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SIMULATION OF THE IMPACT OF CONNECTED AND AUTOMATED VEHICLES AT A SIGNALIZED INTERSECTION

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Intersections are locations with higher likelihood of crash occurences and sources of traffic congestion as they act as bottlenecks compared with other parts of the roadway networks. Consequently, connected and automated vehicles (CAVs) can help to improve the efficiency of the roadways by reducing traffic congestion and traffic delays. Since CAVs are expected to take control from drivers (human control) in making many important decisions, thus they are expected to minimize driver (human) errors in driving tasks. Therefore, CAVs potential benefits of eliminating driver error include an increase in safety (crash reduction), smooth vehicle flow to reduce emissions, and reduce congestion in all roadway networks. Since CAV implementations are currently in early stages, researchers have found that the use of traffic modeling and simulation can assist decision makers by quantifying the impact of increasing levels of CAVs, helping to identify the effect this will have on future transportation facilities. The main objective of the current study was to simulate the potential impacts CAVs may have on traffic flow and delay at a typical urban signalized intersection. Essentially, to use a microscopic traffic simulation software to test future CAV technology within a virtual environment, by testing different levels of CAVs with their associated behaviors across several scenarios simulated. This study tested and

simulated the impact of CAVs compared with conventional vehicles at a signalized intersection. Specifically, I analyzed and compared the operations of the signalized intersection when there are only conventional vehicles, conventional vehicles mixed with CAVs, and when there are only CAVs.

The most current PTV Vissim 11 software was used for simulating different percentages of three different types of CAVs and conventional vehicles in the traffic stream at the intersection. These are three different levels of automated vehicles that are already installed in PTV Vissim 11, which are AV cautious, AV normal, and AV all-knowing. All these automated vehicles were tested in different scenarios in this study. Real data from an existing signalized intersection in the city of Dayton, Ohio were used in the PTV Vissim software simulation. The traffic count data used in the Vissim intersection model were for morning peak hour. The existing signal timing data for the intersection used were first optimized using Synchro. The results from Vissim simulation show that CAVs could reduce the queue delay by about 12%, the stopped delay by about 17%, the vehicle travel time by about 17%, and the queue length by about 22%. Because of that, CAVs can substantially reduce congestion at urban signalized intersections.

Dedicated

to my parents, family, and friends.

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TABLE OF CONTENTS

ABSTRACTiii
DEDICATIONv
ACKNOWLEDGMENTS vi
LIST OF FIGURES xiii
LIST OF TABLES xx
LIST OF ABBREVIATIONS AND NOTATIONS xxi
CHAPTER I INTRODUCTION 1
1.1 Introduction
1.2 The significance of the Study2
1.3 Connected and Autonomous Vehicles
1.4 Connected and Automated Vehicles and Transportation Safety
1.5 Connected and Autonomous Vehicles and Mobility
1.6 Problem Statement
1.7 Objectives of the Study9
1.8 Organization of the Thesis 10
CHAPTER II LITERATURE REVIEW11
2.1 Introduction
2.2 Automation in Transportation11

2.3 Connected and Automated Vehicles on Roads and Intersections	13
2.4 Compromises to Safety	15
CHAPTER III DATA COLLECTION AND METHODOLOGY	18
3.1 Source of Data	18
3.1.1 Intersection Data	18
3.1.2 Traffic Data	20
3.1.3 Traffic Signal Data2	22
3.1.4 Driving Behavior Parameters for Autonomous Vehicles	22
3.1.4.1 Following Behavior Model Parameters	24
3.1.4.2 Lane Changing Behavior Logic Data	26
3.1.4.3 Behavior at Signal Control Data	27
3.2 Methodology	28
3.2.1 Comparison Scenarios	29
3.2.2 Sensitivity Analysis	30
3.2.3 Microscopic Simulation Development	31
3.2.3.1 Building PTV Vissim Base Model	31
3.2.3.2 Simulation Parameters	35
3.2.3.3 Base Data in PTV Vissim	37
3.2.3.3.1 PTV Vissim Acceleration and Deceleration Functions	37
3.2.3.3.2 Desired Speed Distribution	40

3.2.3.3 Vehicle Types and Vehicle Class	42
3.2.3.3.4 Driving Behaviors and Link Behavior Type	44
3.2.4 Signal Design Development	46
3.2.5 Evaluation Method	47
3.2.5.1 Data Collection Points	
3.2.5.2 Queue Counters	49
3.2.5.3 Vehicle Travel Time	50
CHAPTER IV RESULTS AND DISCUSSION	53
4.1 Introduction	53
4.2 Simulation Results for the Optimized Signal Timing in PTV Vissim	53
4.3 Simulation Results for Comparison Scenarios	60
4.4 Summary Results for Comparison Scenarios	67
4.5 Simulation Results for Sensitivity Analysis	71
4.6 Summary Results for Sensitivity Analysis	76
CHAPTER V CONCLUSIONS AND RECOMMENDATIONS	79
5.1 Conclusions	79
5.2 Recommendations	81
REFERENCES	82
APPENDIX A Source of Data	88
APPENDIX B The Optimized Signal Timing Design by Synchro 10	91

APPENDIX C	The Intersection Model by PTV Vissim	93
APPENDIX D	The Signal Timing Design in PTV Vissim1	12
APPENDIX E	Simulation Results by PTV Vissim for The Comparison Scenarios 1	14

LIST OF FIGURES

Figure 3.1 Location of Main St and Nottingham Rd Intersection (from Google Maps) . 19
Figure 3.2 Geometry and Layout of the Study Intersection (from Google Earth)
Figure 3.3 Turning Movement Data Used in Simulation Analysis
Figure 3.4 Existing Traffic Signal Timing Details
Figure 3.5 Following Distance Parameters for Car-Following Model
Figure 3.6 Example of the number of interaction vehicles and objects
Figure 3.7 A Snapshot of PTV Vissim 11 – Scenario Management
Figure 3.9 Units Tab in PTV Vissim (PTV Group 2018)
Figure 3.10 Background Image of the Study Site in PTV Vissim
(Bing Maps Aerial View)
Figure 3.11 Intersection Layout in PTV Vissim Using Links and Connecters
Figure 3.12 A Snapshot of PTV Vissim Links Definition for a SB Link approach of
the Study Intersection
Figure 3.13 Reduced Speed Areas of the Intersection Model in PTV Vissim
Figure 3.14 Conflict Areas of the Intersection Model in PTV Vissim
Figure 3.15 Simulation Parameters in PTV Vissim
Figure 3.16 A Snapshot of PTV Vissim Functions Page
Figure 3.17 Example of the Assumption for Conventional and Automated Vehicles'
Maximum Acceleration in PTV Vissim
Figure 3.18 Example of the Assumption for Conventional and Automated Vehicles'
Desired Acceleration in PTV Vissim

Figure 3.19 Example of the Assumption for Conventional and Automated Vehicles'
Maximum Deceleration in PTV Vissim 40
Figure 3.20 Example of the Assumption for Conventional and Automated Vehicles'
Desired Deceleration in PTV Vissim
Figure 3.21 Desired Speed Distribution for Conventional and Automated Vehicles in
PTV Vissim
Figure 3.22 Vehicle Types for the Simulation Model in PTV Vissim
Figure 3.23 Example of Vehicle Functions of Vehicle Types in PTV Vissim
Figure 3.24 Vehicle Classes/Vehicle Types for the Simulation Model in PTV Vissim 44
Figure 3.25 A Snapshot of Driving Behaviors Available in PTV Vissim
Figure 3.26 Example of an AV All-knowing Car Following Model in PTV Vissim 45
Figure 3.27 Link Behavior Types / Driving Behaviors by Vehicle Class in
PTV Vissim
Figure 3.28 the Optimized Signal Timing by Synchro Software
Figure 3.29 Optimized Traffic Signal Phase Diagram by Synchro
Figure 3.30 Signal Timing in PTV Vissim
Figure 3.31 Setup Attributes in Evaluation Configuration in PTV Vissim
Figure 3.32 Data Collection Points for the Intersection Simulation Model in
PTV Vissim
Figure 3.33 Queue Counters for the Intersection Simulation Model in PTV Vissim 49
Figure 3.34 Vehicle Travel Time Settings for the intersection model in PTV Vissim 50
Figure 3.35 Vehicle Travel Time Measurement on the intersection layout model in
PTV Vissim

Figure 3.36 Illustration of Stopped Delay as Part of Travel Time
Figure 4.1 Simulation Results for Average Queue Delay at the Intersection Comparing
Existing and Optimized Traffic Signal Timings
Figure 4.2 Simulation Results Showing Decreasing Percentages in Average Queue
Delays at the Intersection Due to Traffic Signal Timing Optimization
Figure 4.3 Simulation Results for Average Stopped Delay at the Intersection Comparing
Existing and Optimized Traffic Signal Timings
Figure 4.4 Simulation Results Showing Decreasing Percentages in Average Stopped
Delays at the Intersection Due to Traffic Signal Timing Optimization
Figure 4.5 Simulation Results for the Average Travel Time at the Intersection
Comparing Existing and Optimized Traffic Signal Timings 57
Figure 4.6 Simulation Results Showing Decreasing Percentages in Average Travel
Times at the Intersection Due to Traffic Signal Timing Optimization
Figure 4.7 Simulation Results for Average Queue Length at the Intersection Comparing
Existing and Optimized Traffic Signal Timings59
Figure 4.8 Simulation Results Showing Decreasing Percentages in Average Queue
Lengths at the Intersection Due to Traffic Signal Timing Optimization 59
Figure 4.9 Simulation Results of the Average Queue Delay for all Scenarios in
this Study61
Figure 4.10 Percent Changes in Simulated Results of Average Queue Delays for
all Scenarios
Figure 4.11 Simulation Results of Average Stopped Delays for all Scenarios

Figure 4.12 Percent Changes in Simulation Results of Average Stopped Delays for
All Scenarios
Figure 4.13 Simulation Results of Average Vehicle Travel Time for all Scenarios in
this Study
Figure 4.14 Percent Change in Simulation Results of Average Vehicle Travel Time for
all Scenarios
Figure 4.15 Simulation Results of Average Queue Lengths for all Scenarios in
this Study
Figure 4.16 Percent Changes in Simulation Results of Average Queue Lengths in
All Scenarios
Figure 4.17 Overall Intersection Average Queue Delay for Each Scenario
Figure 4.18 Overall Intersection Average Stopped Delay for Each Scenario
Figure 4.19 Overall Intersection Average Vehicle Travel Time for Each Scenario 69
Figure 4.20 Overall Intersection Average Queue Length for Each Scenario
Figure 4.21 Overall Intersection Maximum Queue Length for Each Scenario
Figure 4.22 Sensitivity Analysis Results for SB Movement in Scenario 2
Figure 4.23 Sensitivity Analysis Results for NB Movement in Scenario 2
Figure 4.24 Sensitivity Analysis Results for WB Movement in Scenario 2
Figure 4.25 Sensitivity Analysis Results for EB Movement in Scenario 2
Figure 4.26 Sensitivity Analysis Results for SB Movement in Scenario 4
Figure 4.27 Sensitivity Analysis Results for NB Movement in Scenario 4
Figure 4.28 Sensitivity Analysis Results for WB Movement in Scenario 4
Figure 4.29 Sensitivity Analysis Results for EB Movement in Scenario 4

Figure 4.30 Comparing Average Quaue Lengths as Traffic Demand Increases for
the Entire Intersection77
Figure 4.31 Percentage Change in Average Queue Lengths for CAVs Scenarios as
Compared with Conventional Vehicles (Base Scenario)
Figure A-1 Northbound Segment for the Intersection
Figure A-2 Westbound Segment for the Intersection
Figure A-3 Southbound Segment for the Intersection
Figure A-4 Eastbound Segment for the Intersection
Figure A-5 Turning Movement Peak Hour Data from LJB Inc
Figure B-1 Intersection layout in Synchro
Figure B-2 Optimized Signal Timing by Synchro
Figure B-3 Optimized Signal Timing by Synchro
Figure B-4 Optimized Signal Timing by Synchro
Figure C-1 N Main Street and Nottingham Road Intersection Layout and the
Background Image in PTV Vissim92
Figure C-2 Intersection Layout and the Background Image in PTV Vissim
Figure C-3 Intersection Layout (Links and Connecters) in PTV Vissim
Figure C-4 Intersection Layout (Links and Connecters) in PTV Vissim
Figure C-5 Intersection (3D Model) in PTV Vissim
Figure C-6 Intersection (3D Model) in PTV Vissim
Figure C-7 Intersection (3D Model) in PTV Vissim
Figure C-8 Southbound Pocket Lane in PTV Vissim
Figure C-9 Eastbound Pocket Lane in PTV Vissim

Figure C-10 Vehicle Types in PTV Vissim
Figure C-11 Vehicle Classes / Vehicle Types in PTV Vissim
Figure C-12 Driving Behaviors in PTV Vissim
Figure C-13 Link Behavior Types / Driving Behaviors by Vehicle Class
Figure C-14 Desired Speed Distribution of the Conventional Vehicle in PTV Vissim 99
Figure C-15 Desired Speed Distribution for Autonomous Vehicle in PTV Vissim 99
Figure C-16 Max Acceleration of Conventional Car & Conventional Bus in
PTV Vissim 100
Figure C-17 Maxi Acceleration of Autonomous Car & Autonomous Bus in
PTV Vissim 101
Figure C-18 Desired Acceleration of Conventional Car & Conventional Bus in
PTV Vissim 102
Figure C-19 Desired Acceleration of Autonomous Car & Autonomous Bus in
PTV Vissim
Figure C-20 Max Deceleration of Car & Bus in PTV Vissim
Figure C-21 Max Deceleration of Autonomous Car & Autonomous Bus in
PTV Vissim 105
Figure C-22 Desired Deceleration of Conventional Car & Conventional Bus in
PTV Vissim
Figure C-23 Desired Deceleration of Autonomous Car & Autonomous Bus in
PTV Vissim 107
Figure C-24 Example; the Vehicle Compositions for the Vehicle Input in Scenario 1.108
Figure C-25 Example; the Vehicle Compositions for the Vehicle Input in Scenario 5.108

Figure C-26 Example; Vehicle Inputs / Vehicle Volume for NB in PTV Vissim 109
Figure C-27 Turning Movement Data for SB and WB in PTV Vissim 110
Figure C-28 Turning Movement Data for NB and EB in PTV Vissim 111
Figure D-1 Ring Barrier Controller in PTV Vissim 112
Figure D-2 Ring Barrier Controller in PTV Vissim 113
Figure E-1 Average Queue Delay for the intersection by PTV Vissim 114
Figure E-2 Average Queue Delay for the intersection by PTV Vissim 114
Figure E-3 Average Stopped Delay for the intersection by PTV Vissim 115
Figure E-4 Average Stopped Delay for the intersection by PTV Vissim 115
Figure E-5 Average Vehicle Delay for the intersection by PTV Vissim 116
Figure E-6 Average Vehicle Delay for the intersection by PTV Vissim
Figure E-7 Average Vehicle Travel Time for the intersection by PTV Vissim 117
Figure E-8 Average Vehicle Travel Time for the intersection by PTV Vissim 117
Figure E-9 Average Queue Length for the intersection by PTV Vissim
Figure E-10 Average Queue Length for the intersection by PTV Vissim

LIST OF TABLES

Table 1.1	SAE's Levels of Autonomous Vehicle	4
Table 3.1	Traffic Counts for Morning Peak Hour Used in Simulation Analysis	21
Table 3.2	Automated Vehicle Assumptions by CoEXist in PTV Vissim 11	23
Table 3.3	Automated Vehicle – Car-Following Model Assumptions in PTV Vissim 2	24
Table 3.4	Automated Vehicle – Following Behavior Parameters	25
Table 3.5	Automated Vehicle – Lane Changing Behavior	26
Table 3.6	Automated Vehicle - Behavior at Signal Control	27
Table 3.7	Comparison Scenarios for this Study	29
Table 3.8	Traffic Turning Volume Used in Sensitivity Analysis	31
Table 3.9	An Example of Simulation Random Seeds in PTV Vissim for	
	One Simulation Scenario	37
Table 4.1	Summary Results Comparing Overall Intersection's Performances	70

LIST OF ABBREVIATIONS AND NOTATIONS

- AAA American Automobile Association
- ADSs Automated Driving Systems
- AV Automated Vehicle
- CAV Connected and Automated Vehicle
- COM Component Object Model
- CTR Cumulative Travel-time Responsive
- EB Eastbound
- EBL Eastbound Left-turn
- EBR Eastbound Right-turn
- EBT Eastbound Through
- FHWA Federal Highway Administration
- IEEE The Institute of Electrical and Electronics Engineers
- IIHS The Insurance Institute for Highway Safety
- LOS Level of Service
- MOEs Measures of Effectiveness
- NB Northbound
- NBL Northbound Left-turn
- NBR Northbound Right-turn
- NBT Northbound Through
- NTOC National Transportation Operations Coalition
- OECD The Organization for Economic Co-operation and Development

- PMSA Predictive Microscopic Simulation Algorithm
- RBC Ring Barrier Controller
- RU Roadside Unit
- SAE The Society of Automotive Engineers
- SB Southbound
- SBL Southbound Left-turn
- SBR Southbound Right-turn
- SBT Southbound Through
- SHSOs State Highway Safety Offices
- USDOT US Department of Transportation
- V2I Communications between (Vehicle to Infrastructure)
- V2V Communications between (Vehicle to Vehicle)
- VMT Vehicle Miles of Travel
- WB Westbound
- WBL Southbound Left-turn
- WBR Westbound Right-turn
- WBT Westbound Through

CHAPTER I

INTRODUCTION

1.1 Introduction

According to the US Department of Transportation (USDOT), the US population will increase by 70 million between 2015 and 2045 (USDOT, 2017). Therefore, traffic demand will equally be rising due to anticipation of population growth. In 2010, there were about 1 billion vehicles worldwide, the number increased to about 1.2 billion vehicles in 2014, and by 2035 the number of vehicles will reach about 2 billion vehicles (Voelcker, 2014). Even though the number of vehicles is increasing on roads every year, the constructions of the roadways are not growing at the same rate (FHWA, 2017). From the year 1916 to 2016, which is a 100-year period, the vehicle miles of travel (VMT) increased by 99%, while the public road mileage increased by only about 30% (FHWA, 2017). In the United States, about 50% of road congestion, termed as recurring congestion, occurs due to demand exceeding the road capacity. This is when many vehicles are simultaneously trying to use the same roadways with insufficient capacity to hold all of them. On the other hand, the other 50% of road congestion, termed as non-recurring congestion, is mainly caused by three significant factors: work zone constructions (10%), adverse weather conditions (15%), and traffic crashes (25%) (FHWA, 2019). Eventually, by just adding more lanes, the problem of traffic congestion could not be solved.

Current roadways are insufficient to accommodate the enormous urban demands for transportation in an efficient manner (Kari et al., 2016). In 2017, Los Angeles led the United States' cities in total hours drivers spent in peak hour traffic congestion (102 hours). This translated into \$12.2 billion total cost to the city (\$2,828 cost per driver), while New York city led the country in total costs to the city of about \$33.7 billion, equivalent to \$2,982 per driver (Schneider, 2018). Traffic simulation experiments and field tests show that additional vehicle speed changes in a short period of time like "stop-and-go" at signalized intersections will add approximately an extra 14% of fuel usage compared with a vehicle that moves smoothly at a steady speed flow (Xia et al., 2012).

Over the last few decades, billions of dollars have been invested in the national road network to reduce fatalities, traffic congestion, and vehicular-related injuries caused by human errors (Boonman, 2016). Modern research supports the use of innovative wireless communication along with autonomous and connected vehicles as a viable solution (Goodall, 2013). This thesis study is an investigation of the connected and autonomous vehicle (CAV) as a possible way to improve the current, problematic traffic conditions due to delays at a typical urban signalized intersection.

1.2 The significance of the Study

The United States, Russia, and Brazil are among the countries in the world experiencing the most extreme traffic congestion problems (Schneider, 2018). Attempts to merely widen the roads (adding more lanes) as a solution for the congestion problem have failed, as typically, congestion increases immediately after the widening (Schneider, 2018). Traffic conditions caused by adverse weather condition are due to supply chain disruption and transportation network failures (Bierbaum and Smith, 2013). Extreme weather events have long term, damaging effects on urban transportation systems. Traditional approaches to the urban traffic problem have also failed and some have even exacerbated the problem. The connected and autonomous vehicle capability provides more viable options to decrease the prevailing severe congestion issues in urban transportation networks (Anderson et al., 2014).

1.3 Connected and Autonomous Vehicles

The connected and autonomous vehicle (CAV) is a vehicle that can take all the control and make all the decisions while it is on the road, and it is a driverless vehicle which can sense the environment around it. The CAV, also referred to as "smart," or state-of-the-art, a replacement for a human function (Oonk and Svensson, 2013). A number of automakers have been engaged with the development of private driverless vehicles.

Connected and autonomous vehicles are manufactured to operate at different levels from fully automated or assisted (SAE, 2014):

- Level 1: The vehicle has an assistance system installed. For example, the inclusion of anti-skid braking and electronic traction regulators.
- Level 2: Automated vehicle control systems are designed with limited capabilities to perform some aspects of driving the vehicle. Examples could be the adaptive cruise regulator or lane-keeping support.
- Level 3: The autonomous driving system is designed to perform some aspects of driving and can take control of the environment around it. However, the human driver remains aboard the vehicle; much like the airline pilot with autopilot.

- Level 4: In this level, the vehicle is conditionally automated, the vehicle itself can take all the control without the driver involvement.
- Level 5: The vehicle is completely automated, it can operate itself without a driver and it has all the responsibility of the control and safety.

SAE International and J3016 Levels of Driving Automation (2014)						
SAE level	Name	Narrative Definition	Execution of Steering and Acceleration / Deceleration	<i>Monitoring</i> of Driving Environment	Fallback Performance of <i>Dynamic</i> Driving Task	System Capability (Driving Modes)
Human driver monitors the driving environment				1		
0	No Automation	The full-time performance by the <i>human driver</i> of all aspects of the <i>dynamic driving task</i> , even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a
1	Driver Assistance	The <i>driving mode</i> -specific execution by a driver assistance system of either steering or acceleration / deceleration using information about the driving environment and with the expectation that the <i>human driver</i> preforms all remaining aspects of the <i>dynamic</i> <i>driving task</i>	Human driver and system	Human driver	Human driver	Some driving modes
2	Partial Automation	The <i>driving mode</i> -specific execution by one or more driver assistance systems of both steering and acceleration / deceleration using information about the driving environment and with the expectation that the <i>human driver</i> preforms all remaining aspects of the <i>dynamic driving task</i>	System	Human driver	Human driver	Some driving modes
Auto	mated driving sy	environment				
3	Conditional Automation	The <i>driving mode</i> -specific performance by an <i>automated driving system</i> of all aspects of the dynamic task with the expectation that the <i>human driver</i> will respond appropriately to a <i>request to</i> <i>intervene</i>	System	System	Human driver	Some driving modes
4	High Automation	The <i>driving mode</i> -specific performance be an automated driving system of all aspects of the <i>dynamic driving task</i> , even if a <i>human driver</i> does not respond appropriately to a <i>request to intervene</i>	System	System	System	Some driving modes
5	Full Automation	The full-time performance by an <i>automated driving system</i> of all aspects of the <i>dynamic driving task</i> under all roadway and environmental conditions that can be managed by a <i>human driver</i>	System	System	System	All driving modes

Table 1.1 SAE's Levels of Autonomous Vehicle

Vehicle automation will permit a human driver to devote a large portion of time typically spent in the vehicle engaging in other events (Lutin, 2018). Many automation strategies that can significantly reduce traffic congestion have been presented such as ramp meters, dynamic signal timing, and changing speed limits (Goodall, 2013). The autonomous vehicle can potentially transform the current, inefficient state of urban transportation, the case for mobility, and a closer mark toward the goal of environmental sustainability (USDOT, 2015).

The connected and automated vehicle has communication capabilities with other connected and automated vehicles and uses input data of the geography to form the communication system (Archer, 2017). The CAVs and roadside units (RSU) are the primary components of the autonomous vehicle system. Researchers agree that the CAVs will reduce the frequency of traffic crashes (Archer, 2017).

1.4 Connected and Automated Vehicles and Transportation Safety

It is estimated that connected and automated vehicles can reduce traffic-related fatalities by 30,000 each year in the United States alone (KPMG, 2017). According to the Insurance Institute for Highway Safety (IIHS, 2010) about one of every three fatal crashes could be prevented by using only crash avoidance features which are in the first level of the automated vehicles. These vehicles have all the avoidance features such as the forward collision warning, lane departure warning, side view assists, and adaptive headlights. Therefore, vehicle crashes could be reduced by about 1.9 million every year in the United States (IIHS, 2010). In 2011 the number of vehicle crashes exceeded 5.3 million in the US,

resulting in 32,000 fatalities and 39% of the fatal crashes involved alcohol (Anderson et al. 2014).

1.5 Connected and Autonomous Vehicles and Mobility

Car sharing through transportation and logistics applications, such as Lyft and Uber can improve traffic congestion on roadways and at signalized intersections, as well as reducing parking space shortages. Car sharing leads to fewer vehicles on the roadways, which will reduce traffic congestion as well. In addition, car sharing can reduce the cost to the users utilizing car sharing opportunities in terms of parking fees, car registration fees, insurance cost, and vehicle maintenance cost (AAA, 2013). Thus, these fees could be waived when using autonomous car sharing. According to AAA, car sharing can save the passenger about \$6000 each year (AAA, 2013). Sharing the autonomous vehicle will reduce the usage of public parking, so that could increase the urban space by about 20%, and in the center of London, there are about 7 million parking spaces, which cover about 16% of the city, and in some other large cities, the parking spaces cover about 30% of the city (Hars, 2016). By reducing the space slotted for parking spaces, the cities will be greener, and the quality of life will improve, and there will be more space for housing (Hars, 2016).

Connected and automated vehicles also provide benefits of self-regulation and mobility for those who do not drive, including the disabled and the young (Litman, 2018). The senior citizens in the United States will increase by about 77% by the year 2045, and about 30% of them will have a disability which will limit them from driving (USDOT, 2017). In the United States, the people in the age above 75 are about 16 million, and there

are 50 million people who cannot drive a vehicle (McGrath, 2018). The sharing of the autonomous vehicle could solve the problem of chauffeuring and increase economic productivity.

Using the connected and automated public transportation such as buses will also increase the capacity of the public transportation network, which will decrease the waiting time and congestion as well. In Australia, about 15,000 passengers are carried by bus each hour in the distance of one kilometer of one lane of the freeway, and the number of the passengers could be increased to about 25,000 if the bus is automated and connected (Newman, 2015).

The increase in the autonomous vehicles would remedy the deficiency in parking spaces looking from a logistics point of view as well as improving public transportation in general (Litman, 2018). A need for road signage will be reduced, as autonomous vehicles will receive important information through network communication (Litman, 2018). As a result, using autonomous and connected vehicles will increase safety, capacity, efficiency, and the quality of the roadways. Therefore, vehicle crashes, fatalities, and traffic congestion will be reduced.

1.6 Problem Statement

The problem of traffic congestion, delays, costs, and lost productivity plagues most countries with large urban cities that are overpopulated (Kari et al., 2016). The cost of extreme traffic delays in an economic sense is astounding. Traffic congestion in the United States totaled \$305 billion in 2017, which was an increase of \$10 billion from the total of 2016 (Schneider, 2018). In 2017, drivers in Los Angeles spent 102 hours in congestion in

only one year, which makes it the worst city in traffic delays in the world, and Russia holds the second spot for the world's most congested countries (Schneider, 2018). Moscow drivers spend about 34% of their traveling times in traffic jams (Shpikalov, 2018). Moscow is not the only driver's nightmare in Russia, as other cities, such as Krasnodar and St Petersburg, also produce extremely negative statistics for annual traffic flows (Shpikalov, 2018).

Traffic congestion at intersections, and more particularly, at signalized intersections, has continuously increased in most major metropolitan areas, causing the risks of human driving errors to rise sharply. The congestion conditions in urban areas are beyond traditional fundamental approaches to the solution. The more modern strategies require exploration for efficient baseline signal control (Kari et al., 2016). The signalized intersections have been designed to control traffic flow and to increase safety on the roads. However, unfortunately, signalized intersections significantly contribute to traffic delays in urban road networks. One reason why signalized intersections increase traffic congestion is the longer reaction time that the driver takes to start moving when the signal turns from red to green. The first vehicle in the queue of one lane of the road at a signalized intersection has a longer reaction time than the following vehicles in the queue. The second, third, and fourth vehicles in the queue have a similar process, but each vehicle has shorter headway than the previous vehicle in the queue. After the fourth vehicle in the queue, the headway will be comparatively constant (TRB, 2000). A traffic signal increases the travel time due to control delay at the signalized intersection. Based on a traffic congestion study in the US, about 10 percent of the congestion on major roadways, is estimated to occur at signalized intersections (NTOC, 2012). The increasing and changing travel demands at

urban signalized intersections could cause delays due to inefficient green times for vehicular use (Li et al., 2014). By using the new technologies such as autonomous and connected vehicles and the communication between vehicles and infrastructure, there is a potential of minimizing the problem of traffic congestion at intersections due to reduced human error, longer and unpredictable human reaction time and distraction. The purpose of this thesis research study is to investigate possible ways to improve the problems with current road conditions by using Autonomous vehicles with an approach to improve safety as well as traffic congestion.

1.7 Objectives of the Study

Connected and autonomous vehicles are being considered as part of the solution for tomorrow's transportation systems (Goodall, 2013). The main objective of this thesis research study is to simulate the potential impacts CAVs may have on traffic flow and delay at a typical urban signalized intersection. Essentially, to use a microscopic traffic simulation software to test future CAV technology within a virtual environment, by testing different levels of CAVs with their associated behaviors across several scenarios to be simulated. This study is testing and simulating the impact of autonomous vehicles compared with conventional vehicles at the signalized intersection. Specifically, this research is analyzing and comparing the operations of the signalized intersection when there are only conventional vehicles, conventional vehicles mixed with autonomous vehicles, and when there are only autonomous vehicles. Additionally, this study aims to show how autonomous vehicles can improve and reduce traffic delay (congestion) by quantifying the extent the intersection can be improved.

1.8 Organization of the Thesis

This thesis report consists of six main chapters. Chapter One introduces the study, including a problem statement and objectives of the study. Chapter Two presents the literature review on the connected and autonomous vehicles (CAVs), and Chapter Three contains information on data collection and description of the methodology used in this study. Chapter Four presents the study results and a summary of the findings; and Chapter Five summarizes important findings and provides recommendations for further studies on the topic.

CHAPTER II

LITERATURE REVIEW

2.1 Introduction

This review of literature covers prior research of traffic congestion problems and solutions; signalized intersections; and methods of improvement for safety and traffic flow with connected and autonomous vehicles (CAVs). Governments are obligated to seek economic and environmental development through innovative improvements to any part of the infrastructure including major transportation projects designed to improve safety and the overall quality of life (Othman, 2013). Urban engineering infrastructures are critical as a realization of national, state, and municipal objectives that may only be realized through efficient planning, innovative, sustainable designs, and massive improves to the public infrastructure systems.

2.2 Automation in Transportation

By 2050, the urban city populations in the world will increase by 54%, which will increase the demand for transportation (de Almeida Correia et al., 2016). Modern vehicles are equipped to drive on cruise control, which reduces the input from drivers. In addition, the USDOT (2018) points out that a new era of innovation in transportation and safety will provide national competitiveness in automated technology. Oonk and Svensson (2013)

argue that highly or partially automated vehicles will substantially enhance traffic safety in urban areas by minimizing human errors.

Autonomous vehicles are also considered the latest innovation in smart technology which can be controlled without human drivers. The autonomous vehicle is quickly becoming a reality and may lead the way to future autonomous systems in areas outside transportation (Boonman, 2016). The USDOT (2018) defines automated driving systems (ADSs) as software and hardware compiled for dynamic driving capabilities on a longterm sustainability basis as defined by Society of Automotive Engineers (SAE). The Organization for Economic Co-operation and Development (OECD) (OECD, 2018) defines the autonomous vehicle as a self-driving vehicle with software and hardware systems with rapid performance changes through software upgrades. The United States Department of Transportation (USDOT, 2018) reports that SAE automation levels are defined as 0 = no automation, 1 = driver assistance, 2 = partially automated, 3 = 1conditionally automated, and 4 = highly automated. Anderson et al (2014) presented four levels of benefits from the automation technology as follows: (1) Level 0: the driver has full control of the automobile; (2) Level 1: a single function is automated; (3) Level 2: multiple functions are simultaneously automated; (4) Level 3: all driving functions fully benefit from automation; and (5) Level 4: the automobile can operate in the absence of a human driver.

Guler et al. (2014) argue that the information collected from connected vehicles to include speed and position may serve to optimize the traffic operations at signalized intersections and that could reduce the average delay by 60%.

2.3 Connected and Automated Vehicles on Roads and Intersections

The economic effect of the use of autonomous (a word most people currently use in place of connected and automated vehicles) transportation is provided by reducing the time and cost of transporting goods and passengers and more efficient use of roadway capacity. Reducing fuel consumption will lead to a decrease in the emissions of harmful substances into the atmosphere, which will positively affect the environment to reduce the greenhouse effect. Autonomous transportation management will increase the comfort of passengers expanding the use of vehicles for people with disabilities (Anderson et al., 2014).

Machines-robots can make the transportation system much more efficient. For incidence, each intersection could be controlled by an autonomous intelligent agent, which regulates the movement of each vehicle individually in contrast to traditional traffic lights prohibiting or permitting the movement of the entire stream (Anderson et al., 2014). Simulation of traffic for autonomous vehicles utilizing computer control includes the design of a city intersection on which, traffic is completely regulated without traffic lights (Anderson et al., 2014). Free traffic light at intersections will become possible only when autonomous vehicles equipped with data exchange systems such as vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) will drive along the roads. It will be possible to organize traffic management according to the system of free slots (Goodall et al., 2013).

Researchers consider the opportunity to equip vehicles with devices that can communicate with the road infrastructure. When approaching the intersection, the vehicle will be assigned a driving speed, adhering to which it will be able to enter the intersection just in time for the beginning of its slot. The peculiarity of the technology is that the

13

situation on the road will be analyzed in the complex analysis and vehicles with "nonconflict" trajectories will be combined into groups and cross the intersection together in groups (Gende, 2015). Therefore, based on the calculations performed, the efficiency of navigating through intersections will increase significantly (Gende, 2015).

When an autonomous vehicle operated by a computer is interacting with another similar autonomous vehicle with automatic dispatchers, are potentially able to avoid any crashes, recognize each other and in turn, agree on a maneuver in advance, and instantly react to any unforeseen obstacles within the entire traffic flow at once. In addition, pedestrians will also be able to cross the road at all the time without paying attention to vehicles that will pass by, no matter in which direction and with what speed the vehicle is moving (Goodall, 2013).

The new technology of self-driving cars can lead to a world without traffic lights and speed limits. Researchers also estimate that autonomous vehicles will be able to use 19-22% less fuel compared to conventional vehicles (Goodall, 2013). Connected and automated vehicles (CAVs) can streamline the traffic stream by communicating with each other, rather than waiting for inputs from drivers (Goodall, 2013). Algorithms to control traffic lights continue to be developed and tested predictive microscopic simulation algorithm (PMSA) which tracks the location of vehicles and predicts the direction of movement (or stop) of a vehicle in 15-second intervals (Goodall, 2013).

According to Lee et al. (2013), a cumulative travel-time responsive (CTR) realtime intersection control algorithm can significantly reduce total travel times by about 34% and increasing the average travel speeds by 36% for connected vehicles. This leads to improvement of the throughput of the intersection (Lee et al., 2013). Besides substantial improvement in traffic flow efficiency, Lee et al. (2013) also estimate that CTR algorithm can reduce greenhouse gases by 13% and fuel savings by 10%.

For the development of algorithms that will allow using this technology of the future, control theories and driving simulators are predominantly used. Studies published by IEEE Transactions on Intelligent Transportation Systems show that innovative technologies also provide optimal acceleration and deceleration in the speed reduction zone, while avoiding a rear collision. According to Tiaprasert et al. (2015) models that have been developed estimate that connected vehicles will use 19-22% less fuel and reach their destinations 26-30% faster than people-driven vehicles.

For connected autonomous vehicles (CAVs), data transfer from vehicle to vehicle (V2V) and infrastructure (V2I) is a key element. Analysis of the impact of traffic factors such as throughput, intersection delay and accident rate on an urban corridor in Austin, Texas revealed that connected autonomous vehicles (CAVs) significantly improve these indicators at low cost (Archer, 2017).

2.4 Compromises to Safety

The Governors Highway Safety Association (Hedlund, 2018) reports that more than 90% of automobile crashes are caused by human errors. Because 90% of traffic crashes occur as a result of human error, it is believed that optimistically, the move over to automated vehicles could reduce crashes by nearly 90%, reducing insurance costs and making travel much safer (Litman, 2018). However, it might also introduce new risk factors that could lead to a spike in crashes, including the risk of hacking, hardware or software failures, and increased congestion on roadways. Regardless of the exact percentage of decrease, however, initial studies indicate that they will reduce the total number of crashes in a significant amount (Litman, 2018). There is also enough evidence in preliminary studies to indicate that it will increase the roadway capacity by reducing congestion and improving efficiency (Litman, 2018).

The Insurance Institute for Highway Safety (IIHS, 2010) report claims that frontend crashes are the most common type of motor vehicle collisions that cause fatalities. Drunk drivers, failure to use seat belts, not obeying signals, and other human errors create the greatest risk of fatalities and traffic delays (Hedlund, 2018). However, the OECD (2018) argue that with the implementation of automated vehicles, crashes will continue from drivers with high-risk behaviors. Therefore, several methods have been investigated as mitigation for traffic congestion, driver safety, and increased control management (de Almeida Correia et al., 2016).

The International Monetary Fund (IMF) (IMF 2015) investigated relationships between the improvements to civil critical infrastructure quality, the total public investment, and economic growth; and highlighted inefficiency in the engineering infrastructure as a distraction to the economic growth rate. The Hedlund (2018) report believes that automated vehicles will create new and unanticipated traffic safety issues and recommends that the State Highway Safety Offices (SHSOs) should begin preparing to be ready for such possibilities.

The U.S. Department of Transportation, in partnership with the Volpe National Transportation Systems Center (USDOT, 2015) released a framework for understanding the benefits of automated and autonomous vehicles implementation more clearly and to estimate the impact of those benefits. Metrics addressed included safety, mobility, energy, environmental conservation, accessibility, and economic benefit (USDOT, 2015). In addition, the USDOT/Volpe study found that automated vehicles offer benefits because of their unique capabilities including collision avoidance, traffic jam assistance, adaptive cruise control, and full automation. All metrics were found to show statistically significant improvement as the total number of automated vehicles in use increased.

CHAPTER III

DATA COLLECTION AND METHODOLOGY

3.1 Source of Data

Primarily this thesis study involved simulation and evaluation of the impact of automated and autonomous vehicles at a signalized intersection by using PTV Vissim 11 software. Therefore, the required input data for PTV Vissim microscopic simulation include the location, geometry, and layout of the intersection, traffic turning movement counts, signal timing data, and driving behavior parameters data for the automated and autonomous vehicles. All these data are discussed in this section.

3.1.1 Intersection Data

The intersection selected for this study is located in the city of Dayton, Ohio and its latitude and longitude are 39.805812 and -84.222421, respectively. It is an intersection of North Main Street and East Nottingham Road. This intersection is located approximately 3.5 miles north of downtown Dayton. Figure 3.1 shows the location of North Main Street and East Nottingham Road. Google Maps, Google Earth, and Bing Maps were the sources of some of the intersection data such as geometry and layout, number of lanes on each approach, the width of each lane, and posted speed limits on the intersecting roadways.

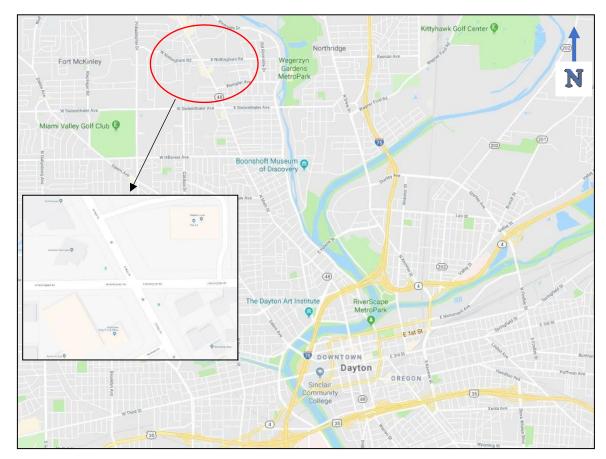


Figure 3.1 Location of Main St and Nottingham Rd Intersection (from Google Maps)

There are two major lanes on the southbound and northbound directions of the intersection, and only one major lane in the westbound and eastbound directions (see Figure 3.2). The width of each lane on North Main Street is 11 ft and 10 ft on East Nottingham Road. The speed limit posted on both North Main Street and East Nottingham Road is 35 mph.

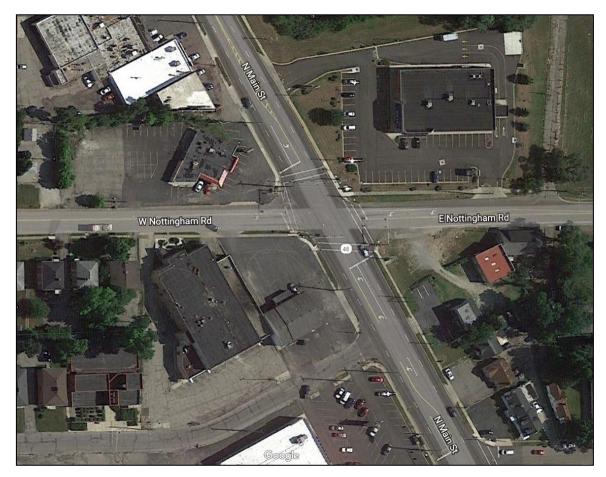


Figure 3.2 Geometry and Layout of the Study Intersection (from Google Earth)

3.1.2 Traffic Data

LJB, Inc., a major consulting firm in Dayton provided the traffic counts and vehicles turning movements. The traffic data that was used in performing microscopic simulation involved the turning movement counts for the morning peak hour collected on 08/28/2018. Table 3.1 shows a summary of these traffic turning movement data. In addition, Figure 3.3 shows detailed information on these turning movement count data.

	Turning Movement Peak Hour Data (7:15 AM)						
Divertiens		Vahieles Court		Movement			
Directions	Vehicle Type	Vehicles Count	Right	Thru	Left		
Main St	Passenger Cars	722	35	679	8		
Main St	Medium Vehicles	18	2	15	1		
(Southbound)	Total	740	37	694	9		
N atting the sec	Passenger Cars	58	25	17	16		
Nottingham	Medium Vehicles	6	4	1	1		
(Westbound)	Total	64	29	18	17		
Main Ct	Passenger Cars	386	15	354	17		
Main St	Medium Vehicles	9	0	9	0		
(Northbound)	Total	395	15	363	17		
Nottingham	Passenger Cars	107	42	28	37		
Nottingham (Eastbound)	Medium Vehicles	4	1	0	3		
(Easibound)	Total	111	43	28	40		

Table 3.1 Traffic	Counts for Morning	g Peak Hour Used	in Simulation Analysis
		7	2

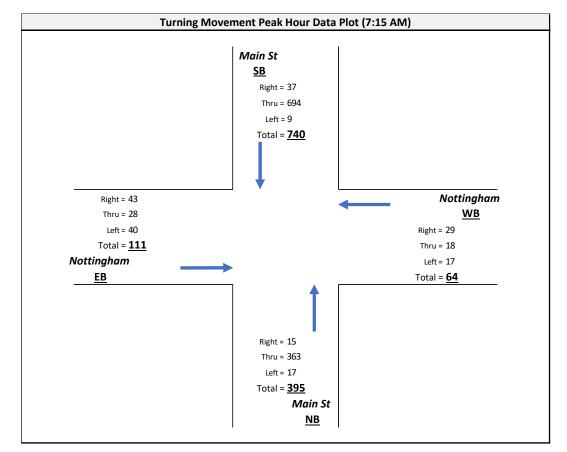


Figure 3.3 Turning Movement Data Used in Simulation Analysis

3.1.3 Traffic Signal Data

LJB, Inc. was also the source of existing traffic signal timing data, which was designed and implemented on December 29, 2014 (Figure 3.4). For this study, the traffic signal timing was optimized by using Synchro software, and then the optimized traffic signal timing data was used in microscopic simulation. Detailed information on optimized traffic signal timing is included in the methodology section.

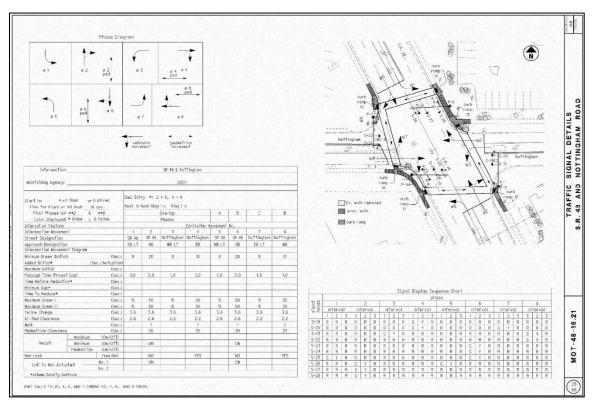


Figure 3.4 Existing Traffic Signal Timing Details

3.1.4 Driving Behavior Parameters for Autonomous Vehicles

The connected vehicles (CVs) driving behavior and driving logic data used in this simulation study were developed and defined by CoEXist, the European Union Funded Horizon 2020 Project (Groves, 2018) and incorporated into PTV Vissim version 11

simulation software. The CoEXist study, is a major ongoing and comprehensive study that began in May 2017 and will run up to April 2020, whose main objective is to prepare the transition phase during which automated and conventional vehicles will co-exist on urban roads and highways (Groves, 2018). CoEXist project came up with four different driving logics for automated vehicles (AVs) which are: AV Rail safe, AV Cautious, AV Normal, and AV All-knowing. Eventually, each type of these AVs has a different driving behavior parameter attached to it (refer to Table 3.2). The PTV Group's proposed parameters were defined based on empirical studies, co-simulation assumptions, and data collected from the CoEXist study (Sukennik, 2018). The automated vehicle behavior and driving logic parameters have been implemented and are available and usable in the microscopic traffic simulation PTV Vissim version 11. Therefore, for this study, the source of data for the AV parameters are PTV Vissim and CoEXist project. The automated vehicle features and driving behavior parameters such as following behavior data, lane changing behavior logics, and signal control behavior data are described in this sub-section.

Definition Under CoEXist Project						
AV Rail Safe	AV Cautious	AV Normal	AV All-knowing			
 Brick wall stop distance. Big gaps. Predefined route. No lane changes. No unprotected signal phases. Higher lateral distance or physical separation. Mostly closed environment. 	 Brick wall stop distance. Big gaps. Cautious behavior. 	Gaps like human drivers but with higher safety.	 Smaller gaps but still safe. Cooperative behavior. Communication is a precondition. 			

Table 3.2 Automated Vehicle Assumptions by CoEXist in PTV Vissim 11

3.1.4.1 Following Behavior Model Parameters

The automated vehicle car-following behavior model parameters incorporated in PTV Vissim 11 software are shown in Table 3.3 and Figure 3.5 illustrates the following distance parameters used in the automated vehicle car-following model. The car-following behavior assumptions are presented in Table 3.4.

Car Following Model					
Parameter	AV	AV	AV		
Falameter	cautious	normal	allknowing		
	(CoEXist)	(CoEXist)	(CoEXist)		
CC0: Standstill distance (ft)	4.92	4.92	3.28		
CC1: Following distance (Headway Time) (Sec)	1.5	0.9	0.6		
CC2: Longitudinal oscillation (Following Variation) (ft)	0	0	0		
CC3: Perception threshold for following (S)	-10	-8	-6		
CC4: Negative speed difference (Negative "Following" Threshold) (ft/s)	-0.1	-0.1	-0.1		
CC5: Positive speed difference (Positive "Following" Threshold) (ft/s)	0.1	0.1	0.1		
CC6: Influence speed on oscillation (Speed Dependency of Oscillation) (1/(ft*s))	0	0	0		
CC7: Oscillation during acceleration (Oscillation Acceleration) (ft/s2)	0.33	0.33	0.33		
CC8: Acceleration starting from standstill (Standstill Acceleration) (ft/s2)	9.84	11.48	13.12		
CC9: Acceleration at 50 mph (ft/s2)	3.94	4.92	6.56		

Table 3.3 Automated Vehicle - Car-Following Model Assumptions in PTV Vissim

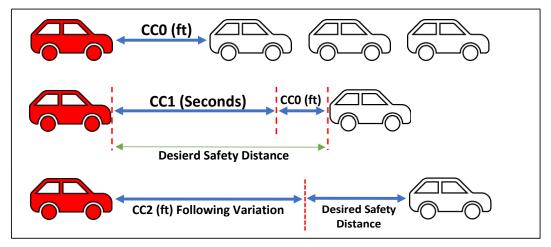


Figure 3.5 Following Distance Parameters for Car-Following Model

Following Behavior					
	[С			
Parameter	AV	AV	AV		
Parameter	cautious	normal	allknowing		
	(CoEXist)	(CoEXist)	(CoEXist)		
Enforce Absolute Braking Distance (EABD)	YES	NO	NO		
Standstill Distance for Static Obstacles (SDSO)	1.64 ft	1.64 ft	1.64 ft		
Look Ahead Distance	Look Ahead Distance				
Minimum	0 ft	0 ft	0 ft		
Maximum	820.21 ft	820.21 ft	984.25 ft		
Number of Interaction Objects	2	2	10		
Number of Interaction Vehicles	1	1	8		
Look Back Distance					
Minimum	0 ft	0 ft	0 ft		
Maximum	492.13 ft	492.13 ft	492.13 ft		

Table 3.4 Automated Vehicle – Following Behavior Parameters

The number of interaction objects implemented for the AV All-knowing driving logic is 10, and 2 for the AV Cautious and AV Normal driving logics. Likewise, while the number of interaction vehicles is 8 for the AV All-knowing driving logic, only1 number of interaction vehicles is used the AV Cautious and AV Normal driving logics. To understand the assumption behind the number of interaction objects and vehicles, Figure 3.6 shows a PTV Vissim example of the use of the number of interaction vehicles and interaction objects. The example in Figure 3.6 shows 3 interaction objects for the automated vehicle (AV) and 1 interaction vehicle for the AV (Sukennik 2018). In this example, the AV can see up to three objects ahead, and can see only the first vehicle in the range of the visible objects.

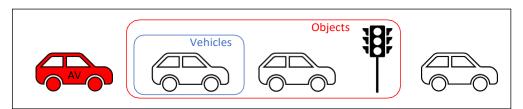


Figure 3.6 Example of the number of interaction vehicles and objects

3.1.4.2 Lane Changing Behavior Logic Data

The logic data for lane changing for automated vehicles can be found in the driving behavior section in PTV Vissim 11 software under "Lane Change" tab, and illustrated in Table 3.5.

Lane Changing Behavior					
	[Driving Log	ic		
Parameter	AV cautious (CoEXist)	AV normal (CoEXist)	AV allknowing (CoEXist)		
Necessary Lane Change (Route)					
Maximum Deceleration					
Own (ft/s2)	-11.48	-13.12	-13.12		
Traviling Vehicle (ft/s2)	-8.2	-9.84	-13.12		
- 1 ft/s2 per distance					
Own (ft)	80	100	100		
Traviling Vehicle (ft)	80	100	100		
Accepted deceleration					
Own (ft/s2)	-3.28	-3.28	-3.28		
Traviling Vehicle (ft/s2)	-3.28	-3.28	-4.92		
Waiting Time Before Diffusion	60 s	60 s	60 s		
Min.net Headway (front to rear)	1.64 ft	1.64 ft	1.64 ft		
To Slower Lane if Collisiom Time is Above	11 s	11 s	11 s		
Safety Distance Reduction Factor	1	0.6	0.75		
Maximum Deceleration for Cooperative Braking	-8.2	-9.84	-19.69		
	ft/s2	ft/s2	ft/s2		
Overtake Reduced Speed Areas	NO	NO	NO		
Advanced Merging	YES	YES	YES		
Vehicle Routing Decisions Look Ahead	YES	YES	YES		
Cooperative Lane Change	NO	YES	YES		
Maximum Speed Difference		6.71 mph	6.71 mph		
Maximum Collision Time	10 s	10 s	10 s		
Rear Correction of Lateral Position	NO	NO	NO		
Maximum Speed	1.86 mph	1.86 mph	1.86 mph		

Table 3.5 Automated Vehicle – Lane Changing Behavior

3.1.4.3 Behavior at Signal Control Data

The data for automated vehicle behavior when reacting to the signal control, can be found in PTV Vissim 11 in driving behavior section under the "Signal Control" tab, also depicted in Table 3.6.

Sig	Signal Control						
		Driving Logic					
Parameter	AV cautious (CoEXist)	AV normal (CoEXist)	AV allknowing (CoEXist)				
Reaction After End of Green	Reaction After End of Green						
Behavior at Amber Signal	Continuous Check	One Decision	One Decision				
Probability Factors	Probability Factors						
Alpha	1.59	1.59	1.59				
Beta 1	-0.26	-0.26	-0.26				
Beta 2	0.27	0.27	0.27				
Reaction After End of Red							
Behavior at Red/Amber Signal	Stop (Same as Red)	Stop (Same as Red)	Stop (Same as Red)				
Reaction Time Distribution	-	-	-				
Reduced Safety Distance Close to a Stop Line							
Factor	1	1	1				
Start Upstream of Stop Line	328.08 ft	328.08 ft	328.08 ft				
End of Upstream of Stop Line	328.08 ft	328.08 ft	328.08 ft				

Table 3.6 Automated Vehicle - Behavior at Signal Control

The decision models for the automated vehicles when they approach an amber (yellow) light signal are shown in (Table 3.6). Continuous check means the vehicle makes an assumption for the amber signal to be visible for two more seconds. Therefore, the driver decides continuously, whether continue to drive or to stop based on the vehicle speed at that moment. The vehicle will stop if it cannot pass through the traffic signal within two seconds. On the other hand, one decision means the vehicle will make the decision when it crosses the stop line (PTV Group 2018). The probability p can be calculated to decide whether the vehicle will stop or not at an onset of a yellow (amber) light, to do that the vehicle uses a logistic regression function as shown in Equation 1 (PTV Group 2018).

where the probability factors Alpha, Beta 1, and Beta 2 were defined by PTV Vissim based on empirical data (Table 3.6).

$$p = \frac{1}{1 + e^{-\alpha - \beta_1 v - \beta_2 dx}} \tag{1}$$

Where:

p = probability of a vehicle to stop or not at an onset of a yellow (amber) light v = approaching vehicle speed

dx = distance from current vehicle's location to stop line

3.2 Methodology

This section presents the methodology that was used in this research study to evaluate the impact of connected and automated vehicles (CAVs) at an urban signalized intersection. In addition, this study examines the impact on the capacity of the intersection and vehicle saturation flow when increasing the travel demand. The evaluation of the effectiveness of operations of the intersection was done by using PTV Vissim microscopic simulation software.

Before starting any simulation of the CAVs, the simulation of the optimized signal timing of the existing traffic counts (conventional vehicles) was done before and after the signal optimization. Therefore, the most optimum signal timing was used in all simulation models in this study to ensure the accuracy of the simulation of the CAVs. This section describes the comparison scenarios, sensitivity analyses, microscopic simulation model development, signal design development, and the evaluation methods performed in the current study.

3.2.1 Comparison Scenarios

There are five different scenarios considered in this study. The first scenario is simulating and testing the efficiency of the intersection when there are only the conventional vehicles at the traffic stream. The second scenario is when there are conventional vehicles mixed with the CAVs All-knowing, and they are mixed equally 50% conventional vehicles with 50% CAV All-knowing in the traffic stream. The third scenario the traffic stream consists of CAVs Cautious only. While the fourth scenario is simulating the operation efficiency of the intersection when there are only CAVs Normal in the traffic stream. The fifth scenario consists of traffic stream composed of 100% of CAVs All-knowing only. Table 3.7 summarizes these scenarios described above.

Scenario	Description
1	100% Conventional Vehicles
2	50% Conventional Vehicles with 50% Automated Vehicles (AV All- knowing CoEXist)
3	100% Automated Vehicles (AV Cautious CoEXist)
4	100% Automated Vehicles (AV Normal CoEXist)
5	100% Automated Vehicles (AV All-knowing CoEXist)

Table 3.7 Comparison Scenarios for this Study

Scenarios were implemented by using the scenario management in PTV Vissim 11. Scenario management provides the opportunity to compare different scenarios in a single project, and to compare results of each scenario with the base network which is the original scenario (conventional vehicles only). In addition, PTV Vissim provides two approaches of scenario management. The first one is "Implicit Approach" where editing and changing the scenario modifications can be done directly in each scenario. The second one is "Constructive Approach" where creating and editing scenario can be made under the modification tab (PTV Group, 2018). The original base scenario in this study is the first scenario where there are 100% conventional vehicles at the intersection model. The base scenario should be designed before creating the other scenarios. After designing the first scenario, other scenarios can be created by the modifications tool. Each scenario modification was saved in a different file (see Figure 3.7). Essentially, the only difference in the modification of each scenario is the driving behavior depending on the scenario's purpose.

Basic sett	ings	Scenarios Modifications					
Count: 5	No	Name	Directory	Modifications	Concatenate:ModifComplete\No	Conc	ate ScenToComp
1	1	Scenario 1 (100% Conventional Vehicles)	C:\Users\hbm	5	5	5	1,2,3,4,5
2	2	Scenario 2 (50% Con Veh & 50% AV all-knowing)	C:\Users\hbm	1	1	1	
3	3	Scenario 3 (100% AV Cautious)	C:\Users\hbm	2	2	2	
4	4	Scenario 4 (100% AV Normal)	C:\Users\hbm	3	3	3	5
5	5	Scenario 5 (100% AV all-knowing)	C:\Users\hbm	4	4	4	

Figure 3.7 A Snapshot of PTV Vissim 11 – Scenario Management

3.2.2 Sensitivity Analysis

The sensitivity analysis was performed to analyze the effectiveness of the signalized intersection when there is an increase in the traffic volume. Therefore, a gradual increase in traffic volume in the simulation model was done by adding 20%, 40%, and 50% to the existing volumes in the model (see Table 3.8). The sensitivity analysis was tested on

all scenarios defined in the current study (refer to Table 3.7), expected to compare how increasing traffic volumes could relatively affect each scenario.

Increasing of Traffic		Approach			
Demand (%)	<u>SB</u>	<u>WB</u>	<u>NB</u>	<u>EB</u>	<u>Total</u>
0% *	740	64	395	111	1310
20%	888	77	474	139	1578
40%	1036	90	553	156	1835
50%	1110	96	592	167	1965

Table 3.8 Traffic Turning Volume Used in Sensitivity Analysis

* The original existing vehicle count at the intersection.

3.2.3 Microscopic Simulation Development

This section describes what were implemented in PTV Vissim simulation model for the current study such as layout, simulation parameters, base data, vehicle type, vehicle class, driving behavior, vehicle composition, vehicle input, and vehicle routes.

3.2.3.1 Building PTV Vissim Base Model

This subsection provides highlights on units, layout, roads design, reduced speed areas, and conflict areas design that were used in network model design. In all simulation models in this study, all parameters for length, speed, and acceleration are in imperial units (see Figure 3.9). The length units used are miles, feet, and inches depending on the length of the object in the network. Therefore, units used for speed are miles per hour (mi/h).

Retwork settings					?	\times	
Vehicle Behavior	Pedestrian Behavior	Units	Attributes	Display	Stand	•	Þ
All Imperial	Length:	Miles	~				
All Metric		Feet	~	·			
	-	Inches	~				
	Speed:	Miles/H	our ~	~			
		Feet/Mi	nute ~	,			
	Acceleration:	Feet/See	cond ² ~				

Figure 3.9 Units Tab in PTV Vissim (PTV Group 2018).

The PTV Vissim background image for the location of Main Street and Nottingham Road intersection was used for designing the intersection layout (refer to Figure 3.10). Figure 3.11 shows Vissim links and connectors just laid out on the background image in the position of the existing intersection of Main Street and Nottingham Road.



Figure 3.10 Background Image of the Study Site in PTV Vissim (Bing Maps Aerial View)

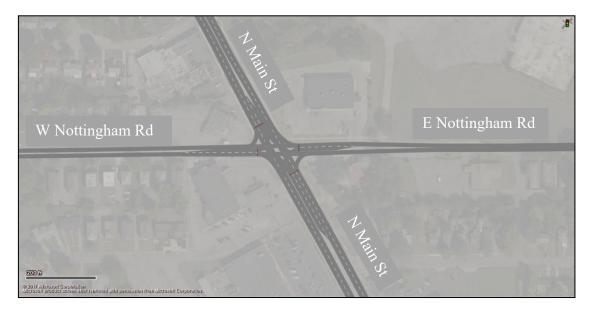


Figure 3.11 Intersection Layout in PTV Vissim Using Links and Connecters

All links used in this PTV Vissim intersection model were defined as urban (motorized) link behavior type (refer to Figure 3.12).

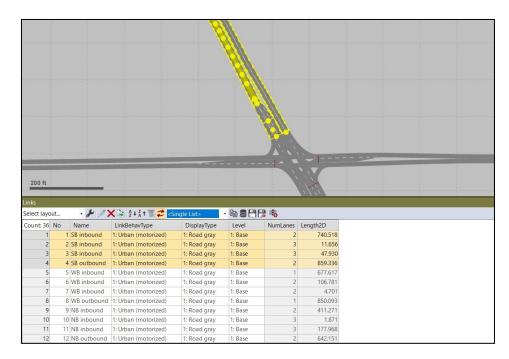


Figure 3.12 A Snapshot of PTV Vissim Links Definition for a SB Link approach of the Study Intersection

The function of reduced speed areas in PTV Vissim software was used in this study. Reduced speed areas make the vehicles which are entering these areas to decelerate and reduce speeds, and then accelerate until they reach their previous speeds after leaving the reduced speed areas (PTV Group 2018). The reduced speed areas were designed in a curvilinear shape, and for this intersection design, tracing how turning vehicles (right or left) traverse through the intersection (refer to Figure 3.13).

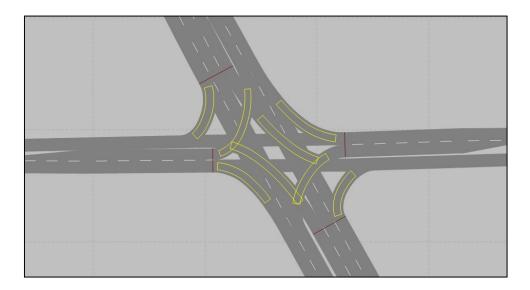


Figure 3.13 Reduced Speed Areas of the Intersection Model in PTV Vissim

The conflict areas tool in PTV Vissim was utilized for all overlapping areas in the intersection. Conflict areas are basically areas of shared right-of-way for various vehicle trajectories. Therefore, it is important to define the right-of-way for the main flows and minor flows. The main flows marked with a green color in Figure 3.14, that means these movements have the right-of-way priority. Consequently, vehicles in minor flows marked with a red color, must yield or slow down to make sure that there is no vehicle in the conflict area before proceeding forward. Then, if there is no vehicle in the conflict area of

the main stream, the vehicle in the minor stream can pass the intersection safely (PTV Group, 2018). The conflict areas for the Main Street and Nottingham Road intersection model can be seen in Figure 3.14.



Figure 3.14 Conflict Areas of the Intersection Model in PTV Vissim

3.2.3.2 Simulation Parameters

All PTV Vissim simulations performed in this study are microscopic simulations. The evaluation of the intersection operation performance for the five different scenarios during the morning peak hour (AM peak) was the main objective of this study. Therefore, the period of the simulation run was one hour (3600 sec) and therefore vehicles were entering in the network during the first 3600 sec of the simulation. However, additional 15 min (900 sec) were added to the period of the simulation run so that to provide an extra time for vehicles in the network to leave the network properly. The start time for the simulation was 7:15 am for 8/28/2018 when the original existing traffic volumes were

counted. The simulation resolution can affect the behavior of vehicles and how they interact in the network. The range value for the resolution as defied in PTV Vissim is an integer from 1 to 20. The simulation resolution for the current microscopic simulation study was set to equal the default value of 10 time-steps per simulation second (see Figure 3.15). According to PTV Group (2018) a value ranging between 10 and 20 produces smoother vehicle movements.

Simulation parameters ?	×
General Meso	
Comment:	
Period: 4500 s Simulation seconds	
Start time: 07:15:00	
Start date: 8/28/2018 ~	
Simulation resolution: 10 Time step(s) / simulation secon Random Seed: 42	ıd
Number of runs: 5 Random seed increment: 10	
Dynamic assignment volume increment: 0.00 %	
Simulation speed: O Factor: 10.0	
Retrospective synchronization	
Break at: 0 s Simulation seconds	
Number of cores: use all cores	~

Figure 3.15 Simulation Parameters in PTV Vissim

The Random Seed parameter in PTV Vissim (Figure 3.15) is used for stochastic functions such as traffic flow for vehicles entering a network and this parameter might affect the results of the simulation. Therefore, each simulation scenario was designed to

run 5 times and each time used a different random seed (see Table 3.9), then the average result from all the five simulation runs was computed, which expected to improve the accuracy of the results for each simulation scenario.

Simulation Run No.	Random Seed	Start Time	Simulation End (sec)
1	42	0:00:00	4500
2	52	0:00:00	4500
3	62	0:00:00	4500
4	72	0:00:00	4500
5	82	0:00:00	4500

Table 3.9 An Example of Simulation Random Seeds in PTV Vissim for One Simulation Scenario

3.2.3.3 Base Data in PTV Vissim

This subsection presents important information about PTV Vissim functions that were used in this study such as vehicle acceleration. deceleration, and PTV Vissim distributions such as desired speed. In addition, it provides information on vehicle type, vehicle class, and the driving behaviors that that selected use for traffic simulation.

3.2.3.3.1 PTV Vissim Acceleration and Deceleration Functions

PTV Vissim defines maximum acceleration, desired acceleration, maximum deceleration, and desired deceleration for all conventional vehicle types. These values can also be modified by a user in PTV Vissim (Figure 3.16).

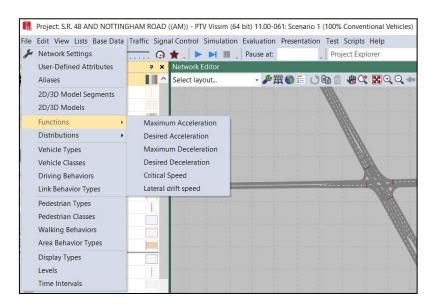


Figure 3.16 A Snapshot of PTV Vissim Functions Page

The range of stochastic values of acceleration or deceleration rates for each conventional vehicle in the simulation should be chosen automatically and randomly between the two small dotted curves as shown in Figure 3.17. The horizontal scale (abscissa) shows vehicle speeds and the vertical scale (ordinate) shows the acceleration value. The conventional vehicle graph in Figure 3.17, that describes the stochastic values for acceleration rates, has three curves; the middle curve is for median values where the two boundary curves define the bandwidth values (PTV Group 2018).

Since connected and automated vehicle (CAV) is computerized for all functions, the acceleration and deceleration can be automatically constant. Therefore, the assumption has been made that autonomous vehicles accelerate and decelerate the same and very similar way in this study. Thus, the two stochastic boundary curves were canceled, so all CAVs were assumed to have the same value for each parameter considered, i.e., maximum acceleration/deceleration and desired acceleration/deceleration rates (refer to Figures 3.17

through 3.20). That assumption comprises the automated passenger cars and the automated medium vehicles.

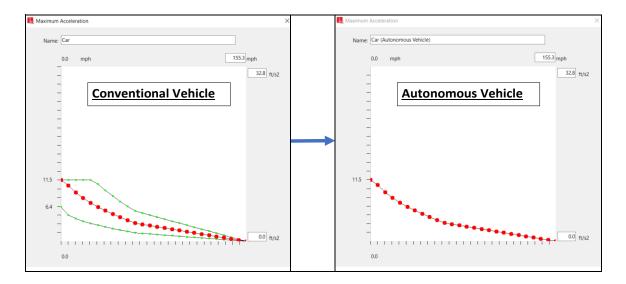


Figure 3.17 Example of the Assumption for Conventional and Automated Vehicles' Maximum Acceleration in PTV Vissim

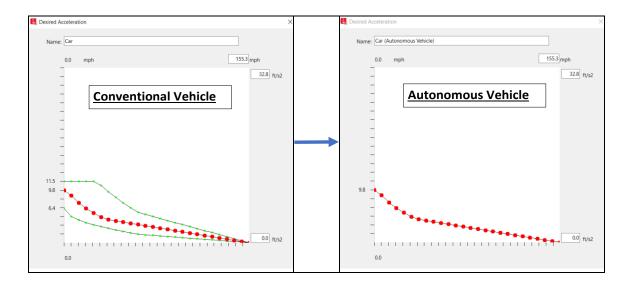


Figure 3.18 Example of the Assumption for Conventional and Automated Vehicles' Desired Acceleration in PTV Vissim

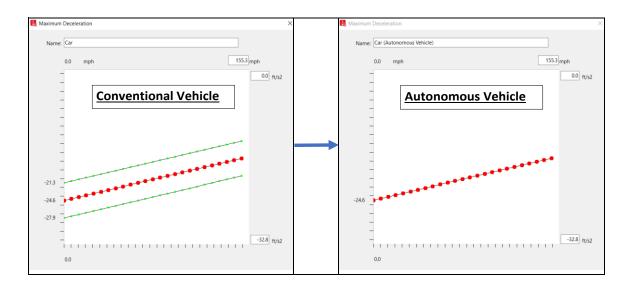


Figure 3.19 Example of the Assumption for Conventional and Automated Vehicles' Maximum Deceleration in PTV Vissim

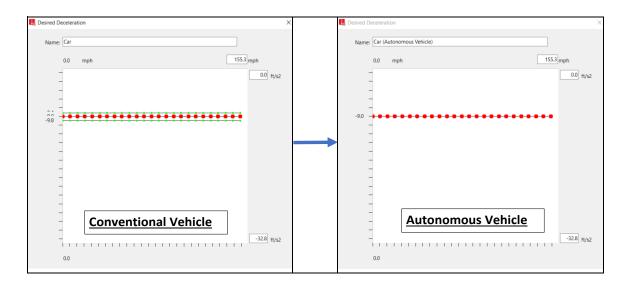


Figure 3.20 Example of the Assumption for Conventional and Automated Vehicles' Desired Deceleration in PTV Vissim

3.2.3.3.2 Desired Speed Distribution

The distribution function of desired speeds is a critical parameter because it affects road capacity and vehicle travel time. If the vehicle is not stopped by other objects such as other vehicles or a traffic signal, the vehicle will be moving at its desired speed. To define the desired speed distribution, at least two intermediate points must be added to the course of the curve to achieve an S-shaped distribution, so the concentration is around the middle values (PTV Group 2018).

Figure 3.21 shows examples of conventional and automated vehicles desired speed distribution functions. For the typical function, the horizontal axis shows the desired speed and the vertical axis shows the percentage value from the total vehicle count. The leftmost value on the speed axis indicates the minimum desired speed and the rightmost value depicts the maximum desired speed.

For this microscopic simulation study, the desired speed distribution for the conventional vehicles in Figure 3.21 (conventional vehicles curve). was set to be that 10% of the vehicles to travel at speeds between 20 mi/h and 25 mph; another 10% of the vehicles to travel at speeds between 35 mi/h and 40 mi/h. Thus, most of the traffic, 80% of the vehicle, will travel in the speed range between 25 mi/h and 35 mi/h.

For the CAVs, the assumption was made that the range of desired speeds for these vehicles will be much smaller and they will obey the speed limit as opposed to most human drivers who do not do so. Therefore, it was assumed that the CAVs move in steady speeds between 35 mi/h and 36 mi/h as shown in Figure 3.21 (the autonomous vehicles curve). The assumption for the desired speed for the autonomous vehicles was considered for AV All-knowing, AV Normal, and AV Cautious.

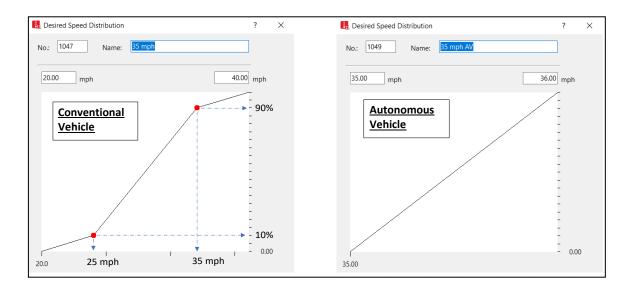


Figure 3.21 Desired Speed Distribution for Conventional and Automated Vehicles in PTV Vissim

3.2.3.3.3 Vehicle Types and Vehicle Class

The vehicle type in PTV Vissim provides the opportunity to define a group of vehicles with similar technical features such as automated vehicles (AVs), and then classify those vehicles in the vehicle class in PTV Vissim (PTV Group 2018). The vehicle types defined in the current study are shown in Figure 3.22. Each vehicle type is linked to a specific function defined in detail in subsection 3.2.3.3. The functions used for each vehicle type are maximum acceleration, desired acceleration, maximum deceleration, and desired deceleration (an example is shown in Figure 3.23). The vehicle classes used to classify each vehicle type to be linked to different driving behaviors are shown in Figure 3.24.

Vehicle Ty	pes						
Select layo	Select Iayout 🔹 🌽 🕂 🥢 🗙 🏠 🛔 🕻 🕇 🐺 🧩 <single list=""> 🔹 💀 😫 💾 😫 🛤</single>						
Count: 8	No	Name	Category	Model2D3DDistr			
1	100	Car	Car	10: Car			
2	300	Bus	Bus	30: Bus			
3	630	Car AV cautious	Car	10: Car			
4	640	Bus AV cautious	Bus	30: Bus			
5	650	Car AV normal	Car	10: Car			
6	660	Bus AV normal	Bus	30: Bus			
7	670	Car AV allknowing	Car	10: Car			
8	680	Bus AV allknowing	Bus	30: Bus			

Figure 3.22 Vehicle Types for the Simulation Model in PTV Vissim

Vehicle Types	6					
Select layout Count: 8 No		+ ∥ × № ² / ₂ + ⁷ / ₄ † ▼ 3 Name		- 🗈 🛢 🂾 😫 🎼 Model2D3DDistr		
	100	Car	Category Car	10: Car		
Wehicle type ? ×						
No.: 100	Ν	lame: Car				
Static Func	tions & Di	stributions Special External D	Priver Model			
Maximum ac	celeration	1: Car		\sim		
Desired accel	leration:	1: Car		\sim		
Maximum de	celeration	: 1: Car		\sim		
Desired dece	leration:	1: Car		~		
Weight:				\sim		
Power:				\sim		
Occupancy:	1: Single (Dccupancy		\sim		
				OK Cancel		

Figure 3.23 Example of Vehicle Functions of Vehicle Types in PTV Vissim

Vehicle C	lasse	s / Vehicle Types			
Select lay	out	- 🎤 🕂 泽	A ↓ Z ↑ 😿 🛪	Vehicle types	- 🗈 🛢 💾 😫 👫
Count: 8	No	Name	VehTypes	UseVehTypeColor	Color
1	10	Car	100	✓	(255, 0, 0, 0)
2	30	Bus	300	✓	(255, 0, 0, 0)
3	40	Car AV cautious	630	 Image: A set of the set of the	(255, 255, 106, 0)
4	50	Bus AV cautious	640	✓	(255, 255, 106, 0)
5	60	Car AV normal	650	✓	(255, 255, 0, 0)
6	70	Bus AV normal	660	✓	(255, 255, 0, 0)
7	80	Car AV allknowing	670	 Image: A set of the set of the	(255, 0, 38, 255)
8	90	Bus AV allknowing	680	 Image: A set of the set of the	(255, 0, 38, 255)

Figure 3.24 Vehicle Classes/Vehicle Types for the Simulation Model in PTV Vissim

3.2.3.3.4 Driving Behaviors and Link Behavior Type

Several driving behaviors can be used in PTV Vissim such as following behavior, lateral behavior, lane change behavior, and behavior at signal controls. Driving behaviors of CAVs developed and built into PTV Vissim software are based on driving logics supported by data from the CoEXist project described in section 3.1.4 and summarized in Figure 3.25, which shows the driving behavior categories of CAVs currently available in PTV Vissim that were utilized in the current study. Figure 3.26 shows a snapshot of an example of a car following model page in PTV Vissim software. Each AV class in this study was assigned a driving behavior and the vehicle class is linked to the driving behavior through the link behavior type (see Figure 3.27).

Driving Behaviors						
Select lay	- 🗈 🛢 💾 😫 🎼					
Count: 8	Name	NumInteractObj	NumInteractVeh	CarFollowModType		
1	Urban (motorized)	4	99	Wiedemann 74		
2	Right-side rule (motorized)	2	99	Wiedemann 99		
3	Freeway (free lane selection)	2	99	Wiedemann 99		
4	Footpath (no interaction)	2	99	No interaction		
5	Cycle-Track (free overtaking)	2	99	Wiedemann 99		
6	AV cautious (CoEXist)	2	1	Wiedemann 99		
7	AV normal (CoEXist)	2	1	Wiedemann 99		
8	AV all-knowing (CoEXist)	10	8	Wiedemann 99		

Figure 3.25 A Snapshot of Driving Behaviors Available in PTV Vissim

🛃 Driving Behavior		? ×
No.: 103 Name: AV all-knowing (CoEX	(ist)	
Following Car following model Lane Change Late	ral Signal Control	
Wiedemann 99		~
Model parameters		
CC0 (Standstill Distance): 3.2	28 ft CC5 (Positive 'Following' Threshold): 0.10	
CC1 (Headway Time): 103: 0.6	· V CC6 (Speed dependency of Oscillation): 0.00	
CC2 ('Following' Variation): 0.0	00 ft CC7 (Oscillation Acceleration): 0.33 ft/s2	
CC3 (Threshold for Entering 'Following'):	6.00 CC8 (Standstill Acceleration): 13.12 ft/s2	
CC4 (Negative 'Following' Threshold):	0.10 CC9 (Acceleration with 50 mph): 6.56 ft/s2	

Figure 3.26 Example of an AV All-knowing Car Following Model in PTV Vissim

	Link Behavior Types / Driving Behaviors By Vehicle Class					
Count: 6	LinkBehavType	VehClass	DrivBehav			
1	1: Urban (motorized)	40: Car AV cautious	101: AV cautious (CoEXist)			
2	1: Urban (motorized)	50: Bus AV cautious	101: AV cautious (CoEXist)			
3	1: Urban (motorized)	60: Car AV normal	102: AV normal (CoEXist)			
4	1: Urban (motorized)	70: Bus AV normal	102: AV normal (CoEXist)			
5	1: Urban (motorized)	80: Car AV allknowing	103: AV all-knowing (CoEXist)			
6	1: Urban (motorized)	90: Bus AV allknowing	103: AV all-knowing (CoEXist)			

Figure 3.27 Link Behavior Types / Driving Behaviors by Vehicle Class in PTV Vissim

3.2.4 Signal Design Development

The existing traffic signal timing was optimized by using Synchro 10 software (see Synchro results snapshots in Figures 3.28 and 3.29) and then the optimized signal timing parameters were then used in PTV Vissim simulations.

	٠	-	*	*	-	*	1	Ť	1	1	Ļ	1
Lane Group	EBL	EBT	EBR	WBL	WBT	WBR	NBL	NBT	NBR	SBL	SBT	SBR
Permitted Phases												
Detector Phase	7	4		3	8		5	2		1	6	
Switch Phase												
Minimum Initial (s)	5.0	5.0		5.0	5.0		5.0	5.0		5.0	5.0	
Minimum Split (s)	9.5	22.5		9.5	22.5		9.5	22.5		9.5	22.5	
Total Split (s)	9.6	22.6		9.5	22.5		9.5	23.4		9.5	23.4	
Total Split (%)	14.8%	34.8%		14.6%	34.6%		14.6%	36.0%		14.6%	36.0%	
Maximum Green (s)	5.1	18.1		5.0	18.0		5.0	18.9		5.0	18.9	
Yellow Time (s)	3.5	3.5		3.5	3.5		3.5	3.5		3.5	3.5	
All-Red Time (s)	1.0	1.0		1.0	1.0		1.0	1.0		1.0	1.0	
Lost Time Adjust (s)	0.0	0.0		0.0	0.0		0.0	0.0		0.0	0.0	
Total Lost Time (s)	4.5	4.5		4.5	4.5		4.5	4.5		4.5	4.5	
Lead/Lag	Lead	Lag		Lead	Lag		Lead	Lag		Lead	Lag	
Lead-Lag Optimize?	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Vehicle Extension (s)	3.0	3.0		3.0	3.0		3.0	3.0		3.0	3.0	
Recall Mode	None	None		None	None		None	Max		None	Max	
Walk Time (s)	0.171.17	7.0		100000	7.0		0.07	7.0		- Cherchesterre	7.0	
Flash Dont Walk (s)		11.0			11.0			11.0			11.0	
Pedestrian Calls (#/hr)		0			0			0			0	
Act Effct Green (s)	5.4	8.5		5.3	6.7		5.3	30.6		5.3	30.6	
Actuated g/C Ratio	0.13	0.21		0.13	0.17		0.13	0.75		0.13	0.75	
v/c Ratio	0.20	0.20		0.08	0.18		0.09	0.18		0.05	0.32	
Control Delay	21.3	9.8		20,4	12.2		20.4	6.8		20.2	7.7	
Queue Delay	0.0	0.0		0.0	0.0		0.0	0.0		0.0	0.0	
Total Delay	21.3	9.8		20.4	12.2		20.4	6.8		20.2	7.7	
LOS	C	A		C	B		C	A		C	A	
Approach Delay		13.9			14.4			7.4			7.8	
Approach LOS		B			В			A			A	

Figure 3.28 the Optimized Signal Timing by Synchro Software



Figure 3.29 Optimized Traffic Signal Phase Diagram by Synchro

The signal controller type that was used in PTV Vissim model is Ring Barrier Controller (RBC) and a fully actuated traffic signal (see Figure 3.30).

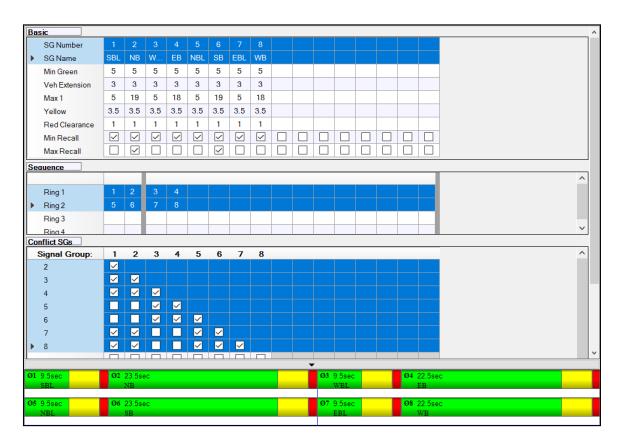


Figure 3.30 Signal Timing in PTV Vissim

3.2.5 Evaluation Method

There are several evaluation tools that can be used in PTV Vissim simulation such as data collection points, vehicle travel time, and queue counters. These tools were used as measures of effectiveness (MOEs) for automated vehicles at the intersection. Specifically, queue delays, stopped delays, queue lengths, and travel times were the MOEs used in evaluating the simulation models. The evaluation time interval for each evaluation parameter for this study was 300 seconds (5 minutes) (see Figure 3.31). Therefore, results were collected every after 5 minutes during the simulation and the simulation run period was one hour and fifteen minutes (4500 Seconds). Thus, the average results from all time intervals for each evaluation parameter were used in the final evaluation of this study.

	Collect data	From-time	To-time	Interval	
Area measurements		0	99999	99999	
Areas & ramps		0	99999	99999	
Data collections	\checkmark	0	99999	300	
Delays	\checkmark	0	99999	300	
Links		0	99999	99999	More
Nodes		0	99999	99999	More
OD pairs		0	99999	99999	
Pedestrian Grid Cells		0	99999	99999	More
Pedestrian network performance		0	99999	99999	
Pedestrian travel times		0	99999	99999	
Queue counters		0	99999	300	More
Vehicle network performance		0	99999	99999	
Vehicle travel times		0	99999	300	More

Figure 3.31 Setup Attributes in Evaluation Configuration in PTV Vissim

3.2.5.1 Data Collection Points

Data collection points are attached to the road to record traffic counts and they are like induction loop detectors. Therefore, they were used in this model network to record traffic volumes and queue delays for each movement (refer to Figure 3.32). A queue delay is the average time in seconds for the vehicle to be stuck in the queue.

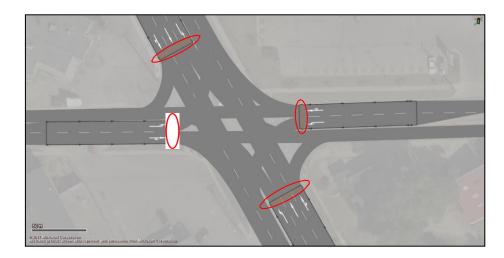


Figure 3.32 Data Collection Points for the Intersection Simulation Model in PTV Vissim

3.2.5.2 Queue Counters

Queue counters are attached to the roads for measuring the queue lengths from specific locations as shown in Figure 3.33. The queue length is a result recorded in terms of length (in feet) and it is not the number of vehicles in the queue (PTV Group 2018). This tool was used in the simulation model for measuring the average queue lengths for all movements.

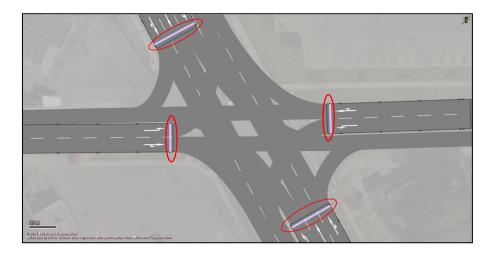


Figure 3.33 Queue Counters for the Intersection Simulation Model in PTV Vissim

3.2.5.3 Vehicle Travel Time

Vehicle travel time measurement works by attaching two points in the road for each movement; that is, the starting point and the ending point. Thus, PTV Vissim starts recording the vehicle travel time (in seconds) between these two points including the vehicle stopped time such as stopped for the red signal at the intersection. For this study, the vehicle travel time distance was designed to be 1000 ft for all movements in all directions (see Figure 3.34) and Figure 3.35 shows an example of vehicles travel time measurements on the southbound direction, including all three available measurements, that is, right turn, through, and left turn movements.

nut	- 🎤 🖉 🗙 🔖 🛔	- 🌽 🖉 🗙 🏠 🛔 🕻 t 🛣 🥏 <single list=""></single>			
	StartLink	EndLink	Dist		
	1: SB inbound	16: EB outbound	1000.00		
	mbound	12: NB outbound	1000.00		
	ন	8: WB outbound	1000.00		
		4: SB outbound	1000.00		
		¹ 6: EB outbound	1000.00		
		⊂ outbound	1000.00		
		rind	1000.00		
			1000.00		
			1000.00		
			1000.00		
			20		

Figure 3.34 Vehicle Travel Time Settings for the intersection model in PTV Vissim

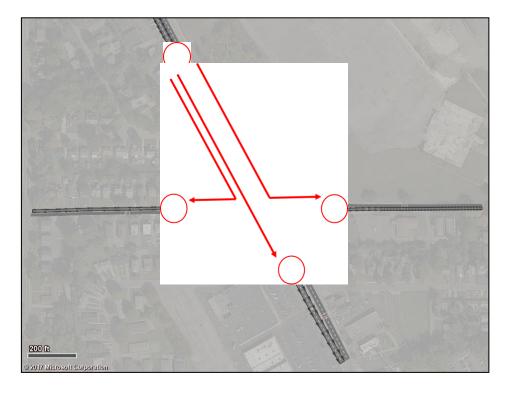


Figure 3.35 Vehicle Travel Time Measurement on the intersection layout model in PTV Vissim

Eventually, the average vehicle travel time and the average stopped delay for this study were measured by using the vehicle travel time tool in PTV Vissim. The average vehicle travel time is the average time that the vehicle takes to travel from the starting point to the ending point. The average stopped delay is the average stopped time that the vehicle spent stopped while it was traveling from the starting point to the ending point (refer to Figure 3.36).

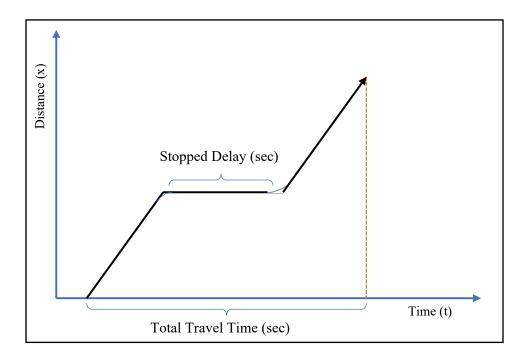


Figure 3.36 Illustration of Stopped Delay as Part of Travel Time

CHAPTER IV

RESULTS AND DISCUSSION

4.1 Introduction

After optimizing the signal timing for the Main Street and Nottingham Road intersection by using Synchro, these optimized parameters were used in microscopic simulations in PTV Vissim. First, the simulation of existing traffic counts (composed of conventional vehicles only) was done by using the existing signal timing data provided by the consultants. Then, another simulation was performed using the same traffic counts and vehicle types, but this time utilizing the Synchro optimized traffic signal timing data. Therefore, we could observe how the new optimized traffic signal performed with conventional vehicles. Thence, the same optimized traffic signal timings were used for all simulation scenarios formulated for this study. The sensitivity analyses were then performed for the intersection by systematically adding more vehicles for all turning movements for each scenario. This chapter presents all the simulation results from all scenarios formulated and discussed in the methodology section.

4.2 Simulation Results for the Optimized Signal Timing in PTV Vissim

The simulation results in this section show how the optimization of a traffic signal timing can improve the operation of the intersection for conventional vehicles in terms of selected MOEs such as queue delay, stopped delay, vehicle travel time, and queue length. Figure 4.1 shows a comparison of predicted average queue delay results between the existing traffic signal timing the optimized traffic signal timing for the same morning peak hour traffic volume. The results in Figure 4.1 show that the average queue delays were substantially decreased for all turning movements simply by optimizing the traffic signal timing. It can also be seen in Figure 4.2 that the average queue delay decreased by about 50% for the southbound and northbound movements, which are movements on the major road, i.e., Main Street. On the other hand, the average queue delay on the minor road, Nottingham Road, for westbound and eastbound movements decreased by about 10%-15%.

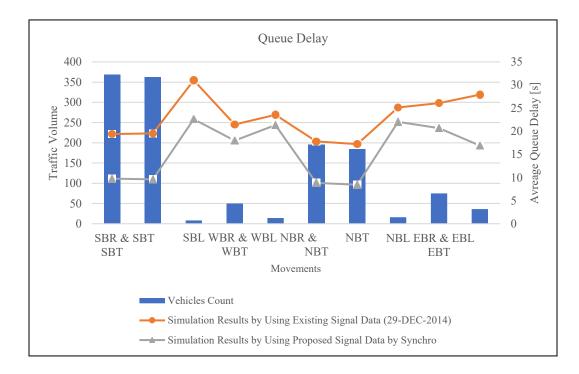


Figure 4.1 Simulation Results for Average Queue Delay at the Intersection Comparing Existing and Optimized Traffic Signal Timings

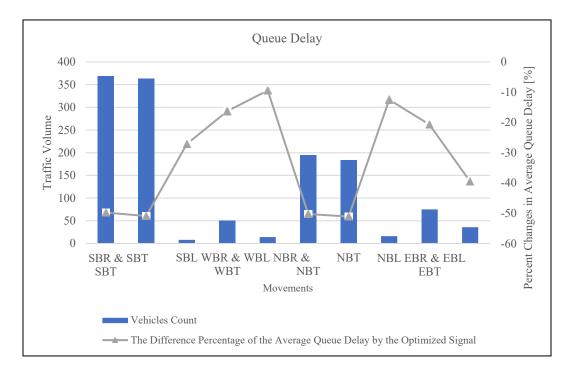


Figure 4.2 Simulation Results Showing Decreasing Percentages in Average Queue Delays at the Intersection Due to Traffic Signal Timing Optimization

Figure 4.3 shows the comparison in the predicted average stopped delay at the intersection between existing and optimized traffic signal timings. The average stopped delay is the average time in seconds where the vehicle must stop for the red signal time or due to congestion at the intersection. Similarly, Figure 4.4 shows that average stopped delay decreased by about 55% for the southbound and northbound movements and by about 30% for the westbound movements and by about 15% for the eastbound movements.

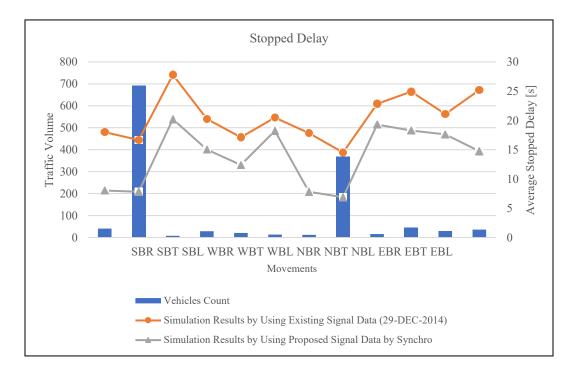


Figure 4.3 Simulation Results for Average Stopped Delay at the Intersection Comparing Existing and Optimized Traffic Signal Timings

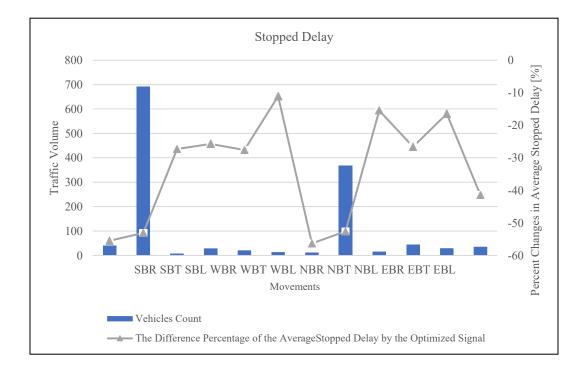


Figure 4.4 Simulation Results Showing Decreasing Percentages in Average Stopped Delays at the Intersection Due to Traffic Signal Timing Optimization

Figure 4.5 show that there was a drop in average vehicle travel time for all movements when the traffic signal was optimized. Likewise, Figure 4.6 quantifies the amount of average travel time decreases for each movement. The average vehicle travel time for southbound right-turn (SBR) and northbound right-turn (NBR) decreased by about 22%. Meanwhile the decrease in average travel times for southbound through (SBT) and northbound through (NBT) movements was about 20%. Drops of about 10% and 12% in average travel time were observed for westbound through (WBT) and eastbound through (EBT) movements, respectively.

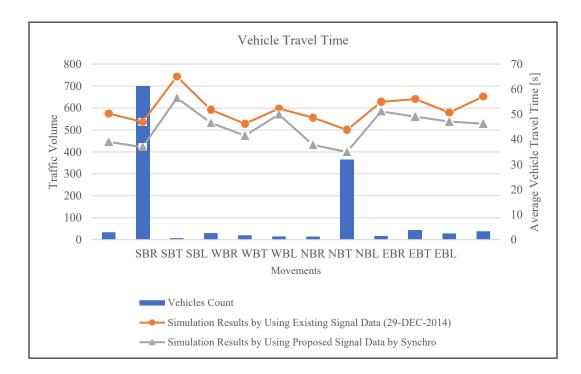


Figure 4.5 Simulation Results for the Average Travel Time at the Intersection Comparing Existing and Optimized Traffic Signal Timings

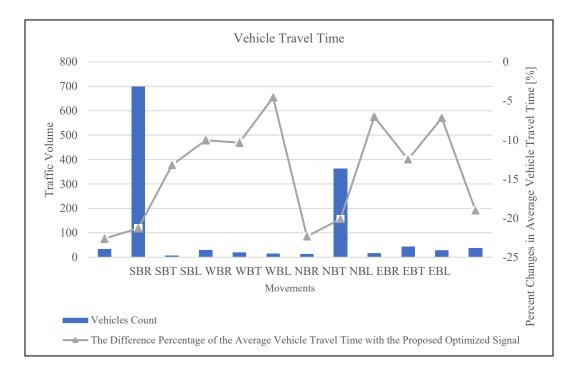


Figure 4.6 Simulation Results Showing Decreasing Percentages in Average Travel Times at the Intersection Due to Traffic Signal Timing Optimization

Figure 4.7 also shows that there was a decreasing trend in average queue lengths at the intersection because of using optimized traffic signal timing parameters from Synchro. In Figure 4.8 we can see that optimizing traffic signal timings decreased the average queue lengths for southbound and northbound movements by about 45% and decreased by about 25% for westbound and eastbound movements.

In summary, as it is shown in Figures 4.1 through 4.8, all turning movements at the intersection received substantial improvements in terms all the MOEs considered when the Synchro optimized traffic signal timings were applied to the exiting signal. This is the main reason why the proposed optimized traffic signal timing data were used for all simulation scenarios for CAVs developed in this study and the results for these scenarios are presented in the next section.

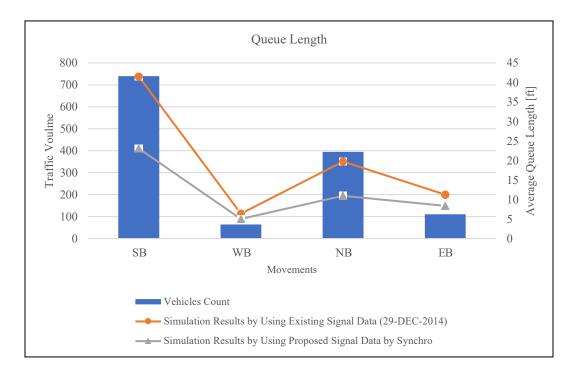


Figure 4.7 Simulation Results for Average Queue Length at the Intersection Comparing Existing and Optimized Traffic Signal Timings

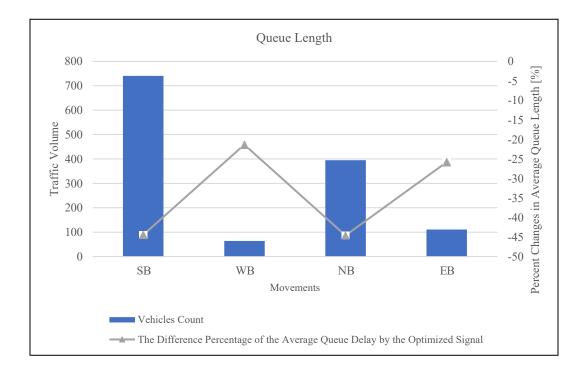


Figure 4.8 Simulation Results Showing Decreasing Percentages in Average Queue Lengths at the Intersection Due to Traffic Signal Timing Optimization

4.3 Simulation Results for Comparison Scenarios

As described in Chapter Three, five scenarios were simulated in PTV Vissim in this study and each scenario represents different driving behaviors. Recalling that these scenarios are; (1) when 100% of the vehicles in the model are conventional vehicles, (2)when 50% of the vehicle are conventional and 50% are CAVs All-knowing (CoEXist), (3) when 100% of the vehicles are CAVs Cautious (CoEXist), (4) when 100% of the vehicles are CAVs Normal (CoEXist), and (5) when 100% of the vehicles are CAVs All-knowing (CoEXist). Eventually, scenarios 3, 4, and 5 are simulating the impact of three different levels of the autonomous vehicles; scenario 2 is simulating the effect of CAVs when they are mixed with conventional vehicles in the traffic stream; and scenario 1 is simulating the existing conventional vehicles. The vehicle turning volumes used in these simulations are based on real existing traffic counts for North Main Street and Nottingham Road intersection within the city of Dayton, Ohio. The turning movement counts used in this study were for the morning peak hour. In addition, existing traffic signal timings for this intersection were optimized by using Synchro software and the optimized traffic signal timings are the ones that were used in Vissim simulations for the intersection. Therefore, the simulation results of queue delay, stopped delay, travel time, and queue length for these scenarios are presented in this section.

Figure 4.9 shows the simulation results for the average queue delay for different scenarios. In conjunction with Figure 4.10, we can see that scenarios 2, 4, and 5 observed decreasing average queue delays since their curves are plotted below 0% mark, which means there will be an improvement in the queue delay on almost all movements except southbound left-tun (SBL) and eastbound left-turn (EBL) movements. It is noteworthy to

mention that the auxiliary (storage) lane for SBL is about 42 ft long (as can be seen in Figure C-8 in Appendix C) and there is a high southbound through (SBT) traffic volume, which most of the time during the morning peak hour traffic rush it affects the SBL vehicles from accessing their turning storage lane.

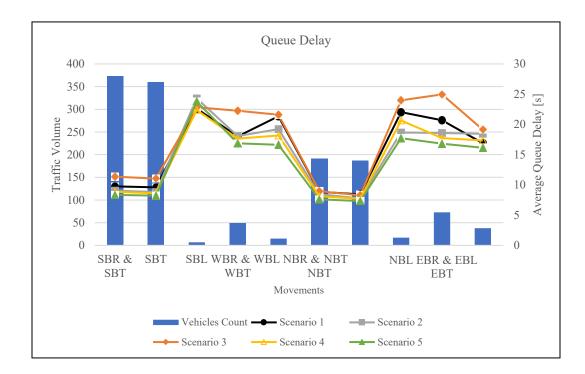


Figure 4.9 Simulation Results of the Average Queue Delay for all Scenarios in this Study

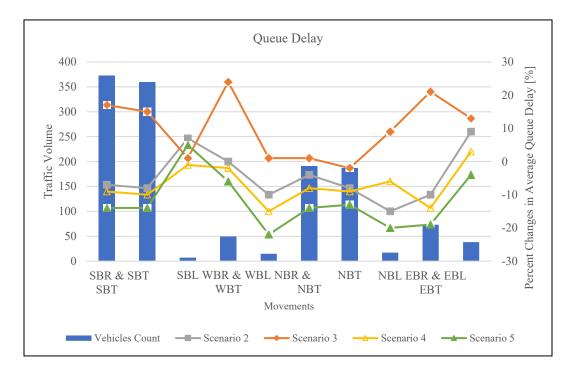


Figure 4.10 Percent Changes in Simulated Results of Average Queue Delays for all Scenarios

In the long run CAVs have a potential of decreasing queue delays at signalized intersection as can be seen for scenarios 4 and 5 (Figure 4.10). However, since the CAVs Cautious is leaving bigger gaps between vehicles than other vehicles in the model, CAVs Cautious scenario has the worst queue delay when compared with other scenarios.

Figure 4.11 presents the average stopped delay results for all scenarios at the intersection. As we can see CAV scenarios 4 and 5 are always below the conventional vehicle scenario. Because of that, CAVs All-knowing and CAVs Normal can go through the intersection with a lower stopped delay than the conventional vehicles. Figure 4.12 compares the average stopped delay for each scenario versus the base scenario, which is scenario 1. For example; for the southbound through (SBT) movement in scenario 5, the CAVs All-knowing are expected to experience an average stopped delay of about 17%

lower than if the SBL movement consisted of conventional vehicles only. Likewise, in scenario 4, the CAVs Normal can expect a decreased average stopped delay of about 15%. In addition, for the northbound through (NBT) movement, CAVs All-knowing experienced a reduced average stopped delay by 16%, and for CAVs Normal they also experienced a reduced average stopped delay by about 11%. However, the westbound through (WBT) movement did not experience reduction in average stopped delays in both scenarios 4 and 5. This can be explained that for low traffic volumes no substantial benefits can be accrued in terms of average stopped delays from CAVs Normal and CAVs All-knowing when compared with conventional vehicles. The CAVs benefits become more recognizable as traffic volumes increase and the challenge of controlling them increases. One can see that in this case study, the WBT movement consisted of 20 vehicles/hour, which is much lower than that of SBT movement with about 700 vehicles/hour.

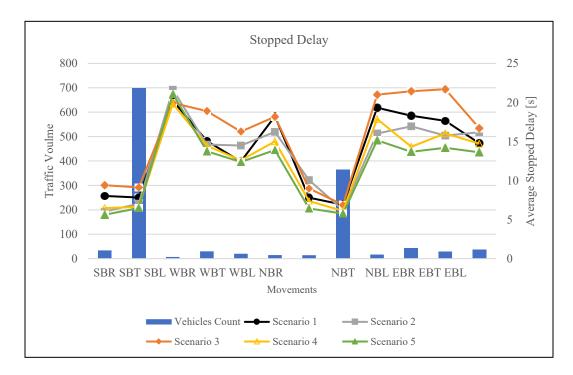


Figure 4.11 Simulation Results of Average Stopped Delays for all Scenarios

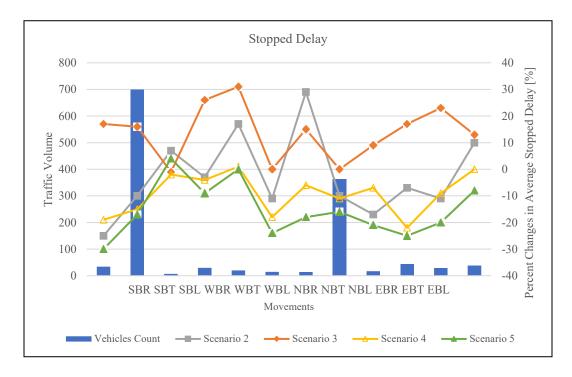


Figure 4.12 Percent Changes in Simulation Results of Average Stopped Delays for All Scenarios

Figure 4.13 compares the average vehicle travel time for all scenarios in the model and as it can be seen that almost all CAV scenarios such as scenarios 3, 4, and 5 can improve the operation of the intersection by reducing the average travel time. Figure 4.14 clarifies this by showing the percent decrease in the average travel time experienced by vehicles in scenarios 4 and 5. For scenario 4, overall average travel times were decreased between 4% and 14% for all movements. For the CAV scenario 5, the reduction in average travel time ranged between 8% and 25% for all movements.

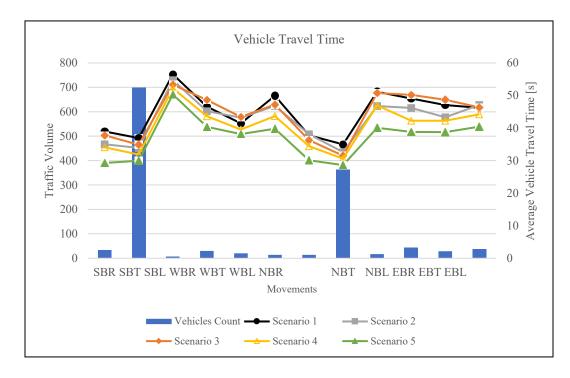


Figure 4.13 Simulation Results of Average Vehicle Travel Time for all Scenarios in this Study

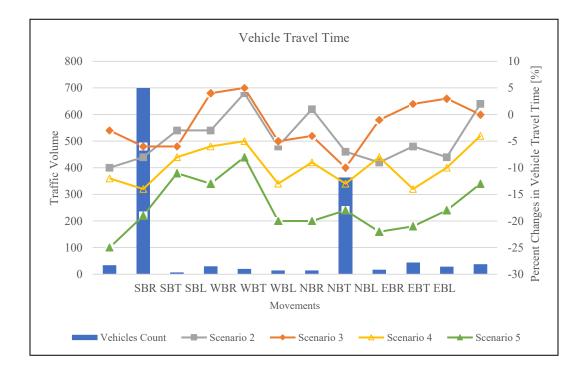


Figure 4.14 Percent Change in Simulation Results of Average Vehicle Travel Time for all Scenarios

Figure 4.15 presents the results of average queue lengths for all scenarios considered in this study. Curves for scenarios 2, 4 and 5 plot below the curve for conventional vehicles (scenario 1), while the curve for scenario 3 (CAVs Cautious) is plotted above the curve for scenario 1. That means scenarios 4 and 5 experience lower queue lengths than scenario 1 and scenario 3 has a higher queue length than scenario 1 (the base scenario). In Figure 4.16 we can see that when a movement has a higher traffic volume, it is expected to experience a higher average queue length. However, when there is a higher volume in any movement at the intersection, the presence of CAVs Normal and CAVs All-knowing can improve that movement by reducing the average queue length. Figure 4.16 clearly show that SB and NB movements, which have higher traffic volumes compare to WB and EB movements, the CAVs in scenarios 2, 4, and 5 tend to substantially decrease the average queue lengths for those movements.

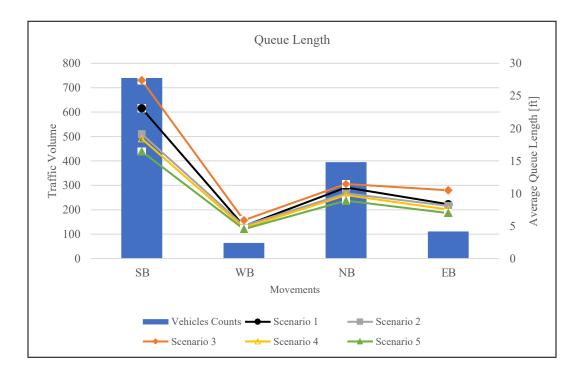


Figure 4.15 Simulation Results of Average Queue Lengths for all Scenarios in this Study

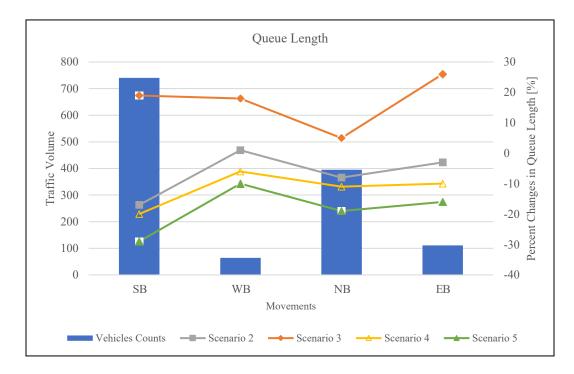


Figure 4.16 Percent Changes in Simulation Results of Average Queue Lengths in All Scenarios

4.4 Summary Results for Comparison Scenarios

This subsection presents the summary results for the comparison scenarios in terms of the overall intersection performance measures of effectiveness (MOEs) in each situation. Figure 4.17 represents the overall intersection average queue delay for each scenario while Figure 4.18 shows the overall intersection average stopped delays for all scenarios. Figure 4.19 shows that the average vehicle travel time dropped from 44.71 sec to 37.03 sec when there are only CAVs All-knowing on the intersection. Similarly, Figures 4.20 and 4.21 present results for average queue lengths and maximum queue lengths, respectively. We can see that the average queue and maximum queue lengths were reduced by 22% and 21%, respectively when the traffic stream consists of CAVs All-knowing only at the intersection.

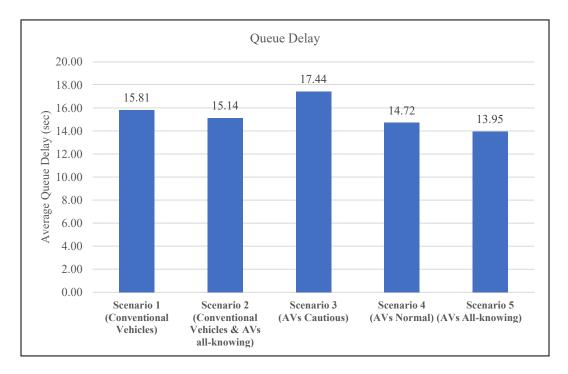


Figure 4.17 Overall Intersection Average Queue Delay for Each Scenario

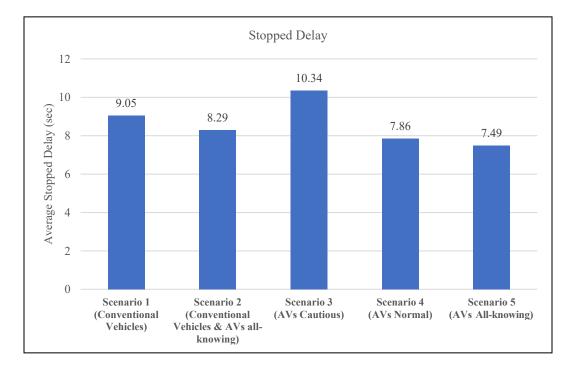


Figure 4.18 Overall Intersection Average Stopped Delay for Each Scenario

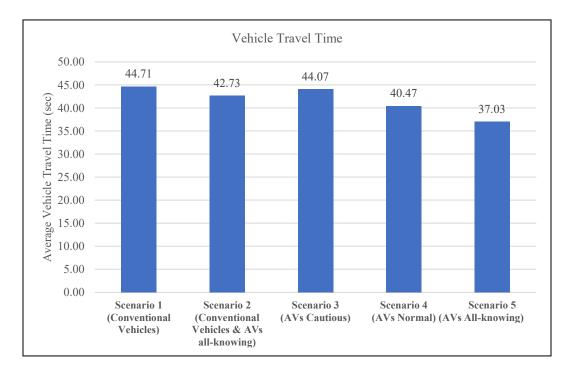


Figure 4.19 Overall Intersection Average Vehicle Travel Time for Each Scenario

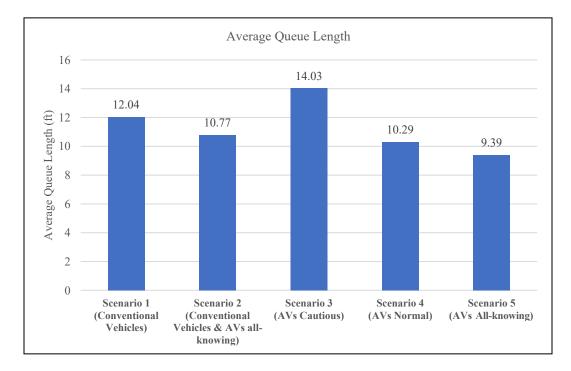


Figure 4.20 Overall Intersection Average Queue Length for Each Scenario

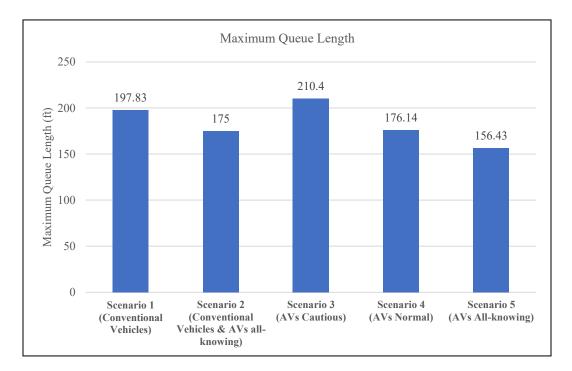


Figure 4.21 Overall Intersection Maximum Queue Length for Each Scenario

Table 4.1 summarizes all the results that have been presented in Figures 4.17 through 4.21 above. Again, scenario 1 was a base scenario, for which all other scenarios were compared to, and that is why it has a percent change of 0% value for all intersection performance MoEs.

Intersection Performance Measures of Effectiveness (MOEs)	Percent Change in MOEs for Each Scenario				
	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Average Queue Delay (sec)	0%	-4%	10%	-7%	-12%
Average Stopped Delay (sec)	0%	-8%	14%	-13%	-17%
Average Vehicle Travel Time (sec)	0%	-4%	-1%	-9%	-17%
Average Queue Length (ft)	0%	-11%	17%	-15%	-22%
Maximum Queue Length (ft)	0%	-12%	6%	-11%	-21%

Table 4.1 Summary Results Comparing Overall Intersection's Performances

In summary, based on the results presented in this section, CAVs such as CAVs Normal and CAVs All-knowing can improve the operational efficiency of urban signalized intersections by minimizing queue delays, stopped delays, vehicle travel times, and the queue lengths. Essentially, due to the cooperative and communication between Connected and automated vehicles, The benefits of CAVs Normal and CAVs All-knowing could become more pronounced when the travel demands increase at the intersection.

4.5 Simulation Results for Sensitivity Analysis

This section presents simulation results for sensitivity analyses for two scenarios that were selected for this test. Scenarios 2 and 4 are the two selected for this analysis. Recall that scenario 2 is when 50% of the traffic stream is made of conventional vehicles and the other 50% consists of CAVs All-knowing while scenario 4 consists of 100% CAVs Normal only. These two scenarios were selected for sensitivity analysis because these

scenarios might occur earlier in the future. Therefore, this section presents the

performances in terms of queue lengths at the intersection while the demand is systematically increased up to 50% higher than the existing demand. Again, Scenarios 2 and 4 are compared with the base scenario (scenario 1) in terms of average queue lengths as traffic demands increase equally for all turning movements approaching the intersection.

Figures 4.22 through 4.25 show that for scenario 2 the average queue lengths generally decreased when compared to those of scenario 1 when gradually increasing traffic volumes by 10% up to 50 % for all movements at the intersection.

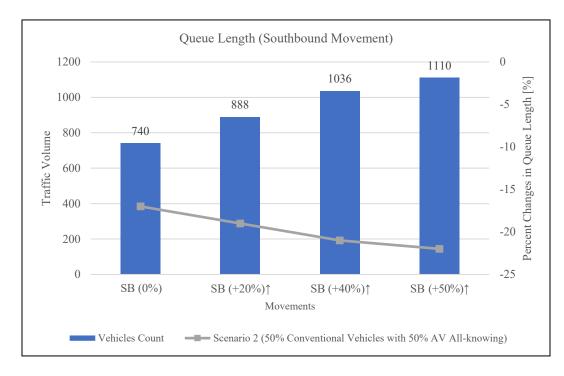


Figure 4.22 Sensitivity Analysis Results for SB Movement in Scenario 2

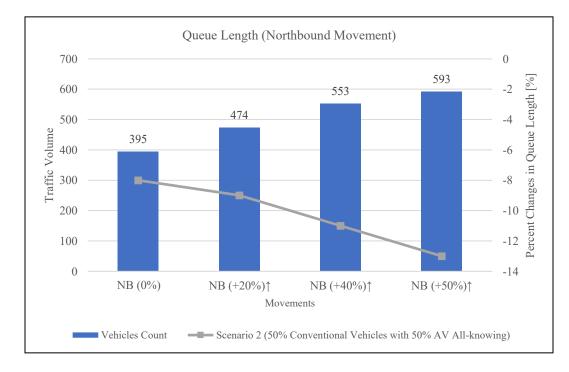


Figure 4.23 Sensitivity Analysis Results for NB Movement in Scenario 2

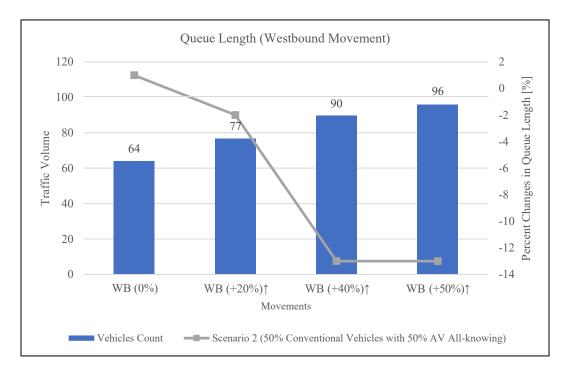


Figure 4.24 Sensitivity Analysis Results for WB Movement in Scenario 2

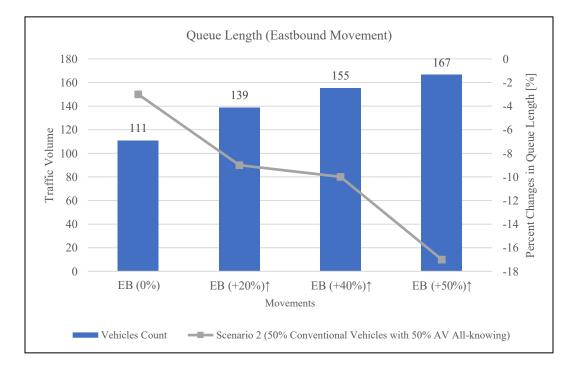


Figure 4.25 Sensitivity Analysis Results for EB Movement in Scenario 2

Similarly, Figures 4.26 through 4.29 show that queue lengths are also decreasing with increasing traffic volumes for all movements for the CAVs Normal scenario 4 when compared to Scenario 1 (conventional vehicles). Once again, microscopic simulation reveals that CAVs can effectively reduce queue lengths as travel demands increase for all movements (left-turn, through, and right-turn) approaching a signalized intersection.

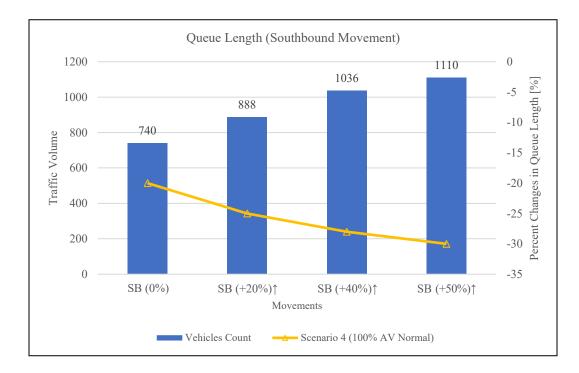


Figure 4.26 Sensitivity Analysis Results for SB Movement in Scenario 4

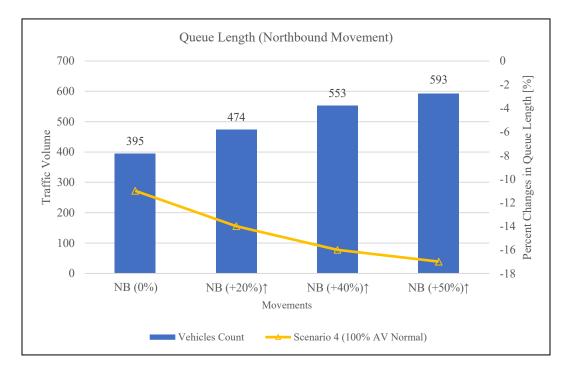


Figure 4.27 Sensitivity Analysis Results for NB Movement in Scenario 4

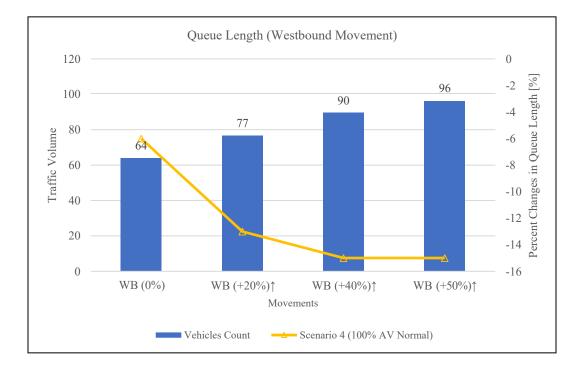


Figure 4.28 Sensitivity Analysis Results for WB Movement in Scenario 4

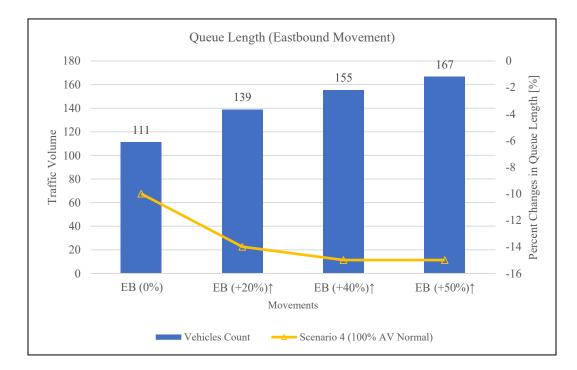


Figure 4.29 Sensitivity Analysis Results for EB Movement in Scenario 4

4.6 Summary Results for Sensitivity Analysis

Results presented in section 4.5 show that both Scenarios 2 and 4 observed decreasing average queue lengths compared to similar demands in scenario 1 as travel demands (traffic volumes) were increased. However, these decreases in queue lengths were not directly compared between scenarios 2 and 4 to see which one was more efficient. Therefore, Figures 4.30 and 4.31 provide such a comparison. Figure 4.30 shows that all three scenarios, i.e., 1, 2, and 4 experienced increased queue lengths as total travel demands approaching the intersection increased, which is logically expected. However, scenario 4, which consists of CAVs only was the most efficient scenario with the lowest average queue length increases as the traffic demand increased followed with scenario 2 that consists of 50% of CAVs in its traffic demand.

Figure 4.31 presents a better quantification of these differences by providing the percent changes in queue lengths for scenarios 2 and 4 over scenario 1 (the base scenario with 0% change). Figure 4.31 shows that the curve for scenario 4 is plotted much lower (below 0% line) than that of scenario 2, predicting that in the future once the traffic volume will be consisted of 100% CAVs will make signalized intersection perform better with improved operating performance.

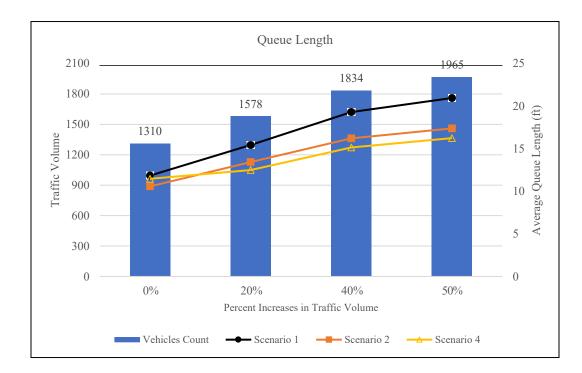


Figure 4.30 Comparing Average Quaue Lengths as Traffic Demand Increases for the Entire Intersection

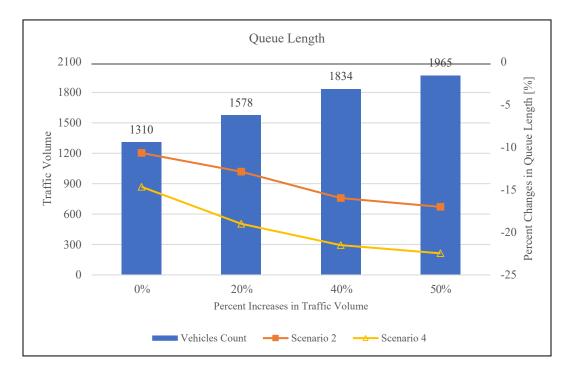


Figure 4.31 Percentage Change in Average Queue Lengths for CAVs Scenarios as Compared with Conventional Vehicles (Base Scenario)

CHAPTER V

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Traffic congestion and dangers of traffic crashes are the main problems facing road users on a regular basis. It is a well-known fact that most traffic crashes occur due to human errors. Additionally, it is well known that most of the recurring traffic congestions are due to bottlenecks, i.e., traffic demand exceeds the available road capacity. Furthermore, driver decision making, and their unpredictable and varied reaction times contribute to increased travel delays especially at intersections. Therefore, by using the new technology of autonomous vehicles (connected and automated), the human errors will be minimized, which will make the roadways safer and make them more efficient by reducing delays. A connected and automated vehicle (CAV) is expected to be computerized and be able travel at a steady desired speed. Additionally, CAVs will be able to leave smaller headways (gaps) between each other in the traffic stream. Therefore, CAVs will increase the efficiency of roadways and intersections. The main aim of thesis study was to evaluate the impact of the connected and automated vehicle at a signalized intersection.

The evaluation method that was used in this study utilized Vissim, a powerful microscopic simulation software. A typical urban signalized intersection located in city of Dayton, Ohio was selected for simulation. This intersection was selected because recent traffic turning counts and signal timing data were available for this study. The existing

signal timing data was first optimized by Synchro software and the optimized data were then used in PTV Vissim's analyses. Three different CAVs were used in this study; these vehicles were defined and designed based on empirical studies and assumptions from the CoEXist study. Fortunately, algorithms and logics for these vehicles have been implemented in the most recent version of PTV Vissim software. Therefore, these CAVs are already installed in PTV Vissim 11.

After performing the microscopic simulations of the intersection, the results show that CAVs Normal (CoEXist) and CAVs All-knowing (CoEXist) can reduce average queue delays by 7%-12%, average stopped delay by 13%-17%, average vehicle travel time by 9%-17%), the average queue length by 15%-22%. Therefore, all these results mean that traffic congestion at signalized intersections will be reduced as the CAVs market penetration increases. The results from this study also show that higher signalized intersection operating benefits are realized with CAVs when traffic volumes approaching the intersection become higher, i.e., AVs perform better in congested volumes when compared to what would have been the situation with conventional vehicles with similar traffic demands.

The current study has also shown that during the transition period (when AVs will coexist with conventional vehicles), signalized intersections will operationally perform better than when the traffic stream consists of conventional vehicles only. It is expected that AVs will be slowly penetrating the vehicles market and eventually all conventional vehicles will be phased out, and that is when the full benefits of AVs will be realized. AVs Knowing and AVs Normal provide the best benefits in terms with the potential of decreasing average delays and queues at signalized intersections. Results of this analysis study are purely based on simulation scenarios, which attempt do model real-world situations and should have limitations like any other simulation results. Specifically, the results of the current study are highly dependent on the simplifications of the real world and assumptions of driver behaviors and car-following logics incorporated into the simulation algorithms and scenario logics. Therefore, these results should be interpreted with caution due these reasons.

5.2 Recommendations

For future work, it is recommended to create a communication algorithm between the autonomous vehicle and signal controllers and defining the algorithm for "vehicle to vehicle" communications for the connected vehicles platooning. These algorithms can be designed in COM interface and then can be used in PTV Vissim simulation. Using the communications features in the autonomous vehicles could increase further the efficiency of signalized intersections.

Additionally, we recommend creating more scenarios that contain a mix of conventional vehicles and automated vehicles, and these scenarios should have a large variety of different types of driving behaviors. It is better to evaluate more realistic scenarios, which will be facilitated by future increase of CAVs market penetration into the vehicle fleets around the world.

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APPENDIX A

Source of Data

Aerial View of the Intersection by Google



Figure A-1 Northbound Segment for the Intersection



Figure A-2 Westbound Segment for the Intersection

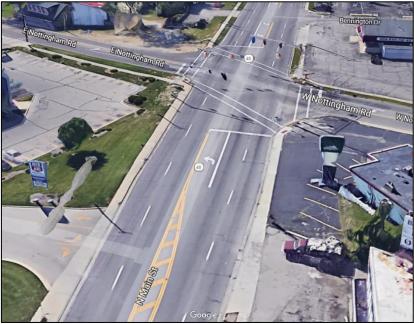


Figure A-3 Southbound Segment for the Intersection



Figure A-4 Eastbound Segment for the Intersection

Source of Data

Turning Movement Peak Hour Data

										Miamist (937) 25	2500 M	LJB Inc Newmar nio, Unite	k Drive	45342 linc.com	1				S	count Na ite Code tart Date age No:	e: 14 e: 08/28	ttingham /2018			
								Turr	ning N	Noven	nent F	Peak	Hour	Data	(7:15	AM)									
			Ma	in St					Notti	ngham					Mai	in St					Nottin	igham			
(2019) (2019) -			South	bound					Wes	tbound					North	bound					East	bound			
Start Time	Right	Thru	Left	U-Turn	Peds	App. Total	Right	Thru	Left	U-Turn	Peds	App. Total	Right	Thru	Left	U-Turn	Peds	App. Total	Right	Thru	Left	U-Turn	Peds	App. Total	Int. T
7:15 AM	8	163	2	0	0	173	6	4	5	0	1	15	2	90	6	0	0	98	14	9	3	0	1	26	313
7:30 AM	9	205	2	0	0	216	11	5	1	0	0	17	6	111	5	0	0	122	9	7	15	0	2	31	38
7:45 AM	12	195	3	0	0	210	7	4	6	0	1	17	5	82	3	0	0	90	11	5	15	0	0	31	34
8:00 AM	8	131	2	0	0	141	5	5	5	0	0	15	2	80	3	0	0	85	9	7	7	0	0	23	264
Total	37	694	9	0	0	740	29	18	17	0	2	64	15	363	17	0	0	395	43	28	40	0	3	111	131
Approach %	5.0	93.8	1.2	0.0			45.3	28.1	26.6	0.0	-		3.8	91.9	4.3	0.0	*	-	38.7	25.2	36.0	0.0	-		· ·
Total %	2.8	53.0	0.7	0.0	*	56.5	2.2	1.4	1.3	0.0	+	4.9	1.1	27.7	1.3	0.0	-	30.2	3.3	2.1	3.1	0.0	-	8.5	-
PHF	0.771	0.846	0.750	0.000		0.856	0.659	0.900	0.708	0.000		0.941	0.625	0.818	0.708	0.000		0.809	0.768	0.778	0.667	0.000		0.895	0.84
Lights	35	679	8	0		722	25	17	16	0		58	15	354	17	0		386	42	28	37	0	~	107	127
% Lights	94.6	97.8	88.9	•		97.6	86.2	94.4	94.1		-	90.6	100.0	97.5	100.0	-	-	97.7	97.7	100.0	92.5	-	-	96.4	97.
Mediums	2	14	1	0		17	4	5.6	1	0		9.4	0	9	0	0		9	1	0	3	0	-	4	36
% Mediums Articulated Trucks	0	1	0	- 0	-	1	13.8	0	0	-	-	9.4	0.0	0	0.0	-	-	2.3	2.3	0.0	0	-	-	3.6	1
% Articulated Trucks	0.0	0.1	0.0		-	0.1	0.0	0.0	0.0	-		0.0	0.0	0.0	0.0	-		0.0	0.0	0.0	0.0	-	-	0.0	0.1
Bicycles on Crosswalk					0						0						0				-		0		
% Bicycles on Crosswalk	· .	<u>_</u>				-					0.0			1		-	14	<u>.</u>	ч.		- 21		0.0	<u>_</u>	
Pedestrians					0	-					2				-		0				-		3		
% Pedestrians											100.0												100.0		

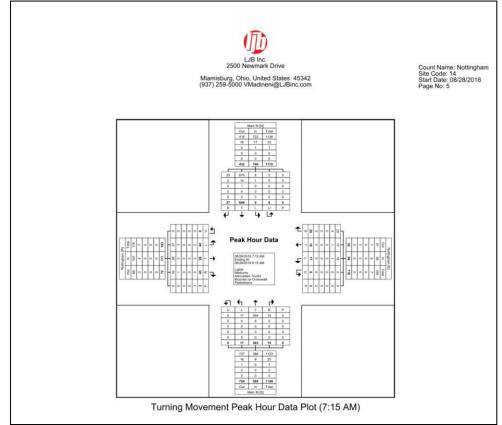


Figure A-5 Turning Movement Peak Hour Data from LJB Inc.

APPENDIX B

The Optimized Signal Timing Design by Synchro 10

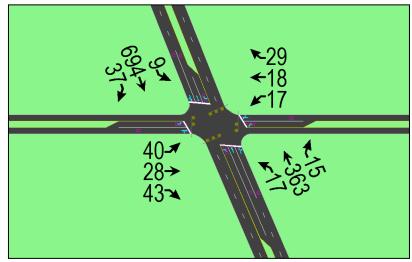


Figure B-1 Intersection layout in Synchro

Lanes, Volumes, Tin 2:	nings										02/	06/2019
	٭	-	\mathbf{F}	•	•	*	•	t	۴	1	ţ	~
Lane Group	EBL	EBT	EBR	WBL	WBT	WBR	NBL	NBT	NBR	SBL	SBT	SBR
Lane Configurations	1	ĥ		1	f,		7	朴		1	↑ Ъ	
Traffic Volume (vph)	40	28	43	17	18	29	17	363	15	9	694	37
Future Volume (vph)	40	28	43	17	18	29	17	363	15	9	694	37
Ideal Flow (vphpl)	1900	1900	1900	1900	1900	1900	1900	1900	1900	1900	1900	1900
Storage Length (ft)	116		0	100		0	172		0	42		0
Storage Lanes	1		0	1		0	1		0	1		0
Taper Length (ft)	25			25			25			25		
Lane Util. Factor	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95	0.95	1.00	0.95	0.95
Frt		0.909			0.907			0.994			0.992	
Flt Protected	0.950			0.950			0.950			0.950		
Satd. Flow (prot)	1671	1706	0	1703	1553	0	1805	3521	0	1626	3506	0
Flt Permitted	0.950			0.950			0.950			0.950		
Satd. Flow (perm)	1671	1706	0	1703	1553	0	1805	3521	0	1626	3506	0
Right Turn on Red			Yes			Yes			Yes			Yes
Satd. Flow (RTOR)		48			31			7			8	
Link Speed (mph)		30			30			30			30	
Link Distance (ft)		833			842			615			839	
Travel Time (s)		18.9			19.1			14.0			19.1	
Peak Hour Factor	0.90	0.90	0.90	0.94	0.94	0.94	0.81	0.81	0.81	0.86	0.86	0.86
Heavy Vehicles (%)	8%	0%	2%	6%	6%	14%	0%	2%	0%	11%	2%	5%
Adj. Flow (vph)	44	31	48	18	19	31	21	448	19	10	807	43
Shared Lane Traffic (%)												
Lane Group Flow (vph)	44	79	0	18	50	0	21	467	0	10	850	0
Enter Blocked Intersection	No	No	No	No	No	No	No	No	No	No	No	No

Figure B-2 Optimized Signal Timing by Synchro

2:											02/0	6/2019
	الر	-	\mathbf{r}	4	+	*	1	1	1	1	↓	~
Lane Group	EBL	EBT	EBR	WBL	WBT	WBR	NBL	NBT	NBR	SBL	SBT	SBR
Permitted Phases												
Detector Phase	7	4		3	8		5	2		1	6	
Switch Phase												
Minimum Initial (s)	5.0	5.0		5.0	5.0		5.0	5.0		5.0	5.0	
Minimum Split (s)	9.5	22.5		9.5	22.5		9.5	22.5		9.5	22.5	
Total Split (s)	9.6	22.6		9.5	22.5		9.5	23.4		9.5	23.4	
Total Split (%)	14.8%	34.8%		14.6%	34.6%		14.6%	36.0%		14.6%	36.0%	
Maximum Green (s)	5.1	18.1		5.0	18.0		5.0	18.9		5.0	18.9	
Yellow Time (s)	3.5	3.5		3.5	3.5		3.5	3.5		3.5	3.5	
All-Red Time (s)	1.0	1.0		1.0	1.0		1.0	1.0		1.0	1.0	
Lost Time Adjust (s)	0.0	0.0		0.0	0.0		0.0	0.0		0.0	0.0	
Total Lost Time (s)	4.5	4.5		4.5	4.5		4.5	4.5		4.5	4.5	
Lead/Lag	Lead	Lag		Lead	Lag		Lead	Lag		Lead	Lag	
Lead-Lag Optimize?	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Vehicle Extension (s)	3.0	3.0		3.0	3.0		3.0	3.0		3.0	3.0	
Recall Mode	None	None		None	None		None	Max		None	Max	
Walk Time (s)		7.0			7.0			7.0			7.0	
Flash Dont Walk (s)		11.0			11.0			11.0			11.0	
Pedestrian Calls (#/hr)		0			0			0			0	
Act Effct Green (s)	5.4	8.5		5.3	6.7		5.3	30.6		5.3	30.6	
Actuated g/C Ratio	0.13	0.21		0.13	0.17		0.13	0.75		0.13	0.75	
v/c Ratio	0.20	0.20		0.08	0.18		0.09	0.18		0.05	0.32	
Control Delay	21.3	9.8		20.4	12.2		20.4	6.8		20.2	7.7	
Queue Delay	0.0	0.0		0.0	0.0		0.0	0.0		0.0	0.0	
Total Delay	21.3	9.8		20.4	12.2		20.4	6.8		20.2	7.7	
LOS	C	A		С	В		С	A		С	A	
Approach Delay		13.9			14.4			7.4			7.8	
Approach LOS		В			В			A			A	

Figure B-3 Optimized Signal Timing by Synchro

2:		02/06/2019
Area Type: Other		
Cycle Length: 65		
Actuated Cycle Length: 40.6		
Natural Cycle: 65		
Control Type: Actuated-Uncoordinated		
Maximum v/c Ratio: 0.32		
Intersection Signal Delay: 8.5	Intersection LOS: A	
Intersection Capacity Utilization 36.7%	ICU Level of Service A	
Analysis Period (min) 15		
90th %ile Actuated Cycle: 56.1		
70th %ile Actuated Cycle: 44.2		
50th %ile Actuated Cycle: 26		
30th %ile Actuated Cycle: 38.4		
10th %ile Actuated Cycle: 38.4		
Splits and Phases: 2:		
▶ø1 1 ø2	√ Ø3 →Ø4	
9.5 s 23.4 s	9.5 s 22.6 s	
▲	<u></u>	
Ø5 ▼ Ø6	9.6 5 22.5 5	

Figure B-4 Optimized Signal Timing by Synchro

APPENDIX C

The Intersection Model by PTV Vissim



Figure C-1 N Main Street and Nottingham Road Intersection Layout and the Background Image in PTV Vissim



Figure C-2 Intersection Layout and the Background Image in PTV Vissim

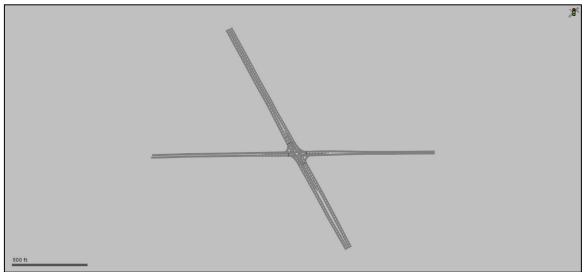


Figure C-3 Intersection Layout (Links and Connecters) in PTV Vissim



Figure C-4 Intersection Layout (Links and Connecters) in PTV Vissim



Figure C-5 Intersection (3D Model) in PTV Vissim



Figure C-6 Intersection (3D Model) in PTV Vissim



Figure C-7 Intersection (3D Model) in PTV Vissim



Figure C-8 Southbound Pocket Lane in PTV Vissim



Figure C-9 Eastbound Pocket Lane in PTV Vissim

Vehicle Ty	pes		
Select layo	out 🔽 🥜 🚽	• 🖉 🗙 🏹 🛔 🖞 🗸 † 😿 💸 <sir< th=""><th>ngle List> 🔹 🗈 🕒 😫 🎼</th></sir<>	ngle List> 🔹 🗈 🕒 😫 🎼
Count: 10	No	Name	Category
1	100	Car	Car
2	300	Bus	Bus
3	510	Man	Pedestrian
4	520	Woman	Pedestrian
5	630	Car AV cautious	Car
6	640	Bus AV cautious	Bus
7	650	Car AV normal	Car
8	660	Bus AV normal	Bus
9	670	Car AV allknowing	Car
10	680	Bus AV allknowing	Bus

Figure C-10 Vehicle Types in PTV Vissim

Vehicle C	lasses /	Vehicle Types			
Select lay	out	- 🖋 🕂 🏹 💱	🛓 🗸 † 🈿 袭 Ve	ehicle types	- 🗈 🛢 💾 🛃 🍀
Count: 8	No	Name	VehTypes	UseVehTypeColor	Color
1	10	Car	100	 Image: A set of the set of the	(255, 0, 0, 0)
2	30	Bus	300	✓	(255, 0, 0, 0)
3	40	Car AV cautious	630	✓	(255, 255, 106, 0)
4	50	Bus AV cautious	640	✓	(255, 255, 106, 0)
5	60	Car AV normal	650	✓	(255, 255, 0, 0)
6	70	Bus AV normal	660	 Image: A set of the set of the	(255, 255, 0, 0)
7	80	Car AV allknowing	670	✓	(255, 0, 38, 255)
8	90	Bus AV allknowing	680	✓	(255, 0, 38, 255)

Figure C-11 Vehicle Classes / Vehicle Types in PTV Vissim

Driving B	ehavi	ors				
Select lay	out	- 🎤 🕇 🖉 🔀 💱	🛓 🕺 🕇 👿 ズ <sin< th=""><th>gle List> 🔹</th><th>le 🛢 💾 😫 I</th><th>⇔</th></sin<>	gle List> 🔹	le 🛢 💾 😫 I	⇔
Count: 8	No	Name	NumInteractObj	NumInteractVeh	LatDistDrivDef	LatDistStandDef
1	1	Urban (motorized)	4	99	3.28	0.66
2	2	Right-side rule (motorized)	2	99	3.28	0.66
3	3	Freeway (free lane selection)	2	99	3.28	0.66
4	4	Footpath (no interaction)	2	99	3.28	0.66
5	5	Cycle-Track (free overtaking)	2	99	0.98	0.33
6	101	AV cautious (CoEXist)	2	1	3.28	0.66
7	102	AV normal (CoEXist)	2	1	3.28	0.66
8	103	AV all-knowing (CoEXist)	10	8	3.28	0.66

Figure C-12 Driving Behaviors in PTV Vissim

Link Beha	vior Types / Driving Behavio	rs By Vehicle Class
<i>▶</i> ^A / _Z ↓ ^Z / _A	† 📡	
Count: 6	VehClass	DrivBehav
1	40: Car AV cautious	101: AV cautious (CoEXist)
2	50: Bus AV cautious	101: AV cautious (CoEXist)
3	60: Car AV normal	102: AV normal (CoEXist)
4	70: Bus AV normal	102: AV normal (CoEXist)
5	80: Car AV allknowing	103: AV all-knowing (CoEXist)
6	90: Bus AV allknowing	103: AV all-knowing (CoEXist)

Figure C-13 Link Behavior Types / Driving Behaviors by Vehicle Class

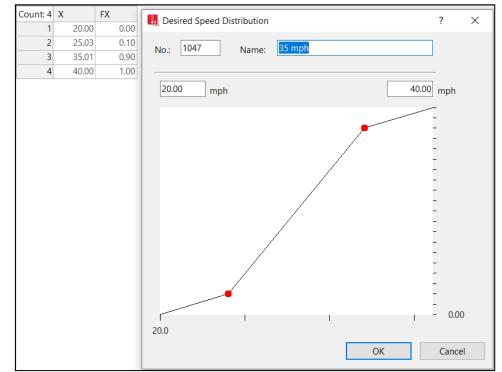


Figure C-14 Desired Speed Distribution of the Conventional Vehicle in PTV Vissim

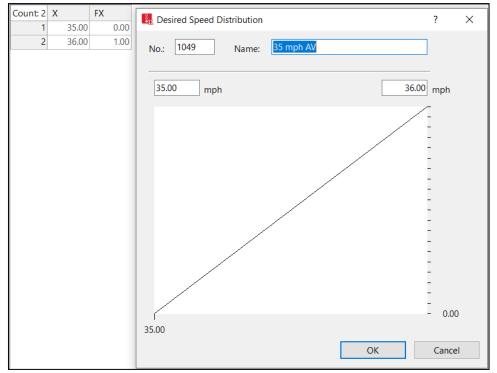


Figure C-15 Desired Speed Distribution for Autonomous Vehicle in PTV Vissim

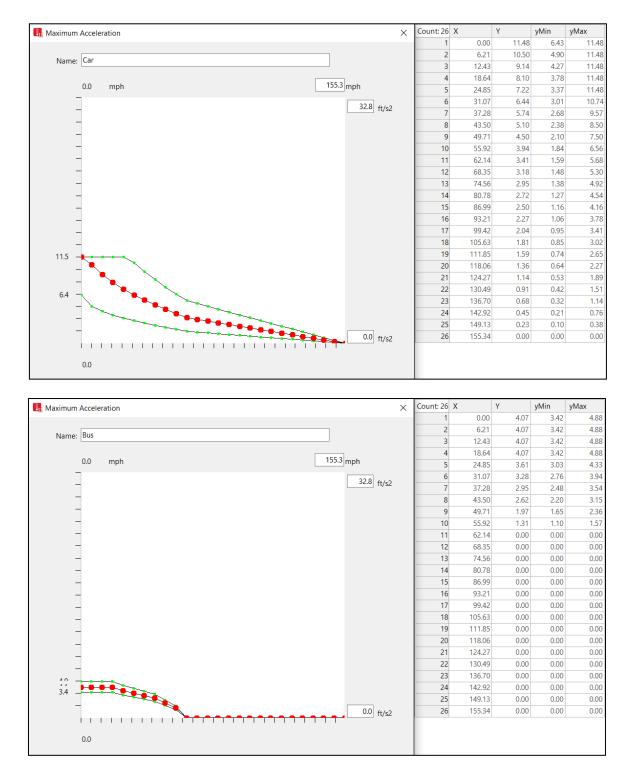


Figure C-16 Max Acceleration of Conventional Car & Conventional Bus in PTV Vissim

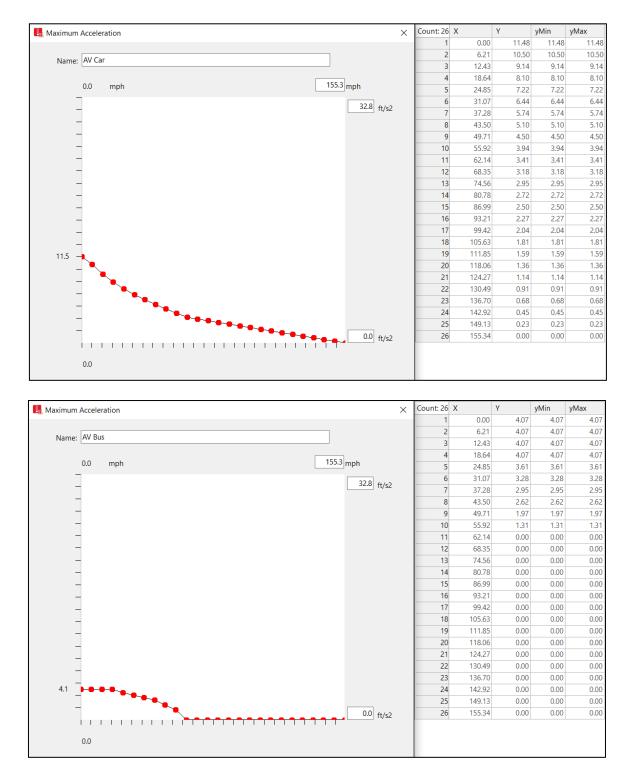


Figure C-17 Maxi Acceleration of Autonomous Car & Autonomous Bus in PTV Vissim

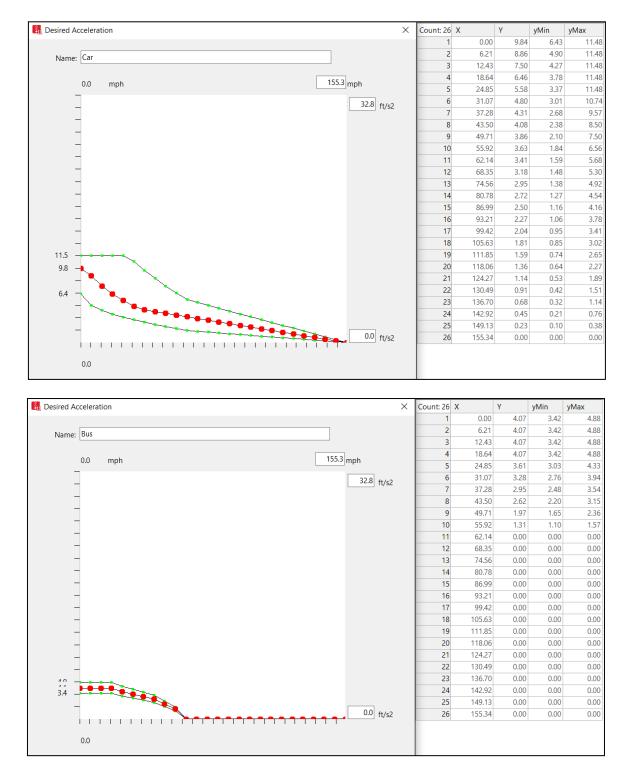


Figure C-18 Desired Acceleration of Conventional Car & Conventional Bus in PTV Vissim

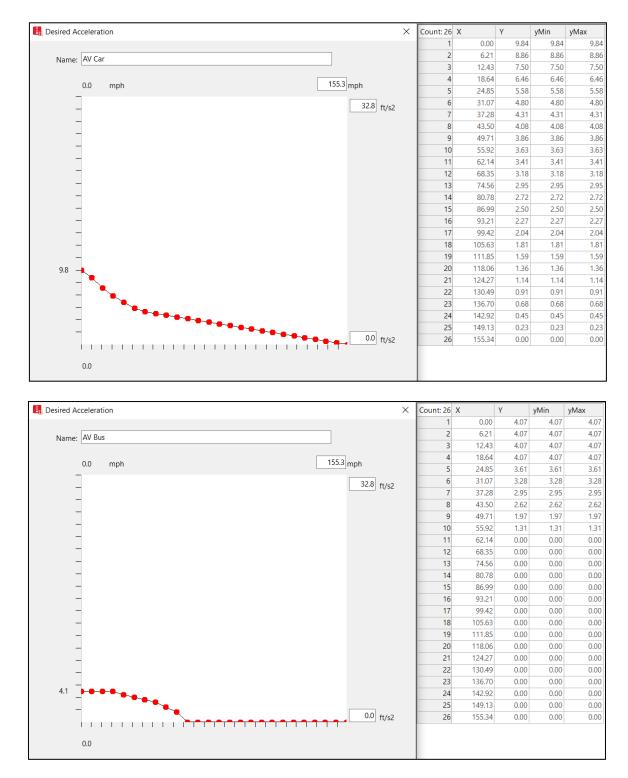


Figure C-19 Desired Acceleration of Autonomous Car & Autonomous Bus in PTV Vissim

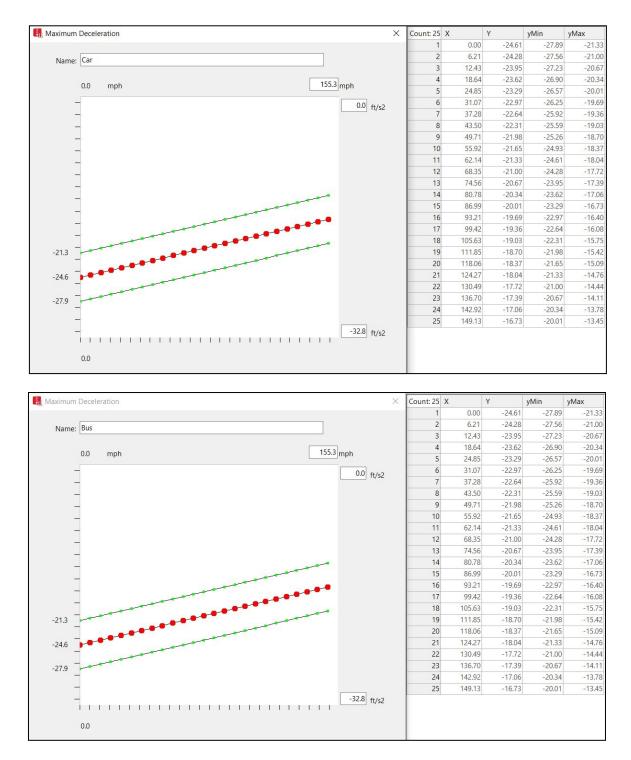


Figure C-20 Max Deceleration of Car & Bus in PTV Vissim

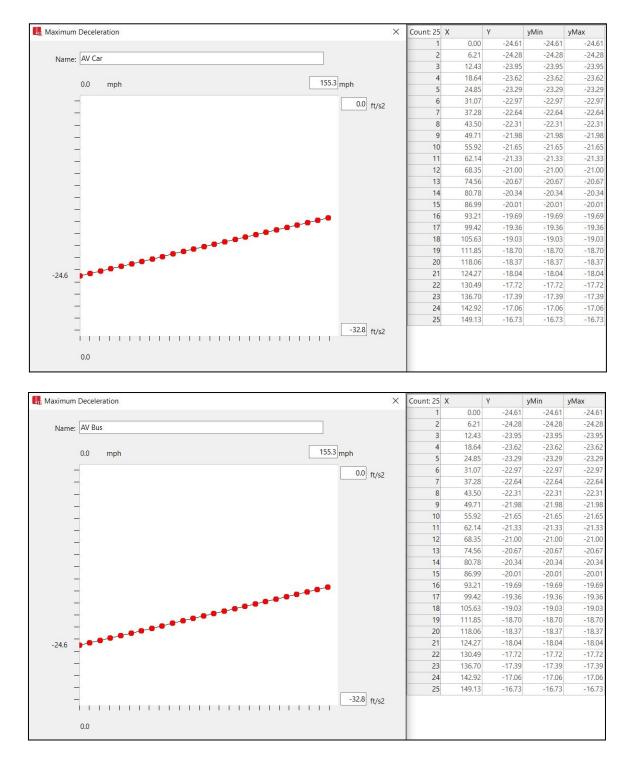


Figure C-21 Max Deceleration of Autonomous Car & Autonomous Bus in PTV Vissim

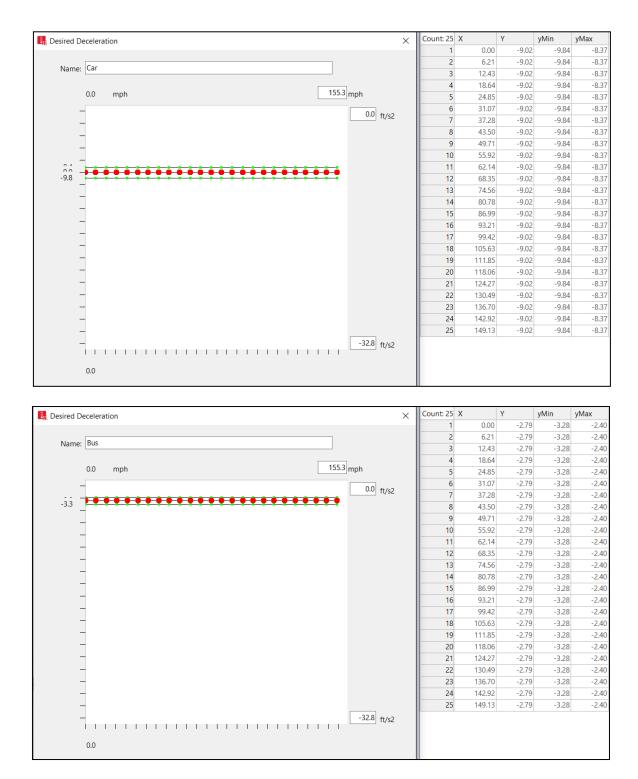


Figure C-22 Desired Deceleration of Conventional Car & Conventional Bus in PTV Vissim

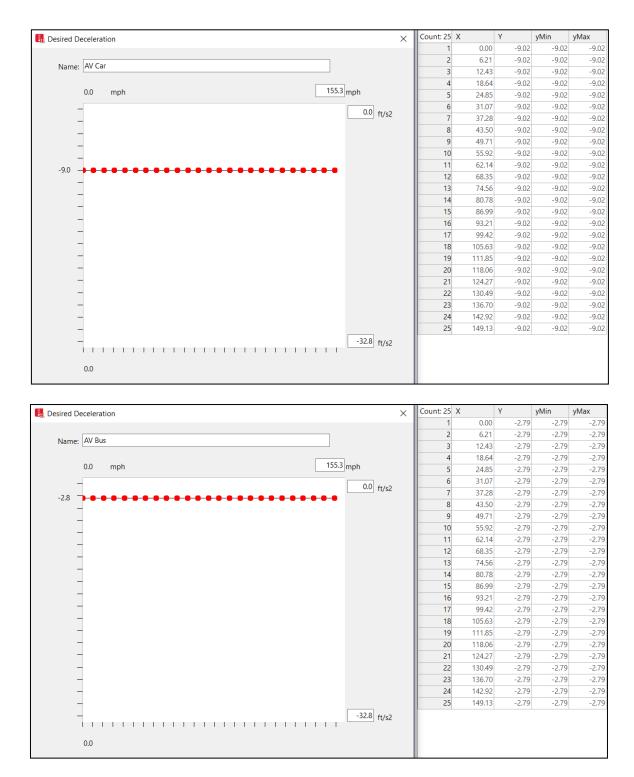


Figure C-23 Desired Deceleration of Autonomous Car & Autonomous Bus in PTV Vissim

Vehicle Cor	mpo	sitions / Relative Flows					
Select layo	ut	· 🎤 🕂 🗙 🖕 🚽	<i>F</i>	t 😿			
Count: 20	No	Name	Count: 8	VehComp	VehType	DesSpeedDistr	RelFlow
1	1	SB (AM) - SCEN 1	1	1: SB (AM) - SCEN 1	100: Car	1047: 35 mph	97.600
2	2	WB (AM) - SCEN 1	2	1: SB (AM) - SCEN 1	300: Bus	1047: 35 mph	2.400
3	3	NB (AM) - SCEN 1	3	2: WB (AM) - SCEN 1	100: Car	1047: 35 mph	90.900
4	4	EB (AM) - SCEN 1	4	2: WB (AM) - SCEN 1	300: Bus	1047: 35 mph	9.400
5	5	SB (AM) - MIX - SCEN 2	5	3: NB (AM) - SCEN 1	100: Car	1047: 35 mph	97.700
6	6	WB (AM) - MIX - SCEN 2	6	3: NB (AM) - SCEN 1	300: Bus	1047: 35 mph	2.300
7	7	NB (AM) - MIX - SCEN 2	7	4: EB (AM) - SCEN 1	100: Car	1047: 35 mph	96.400
8	8	EB (AM) - MIX - SCEN 2	8	4: EB (AM) - SCEN 1	300: Bus	1047: 35 mph	3.600
9	9	SB (AM) - AV C - SCEN 3					
10	10	WB (AM) - AV C - SCEN 3					
11	11	NB (AM) - AV C - SCEN 3					
12	12	EB (AM) - AC C - SCEN 3					
13	13	SB (AM) - AV N - SCEN 4					
14	14	WB (AM) - AV N - SCEN 4					
15	15	NB (AM) - AV N - SCEN 4					
16	16	EB (AM) - AC N - SCEN 4					
17	17	SB (AM) - AV AII - SCEN 5					
18	18	WB (AM) - AV AII - SCEN 5					
19	19	NB (AM) - AV AII - SCEN 5					
20	20	EB (AM) - AC AII - SCEN 5					

Figure C-24 Example; the Vehicle Compositions for the Vehicle Input in Scenario 1

Select layo	out	- 🎤 🕂 🏹 🚊		1 🔣			
Count: 20	No	Name	Count: 8	VehComp	VehType	DesSpeedDistr	RelFlow
1	1	SB (AM) - SCEN 1	1	17: SB (AM) - AV AII - SCEN 5	670: Car AV allknowing	1049: 35 mph AV	97.600
2	2	WB (AM) - SCEN 1	2	17: SB (AM) - AV AII - SCEN 5	680: Bus AV allknowing	1049: 35 mph AV	2.400
3	3	NB (AM) - SCEN 1	3	18: WB (AM) - AV AII - SCEN 5	670: Car AV allknowing	1049: 35 mph AV	90.900
4	4	EB (AM) - SCEN 1	4	18: WB (AM) - AV AII - SCEN 5	680: Bus AV allknowing	1049: 35 mph AV	9.400
5	5	SB (AM) - MIX - SCEN 2	5	19: NB (AM) - AV AII - SCEN 5	670: Car AV allknowing	1049: 35 mph AV	97.700
6	6	WB (AM) - MIX - SCEN 2	6	19: NB (AM) - AV AII - SCEN 5	680: Bus AV allknowing	1049: 35 mph AV	2.300
7	7	NB (AM) - MIX - SCEN 2	7	20: EB (AM) - AC AII - SCEN 5	670: Car AV allknowing	1049: 35 mph AV	96.400
8	8	EB (AM) - MIX - SCEN 2	8	20: EB (AM) - AC AII - SCEN 5	680: Bus AV allknowing	1049: 35 mph AV	3.600
9	9	SB (AM) - AV C - SCEN 3					
10	10	WB (AM) - AV C - SCEN 3					
11	11	NB (AM) - AV C - SCEN 3					
12	12	EB (AM) - AC C - SCEN 3					
13	13	SB (AM) - AV N - SCEN 4					
14	14	WB (AM) - AV N - SCEN 4					
15	15	NB (AM) - AV N - SCEN 4					
16	16	EB (AM) - AC N - SCEN 4					
17	17	SB (AM) - AV AII - SCEN 5					
18	18	WB (AM) - AV AII - SCEN 5					
19	19	NB (AM) - AV AII - SCEN 5					
12							

Figure C-25 Example; the Vehicle Compositions for the Vehicle Input in Scenario 5

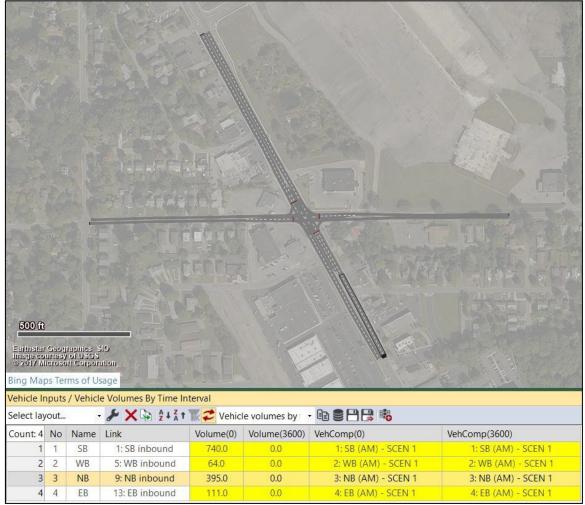
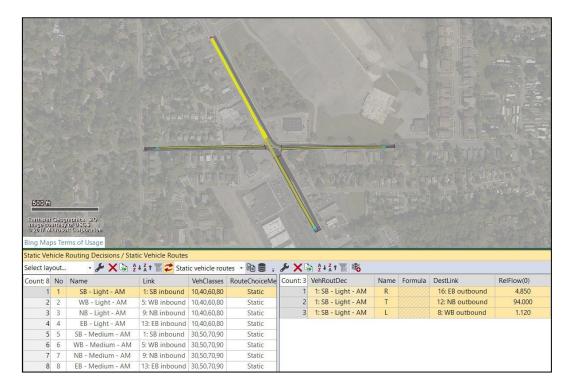


Figure C-26 Example; Vehicle Inputs / Vehicle Volume for NB in PTV Vissim



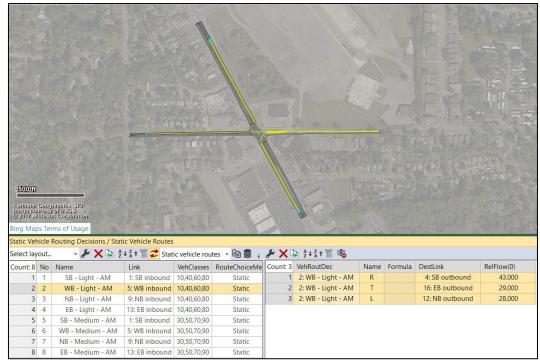
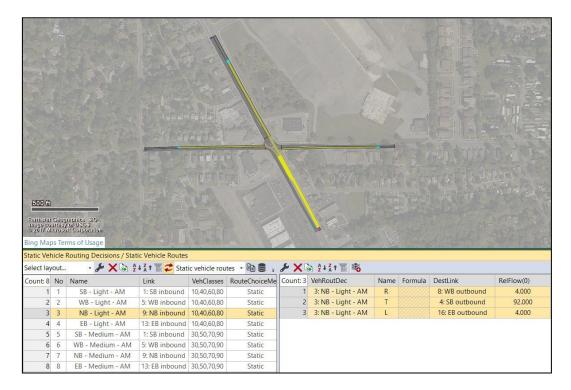


Figure C-27 Turning Movement Data for SB and WB in PTV Vissim



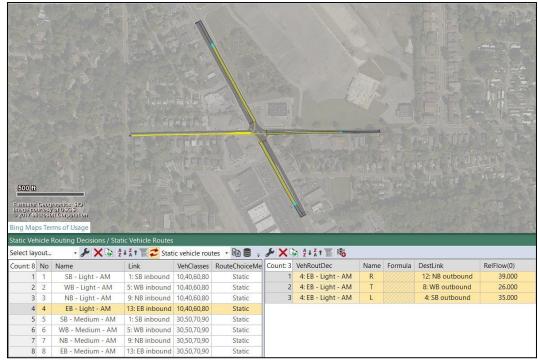


Figure C-28 Turning Movement Data for NB and EB in PTV Vissim

APPENDIX D

The Signal Timing Design in PTV Vissim

File : Traffic Signal Data - Notes :	- Nottingha	am Roa	d.rbc	Ring	Barrier	Control	ler Timi	ng							Date : 3/8/2019 Page 1 of 3		
Offset Reference : Transition Mode :	LeadGr Best	een															
Basic SG Number SG Name Min Green Veh Extension Max 1 Yellow Red Clearance Ped SG Number Walk	1 SBL 5 3 5 3.5 1	2 NB 5 3 19 3.5 1	3 WBL 5 3 5 3.5 1	4 EB 5 3 18 3.5 1	5 NBL 5 3 5 3.5 1	6 SB 5 3 19 3.5 1	7 EBL 5 3 5 3.5 1	8 WB 5 3 18 3.5 1									
Ped Clear (FDW) Start Up Min Recall Max Recall Ped Recall Soft Recall NSE Max Recall Dual Entry Max Speed																	
Sequence Ring 1 Ring 2 Ring 3 Ring 4	1 5	2 6	3 7	4 8													
Conflict SGs 2 3 4 5 6 7 8 Vehicle Detectors			3	4 ■ □ □ □ □	5	6	7	8									
Venicle Detectors Detector Number Delay Extend Carry Over Queue Limit Detector Mode Added Initial Mode Call Yellow Lock Red Lock Extend SGs XSwitch SGs		No Disconnect No			2 3 No Disconnect No Disconnec Disabled Disabled			nect	4 ct No Disconnect Disabled				connect ed	6 No Disconnect Disabled			

Figure D-1 Ring Barrier Controller in PTV Vissim

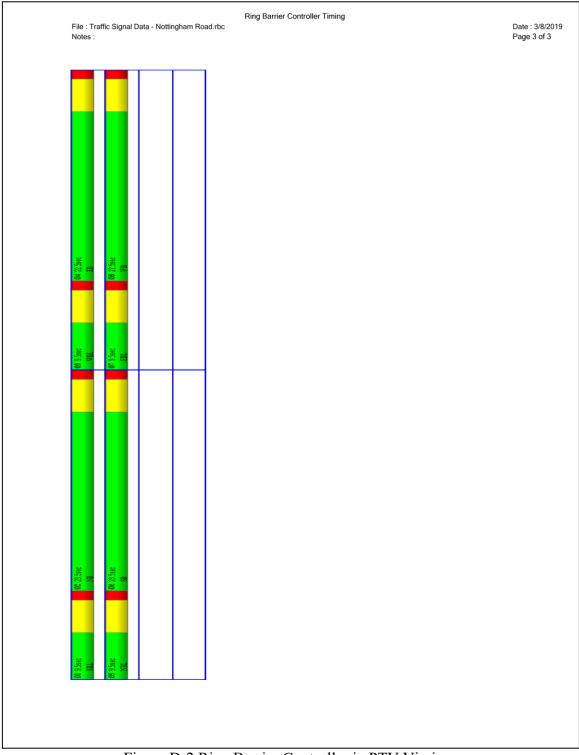
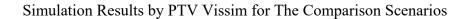


Figure D-2 Ring Barrier Controller in PTV Vissim

APPENDIX E



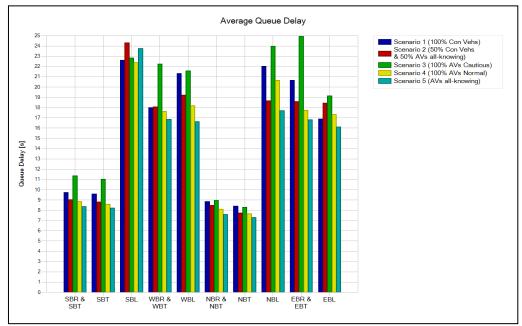


Figure E-1 Average Queue Delay for the intersection by PTV Vissim

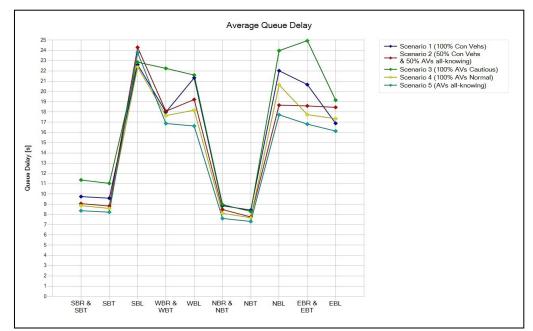


Figure E-2 Average Queue Delay for the intersection by PTV Vissim

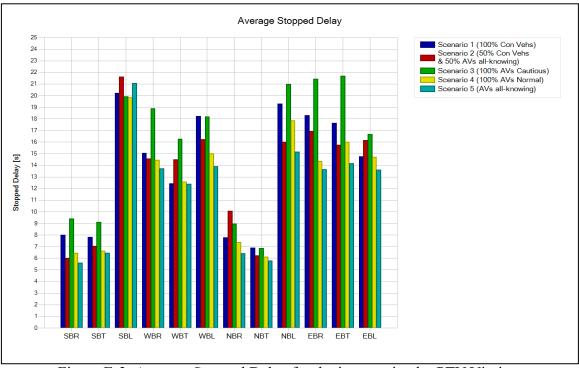


Figure E-3 Average Stopped Delay for the intersection by PTV Vissim

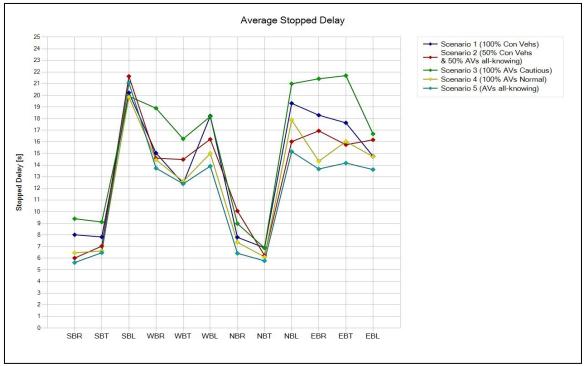


Figure E-4 Average Stopped Delay for the intersection by PTV Vissim

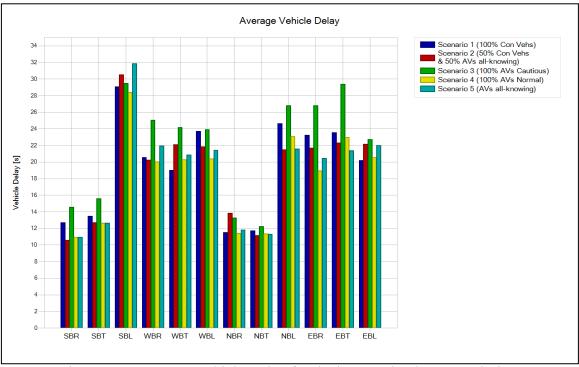


Figure E-5 Average Vehicle Delay for the intersection by PTV Vissim

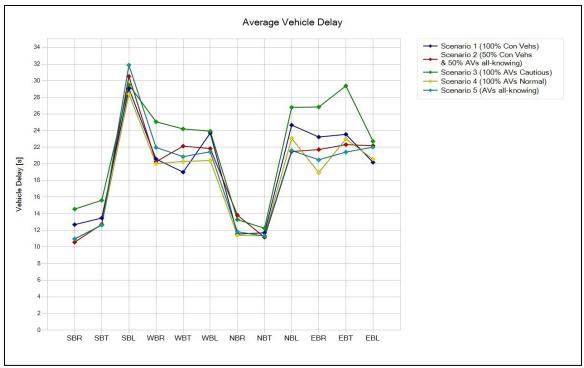


Figure E-6 Average Vehicle Delay for the intersection by PTV Vissim

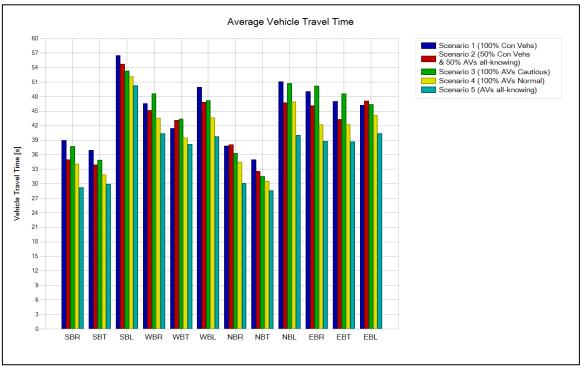


Figure E-7 Average Vehicle Travel Time for the intersection by PTV Vissim

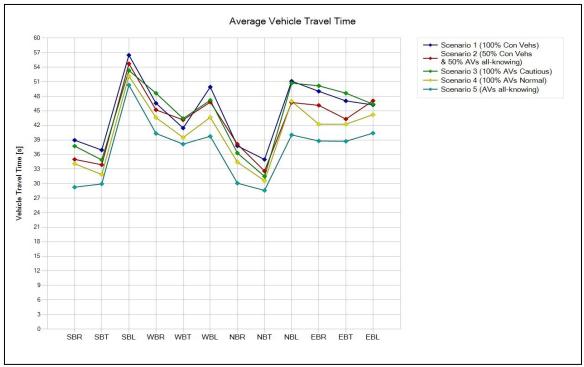


Figure E-8 Average Vehicle Travel Time for the intersection by PTV Vissim

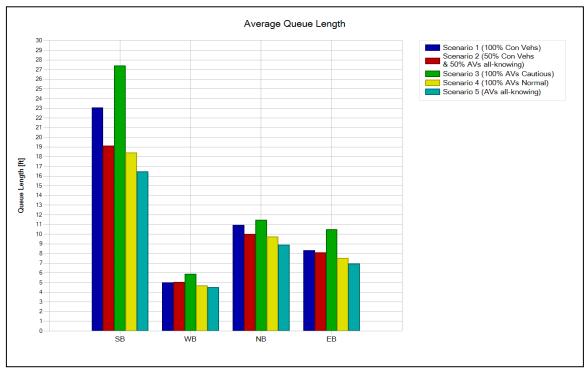


Figure E-9 Average Queue Length for the intersection by PTV Vissim

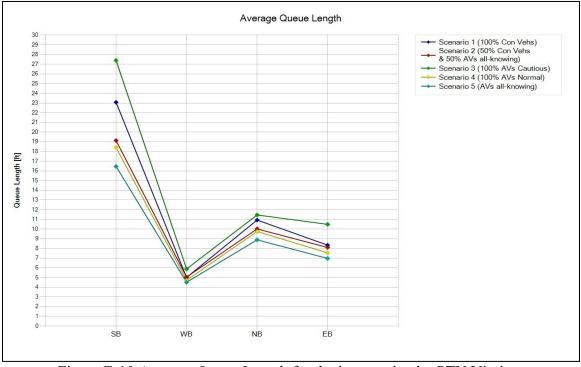


Figure E-10 Average Queue Length for the intersection by PTV Vissim