, T., Steadman, M., Glover, B., & Dell, B. (2016). Managed Lanes in Texas: A Review of the Application of Congestion Pricing.

Baykal-Gürsoy, M., Duan, Z., & Xu, H. (2009). Stochastic models of traffic flow interrupted by incidents. In *IFAC Proceedings Volumes (IFAC-PapersOnline)* (pp. 442–449).

Certified Provider Credentialing Specialist. (2015). Unclogging America ' s Arteries 2015 Prescriptions for Healthier Highways.

DKS. (2014). US 101 Express Lanes Traffic Operations Analysis Report Santa Clara Valley Transportation Authority. URS. Oakland , CA.

FDOT Systems Planning Office. (2014). Traffic Analysis Handbook. Florida Department of Transportaion. Tallahassee.

Florida Department of Transportation. (2010). SunGuide ® Disseminator (Vol. 40). Miami.

Florida Department of Transportation. (2013). 95 Express Annual Report Project Status for Urban Partnership Agreement (Phase 1 Complete). Miami.

Florida Department ofTransportation. (2015). Express Lanes Handbook. Tallahassee.

Gomes, G., May, A., & Horowitz, R. (2004). Congested Freeway Microsimulation Model

Using VISSIM. *Transportation Research Record: Journal of the Transportation Research Board*, *1876*, 71–81.

Hadi, M., Sinha, P., & Wang, A. (2007). Modeling Reductions in Freeway Capacity due to Incidents in Microscopic Simulation Models. *Transportation Research Record: Journal of the Transportation Research Board, 1999*, 62–69.

Machumu, K. S., Sando, T., Mtoi, E., Chimba, D., & Kwigizile, V. (2017). Simulation-Based Determination of the Minimum Routing Decision Distance for Managed Lanes: Case Study of I-295 in Jacksonville, Florida. Washington, D.C.

Michalaka, D., Yin, Y., & Hale, D. (2013). Simulating High-Occupancy Toll Lane Operations. *Transportation Research Record: Journal of the Transportation Research Board*, *2396*, 123–132.

PTV AG. (2015). PTV VISSIM 8 User Manual.

Reynolds Smith and Hills. (2015). System Intechange Modification Report. Jacksonville.

Sajjadi, S. (2017). Macroscopic and microscopic analyses of managed lanes on freeway facilities in South Florida. *Journal of Traffic and Transportation Engineering (English Edition)*, *4*(1), 61–70.

Schultz, G., Mineer, S., & Hamblin, C. (2016). An Analysis of Express Lanes in Utah. *Transportation Research Procedia*, *15*, 561–572.

Shin, H., & Jung, Y. (2011). Assessment of modified Anderson – Darling test statistics for the generalized extreme value and generalized logistic distributions.

Siemens. (2012). Microscopic Traffic Simulation with V ISSIM. Munich.

Siuhi, S. (2006). Simulation Analysis of Truck Restricted and HOV Lanes. Florida State

University.

Stamos, I., Kitis, G., Basbas, S., & Tzevelekis, I. (2012). Evaluation of a High Occupancy Vehicle Lane in Central Business District Thessaloniki. *Procedia - Social and Behavioral Sciences*, *48*, 1088–1096.

Steven Jones, B. L., Sullivan, A. J., Naveen Cheekoti, P., Anderson, M. D., & Dillip Malave, P. (2004). Traffic Simulation Software Comparison Study.

Thas, O., & Ottoy, J. P. (2003). Some generalizations of the Anderson–Darling statistic. *Statistics & Probability Letters*, *64*(3), 255–261.

Velasquez, A., Mulandi, J., & Emam, E. (2016). An Application of Microscopic Dynamic Lane Choice Assignment for Express Lanes. In *Transportation Research Record: Journal of the Transportation Research Board*.

Venglar, S., Fenno, D., Goel, S., & Schrader, P. (2002). Managed Lanes - Traffic Modelling. Austin.

Yin, Y., & Lou, Y. (2009). Dynamic Tolling Strategies for Managed Lanes. *Journal of Transportation Engineering*, *135*(2), 45–52.

Zhang, G., Yan, S., & Wang, Y. (2009). Simulation-Based Investigation on High-Occupancy Toll Lane Operations for Washington State Route 167. *Journal of Transportation Engineering*, *135*(10), 677–686.

VITAE

KELVIN S. MACHUMU

Education

University of North Florida, Jacksonville, Florida

Masters of Science in Civil Engineering, January 2016-Present (3.9 GPA)

University of Dar – es – Salaam, Tanzania

Bachelor of Science in Civil and Transportation Engineering, July, 2015 (3.5 GPA)

Relative Work Experience

Peters and Yaffee, Inc., Jacksonville, Florida. May 2017 - Present

Associate Traffic Engineer, Intern

1. Traffic Study and Traffic Operation Analysis (Signal warrant, land elimination study, Intersection analysis)
2. Quantity Takeoffs
3. Data Collection and Research
4. CADD Design (Microstation with Geopack)

University of North Florida, Jacksonville, Florida. August 2015-Present

Graduate Research Assistant (Transportation modeling, operations, and microscopic traffic simulation studies (VISSIM)

1. Collecting, processing, interpreting, analyzing, and compiling traffic data obtained for research projects.
2. Worked on a FDOT sponsored project "Evaluating processes in relation to Transportation System Management and operation TSM&O with FDOT.

Graduate Teaching/Tutorial Assistant

1. Preparing and carrying out lab tutorials for Microstation (SS4) with Geopack, spring 2016 and Fall, 2016. Lab involved creating roadway centerline, corridor modelling, superelevation, template design, roadway and profile sheets and cutting sheets.
2. Preparing and carrying out lab tutorials for Arc GIS.
3. Tutorial Assistant for Transportation Management class, Spring 2016 and Spring 2017
4. Tutorial Assistant for Geomatics class spring 2016 and spring 2017.

Publications

Published Papers

1. Establishing the Minimum Routing Decision Distance for Express Lanes-Journal of Advances in Transportation Studies.

Peer-reviewed papers conference proceedings

1. Simulation-Based Determination of the Minimum Routing Decision Distance for Managed Lanes: Case Study of I-295 in Jacksonville, Florida. Transportation Research Board, Paper No. 17-05178, Washington D.C., January 2017.
2. Simulation-Based Comparative Performance Measures for I-295 Express Lanes in Jacksonville, Florida. Transportation Research Board, Paper No. 17-06536, Washington D.C., January 2017.
3. Using naturalistic driving data to analyze the effects of drivers’ age deceleration on safety and travel time, a podium presentation done at the Fifth International Naturalistic Driving Research Symposium Blacksburg, Virginia from August 30-September 1, 2016.
4. Impact of pedestrian countdown signals on vehicle approach speed for drivers of different age at signalized intersections. Transportation Research Board, Paper No. 17-06518, Washington D.C., January 2017.

Campus Involvement and Volunteer Experience

1. Member of the Institute of Engineers Tanzania (IET).
2. National Society of Black Engineers, UNF chapter.