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## Performance Predication Model for Advance Traffic Control System (ATCS) using field data

Masood Mirza  
*University of Central Florida*

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PERFORMANCE PREDICTION MODEL FOR ADVANCE TRAFFIC CONTROL  
SYSTEM (ATCS) USING FIELD DATA

by

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A dissertation submitted in partial fulfillment of the requirements  
for the degree of Doctor of Philosophy  
in the Department of Civil, Environmental and Construction Engineering  
in the College of Engineering and Computer Science  
at the University of Central Florida  
Orlando, Florida

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2018

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## ABSTRACT

Reductions in capital expenditure revenues have created greater demands from users for quality service from existing facilities at lower costs forcing agencies to evaluate the performance of projects in more comprehensive and "greener" ways. The use of Adaptive Traffic Controls Systems (ATCS) is a step in the right direction by enabling practitioners and engineers to develop and implement traffic optimization strategies to achieve greater capacity out of the existing systems by optimizing traffic signal based on real time traffic demands and flow pattern.

However, the industry is lagging in developing modeling tools for the ATCS which can predict the changes in MOEs due to the changes in traffic flow (i.e. volume and/or travel direction) making it difficult for the practitioners to measure the magnitude of the impacts and to develop an appropriate mitigation strategy. The impetus of this research was to explore the potential of utilizing available data from the ATCS for developing prediction models for the critical MOEs and for the entire intersection.

Firstly, extensive data collections efforts were initiated to collect data from the intersections in Marion County, Florida. The data collected included volume, geometry, signal operations, and performance for an extended period. Secondly, the field data was scrubbed using macros to develop a clean data set for model development. Thirdly, the prediction models for the MOEs (wait time and queue) for the critical movements were

developed using General Linear Regression Modeling techniques and were based on Poisson distribution with log linear function. Finally, the models were validated using the data collected from the intersections within Orange County, Florida. Also, as a part of this research, an Intersection Performance Index (IPI) model, a LOS prediction model for the entire intersection, was developed. This model was based on the MOEs (wait time and queue) for the critical movements.

In addition, IPI Thresholds and corresponding intersection capacity designations were developed to establish level of service at the intersection. The IPI values and thresholds were developed on the same principles as Intersection Capacity Utilization (ICU) procedures, tested, and validated against corresponding ICU values and corresponding ICU LOS.

بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

In the Name of Allāh, the Most Gracious, the Most Merciful

اقْرَأْ بِسْمِ رَبِّكَ الَّذِي خَلَقَ

Read! In the Name of Allah,  
who has created (all that exists).

To my parents, Mirza Mahmood Afzal and Raeesa Mahmood, who inspire me to dream,  
to believe, and finally, to achieve it.

To my wife, Shazia Mirza who completed me and is pivotal source of support and  
encouragement.

To my Sons, Mohid, Fahad, and Ahad who are the extensions of not only my soul but  
also my heart.

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# CHAPTER ONE: INTRODUCTION

## 1.1 Background

To evaluate traffic performance of networks and/or corridors, various performance management tools are used for diagnosing and solving (or avoiding) problems in traffic engineering. In recent years, Departments of Transportation (DOTS) and local agencies have begun to recognize the need to support decision making at all levels, both large decisions about major projects and everyday decisions with improved and wide-ranging data, measurable goals and objectives, and analysis. (Cambridge Systematics, High Street Consulting, 2010)

Reductions in revenues also created greater demand from users for quality service at lower costs forcing agencies to evaluate the performance of projects in more comprehensive and "greener" ways. As part of developing the Performance Measurement Tool Box and Reporting System for Research Programs and Projects, a survey was conducted; the following summarizes the findings of that survey:

*"A survey of agencies and available literature revealed growing interest and activity in the measurement of research program and project performance. While representatives from a majority of states indicated an interest and some degree of activity, few had developed comprehensive approaches, there were few tools available, and there was little similarity in methodologies among states". (Kevin Fehon, 2012)*

Recently, it was found that the Measures of Effectiveness (MOEs) used in the evaluation of the traffic network and/or corridor synchronization performance can be divided into two basic categories:

### 1.1.1 Environmental MOEs

Environmental MOEs, such as fuel consumption and emissions, have been a part of corridor synchronization performance evaluations for decades. Recently, a renewed/increased awareness of the impacts of fossil fuel burning (the "GREEN" movement) and the rising fuel cost has developed a renewed interest in including these MOEs into the evaluation matrix. Currently, the following environmental MOEs are being used in the evaluation of the corridor synchronization performance: (Ziad A. Sabra, 2010)

- Fuel Consumption
- Noise Emission
- Vehicle Operating Cost
- Personal Time
- Emission (Carbon Dioxide)
- Residential Amenities

### 1.1.2 Traffic MOEs

MOEs associated with the traffic operations, which are recognized and universally accepted by the practitioners, and elected bodies are shown in the Table 1. (James H. Kell, 1998)

The Highway Capacity Manual (HCM) and other commercially available software have documented prediction models for traffic performance measures for non-adaptive traffic control systems; however, there is very little research and insight available for the prediction MOEs such as real-time delay, queue length, queue storage ratios and wait time for adaptive traffic control systems (ATCS).



Table 1: Measure of Effectiveness for Various Controller Types (James H. Kell, 1998)

Intersection Control	Categories	Measure of effectiveness (MOES)
Pre-timed/Actuated	Volume	Maximizing Bandwidth
		Bandwidth Efficiency
		Bandwidth Attainability
		Increase Corridor Throughput
		Volume to Capacity (V/C) ratio
		Total Traffic Flow (Vehicles, Bicycles and Pedestrians)
	Delay	Average Control Delay
		Random Delay
		Stopped Delay
		Total Delay
		Network/Corridor Delay
	Travel Time	Corridor Travel Time
		Improve Travel Time
		Peak Travel Time
		Reliability in Travel Time
	Stops	Number of Stops
		Percent Vehicles Stopped
	Safety	Frequency of Collisions
		Perceived risks at the Intersection
		Safety of Non-Motorized Users
		Number of Stops/Mile
Average Travel Speed		
Queue Length	Average Queue	
	85 <sup>th</sup> Percentile Queue	
Adaptive Traffic Control Systems (ATCS)	Real Time Delay	
	Queue Length	
	Queue Storage Ratios	
	Wait time in the Queue	

## 1.2 Research Approach

The approach for this endeavor can generally be summarized as follows:

1. A literature review of the subject matter was conducted, including currently available Adaptive Traffic Control Systems (ATCS), LOS estimation issues, lack of prediction models for ATCS issues, traffic signal timing issues, and evaluation of development related traffic impacts and lack of standard evaluation procedures for ATCS.
2. Selecting sites with preinstalled ATCS for data collection for model development and calibration. Three sites were selected in Marion County, Florida to collect field data simultaneously for one month at each location. Raw field data was cleaned from all the noise and errors including phase information when the system was operating as free, when there was a pedestrian call, when the system failed to record the data, when there was a communication issue, or when there was a vehicle detection failure and/or traffic signal preemption.
3. Macros using Microsoft Excel software was developed to summarize the data for developing and validating the prediction models. These macros were designed to sort the data into 15-minute interval and to calculate various tendencies (average, 85<sup>th</sup> percentile and maximum) for the two dependent variables (queue and wait time). The 15-minute interval was chosen because the intersections chosen for model development data are designed to

- produce output in 15-minute intervals. Macros were also designed to develop all fourteen-independent variables. Additionally, macros were developed to transpose the data into two distinct databases for the development of left turn and through movement prediction models.
4. After testing several software packages including Microsoft excel, SPSS, JMP for data analysis and statistical model development: JMP was found to be best suited for the development of the prediction models. All prediction models were developed using General Linear Regression Model (GLRM) development procedures using Poisson distribution and log functions were developed for adaptive (In|Sync) traffic signal controller.
  5. Intersection Performance Index (IPI) representing the overall intersection LOS was developed based on predicted queue and wait time for all eight movements. IPI threshold and LOS values were also developed utilizing Intersection Capacity Utilization (ICU) procedures.

Finally, the literature review findings, the process of developing prediction models for left turns and through movements and IPI development was summarized.

### 1.3 Research Objective

The current research is geared towards filling the gap in the prediction-modeling arena for ATCS. The impetus of this research is to explore the potential of utilizing current

available data, such as traffic volumes, cycle length, phase duration, sequence, and geometry from the ATCS in the development of the prediction models for queue length and wait time for left turn, through movements and for the entire intersection.

The ATCS used in this research is In|Sync, which is one of the latest fully adaptive systems available in the market. The Florida Department of Transportation (FDOT) is using and encouraging other agencies to test In|Sync as a tool to address scheduled and un-scheduled congestion conditions. However, the absence of reliable analysis tools to evaluate the impact of changes in traffic flow (i.e. volume and/or direction) due to changes in adjacent developments and/or changes in operational conditions, makes it increasingly difficult for the practitioners to measure the magnitude of the impacts and to develop an appropriate mitigation strategy. This research is intended to provide the traffic engineers and planners the tools needed, which are based on sound engineering assumptions and practices.

#### 1.4 Dissertation Organization

The organization of this document is as follows:

- **Chapter One: Introduction:** – Presents an introduction to the subject matter to be discussed as well as a description of the research approaches and objectives.

- **Chapter Two: Literature Review** – Investigates the literature to discuss the framing of the problem addressed by this research.
- **Chapter Three: Approach/Methodology** – Describes the steps taken to clean the data for use in model development. Also, describes the steps taken for the development of the wait time and queue prediction model and validation process used to select the final recommended models.
- **Chapter Four: Design of Statistical Experiment** – Delves in to the model development approach, using of Linear Regression and General regression models, pros and cons of the two-modeling techniques and experimental design factors.
- **Chapter Five: Prediction Model -Evaluation and Findings**– Discusses the results of the prediction model’s development and validation process. Discusses results of the initial and final model development process and numerous factors including results of F-test and paired T-tests.
- **Chapter Six: Intersection Performance Index (IPI) – Evaluation and Findings** - Discusses the results of the IPI development and validation process. It also discusses results of the IPI Threshold and LOS development process and various factors including the results of the paired T-tests for IPI vs ICU along the results of HCM intersection analysis.
- **Chapter Seven: Conclusions** – This chapter serves as the summary chapter.

## CHAPTER TWO: LITERATURE REVIEW

Traffic control devices are used to ensure safe and efficient operation of a traffic network while addressing the needs of all traffic users. Generally, the selection of a specific traffic control device is based on the need, type of facility, traffic volume and users, land use, and terrain. These devices could be regulatory or advisory. Some of the commonly used traffic control devices are:

- Highways:
  - Regulatory Signs - Speed limit signs, access and direction of travel control signs, and lane marking (White on Black color)
  - Advisory Signs - “Intersection Ahead” sign, curve speed, pedestrian ahead sign (Black on Yellow color)
- Intersections:
  - Regulatory Signs – “YIELD” sign, “STOP” sign, Traffic signal/roundabout

Common criteria in the selection and implementation of any traffic control device should be based on objective and uniform criterion. The Manual on Uniform Traffic Control Devices (MUTCD) states, “*The purpose of traffic control devices, as well as the principals for their use, is to promote highway safety and efficiency by providing for the*

*orderly movement of all road users on streets and highways throughout the Nation”.*

(Roger P.Roess, 2009)

Traffic signals/roundabouts are currently the highest and most advanced form of traffic controls used in managing traffic on the interrupted flow system. Roger P. Roess describe an interrupted flow system as:

*“Interrupted flow facilities are those that incorporate fixed external interruptions into their design and operation”.* (Roger P.Roess, 2009)

The selection and operation of a traffic control device, such as a traffic signal, at an intersection is one of the most vital, technically challenging, and open to litigation tasks for a traffic engineer. The MUTCD states, *“Standards for traffic control signals are important -because traffic control signals need to attract the attention of the variety of road users, including those who are older, those with impaired vision, as well as those who are fatigued or distracted, or who are not expecting to encounter a signal at a particular location”*

The MUTCD not only provides an objective, uniform criteria and guidance to traffic engineers (TE) in making “yes” or “no” decisions but also in the design of various components of the traffic signal which includes signal indications, signal faces and visibility requirements, operational restrictions, and pedestrian needs. The MUTCD

doesn't provide any guidance for any specific traffic controller type; however, it provides general performance specifications for traffic controllers leaving the door open for further research and development. (AASHTO, 2009)

## 2.1 Traffic Operation Strategies

The deployment of traffic signal operation strategies is closely related to the signal technologies available at the time of the initial placement and available funding for initial deployment and ongoing maintenance. The type of traffic operation strategies currently being used are:

- Pre-Timed Operations – This strategy utilizes constant cycle length, phase sequences, and phase lengths during certain hours of the day. An internal clock controls these parameters.
- Semi-Actuated Operations - This strategy requires traffic detection on the minor street for call activation as the system always defaults to the major street. This system has a fixed cycle length and phase length and with the phase sequence determined by the call location from the side street.
- Full-Actuated Operations – This strategy relies on traffic detection from all movements from both major and minor streets and green time allocation is based on the volume of the calls. This strategy does not have fixed cycle length, phase



sequences, or phase lengths as these parameters are dependent on the volume and sequence of the calls.

Table 2 - Traffic Operation Strategies for Various Controller (James Bonneson, 2009)

Type of Operation	Isolated	Arterial	Grid
Pre-Timed	Usually not appropriate.	Appropriate only if always coordinated and the side street volumes are high and consistent.	Appropriate
Semi-actuated	Appropriate only if main street traffic is consistently heavy.	Appropriate if always coordinated.	Appropriate to actuate left turn phases and other minor movements, and mid-block pedestrian signals.
Fully- Actuated	Appropriate	Appropriate if not always coordinated.	Usually not appropriate.
Volume Option for actuated phases	Appropriate for phases with only detectors set back more than 40 meters (125 feet).	Appropriate for phases with only detectors set back more than 40 meters (125 feet).	Usually not appropriate because slow speeds mean less detector set back.
Density Option for actuated phases	Appropriate if high speeds, as higher initial gap can reduce stops.	Appropriate if high speeds, as higher initial gap can reduce stops.	Usually not appropriate due to low speeds.

Table 2 depicts various strategies used to optimize intersections and corridors. These strategies can be deployed for isolated intersections (more than 2 miles apart) or on closely spaced intersections (corridor) in urban cores, i.e. downtowns and/or up-town areas. When signals are ½ mile or less apart, the efficiency (through put) of intersections are greatly influenced by the arrival patterns from the upstream intersections. (James Bonneson, 2009)

The coordination and synchronization methods are the most cost-effective strategies to enhance safety, efficiency, and operations of a traffic corridor. Per one Institute of Transportation Engineers Journal article, benefit-to-cost ratios of 58: 1 and 62: 1 have been measured for signal synchronization programs in California and Texas, respectively. (Srinivasa)

## 2.2 Traffic Control Systems (Controllers)

The above-mentioned strategies are implemented in the field by using the appropriate type of traffic signal controllers specifically designed for the strategy. Traditionally, two types of signal controllers were used at most of the signalized intersections in United States of America (USA):

- **Interval Controllers (Pre-Timed)** - These controllers divide the cycle length into any number of intervals with user defined interval lengths and connects these intervals via output circuits to the external signal indications. For example, an interval may be used to time part of the green signal for one vehicle movement, part of the flashing don't walk for a pedestrian movement, the yellow for another vehicle movement, and part of the red and steady don't walk for others. Additionally, this configuration allows the signal controller to skip selected phases if the demand is not present and the residual green time can be assigned to the next interval.
- **Phase controllers (Actuated)** - Phase controllers take a different approach to signal timing. They divide the cycle into phases, with each phase having five pre-defined intervals - green, yellow, and red clearance for vehicle control; and walk and flashing do not walk for pedestrian control. The user specifies the duration of each of these intervals, or in the case of the green interval, the minimum and

maximum duration. If the signal is coordinated, the user also specifies a split time for each phase and a start-of-cycle offset.

Phase controllers use barriers or phase concurrency groups to define conflicts between phases in different rings. Within a concurrency group (between two barriers), the phases in different rings can time independently but all rings must cross the barrier (move to a different phase concurrency group) simultaneously.

Controllers have internal clocks capable of keeping reasonably accurate time for at least several days. All controllers in a coordination group can be configured to use the same time of day (i.e. Midnight) as the reference point for the offset calculation. The common background cycle is assumed to start at this time of day, and each controller can time its own offset from this common reference point. This is known as the d time base coordination. (Peter Koonce, 2010)

### 2.3 Adaptive Traffic Operation/Strategy

Time of the day (TOD) coordination patterns, operating on a fixed cycle length and offset, operate very satisfactorily if the field conditions and the design assumptions for the coordination patterns stays within tolerance limits of the plan. Generally, physical assumptions such as intersection spacing and geometry does not vary. However, the

traffic demand has the potential to change significantly and very drastically due to several conditions such as special events, weather conditions in coastal areas, and traffic buildup due to accidents. Some of the scheduled events, i.e. ball games, concerts, etc., can be handled by developing and implementing “special event” plans; however, the unscheduled event and sometimes normal traffic demand variation within peak hour or peak period warrants a different optimization and synchronization plan rather than the programmed TOD coordination plan.

In case of several closely spaced intersections with varying natural cycle lengths, the coordination of adjacent signals on a fixed cycle length will be less efficient, due to the possibility of the back of the queue extending to the adjacent downstream intersection, as compared to some form of free, actuated operation. In these cases, a better alternative is to have certain phases at the lower-cycle length intersections maintain a fixed relationship with the critical intersection while it runs in free, actuated mode.

In the situations described above, adaptive signal control may offer an improvement over the existing operation. Not all adaptive systems have the same operating philosophy; some are intended as improvements over fixed cycle length coordination; some are applicable to isolated intersection operation; while others extend the actuated, coordinated concept. (Matt Sellinger, Adaptive Traffic Control Systems in the United States; Updated Summary and Comparison, 2010)

Another advantage of adaptive signal control is that, theoretically, the performance level of the system can stay constant over an extended period as compared to a fixed cycle length coordination system. The industry normal retiming cycle for a fixed cycle length coordination system is three years, after this time the changes in the traffic volume, peak hours, and traffic configuration become significant. Figure 1 depicts the reduction in performance level over time for a fixed cycle length coordination system and adaptive signal control and shows that the efficiency of a fixed cycle length coordination system is decreased approx. 4% per year. (Matt Sellinger, Adaptive Traffic Control Systems in the United States - A review of the cost, maintenance and reliability of popular Adaptive traffic control technologies, 2009)

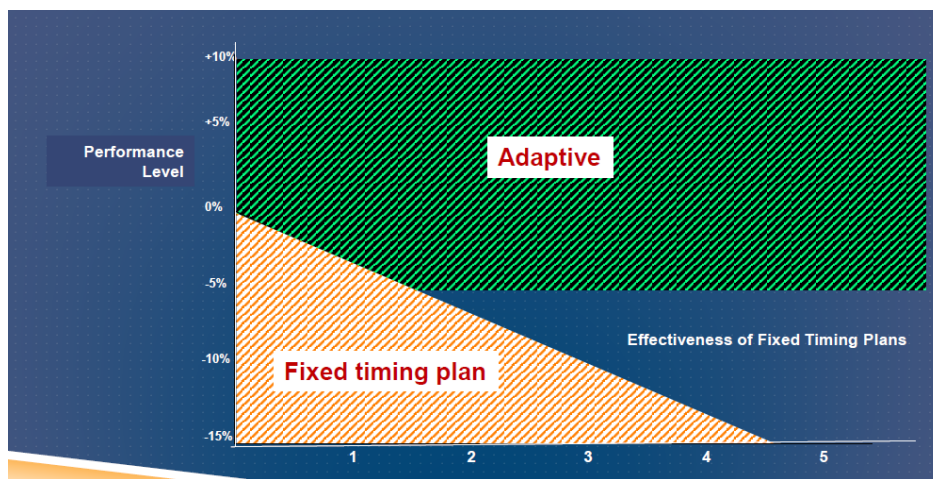


Figure 1: Traffic Signal Performance (Fehon, 2015)

## 2.4 Structure of Adaptive Control Systems

The fundamental structure of all currently in-use ATCS's consists of the following three components:

- **Vehicle Detection:** This is the core of an ATCS. An adaptive system acknowledges the presence and location of a vehicle at the intersection by the process. The devices that can be used for vehicle detection may include loop detectors, laser or radar, and video. The data that may be collected include time of arrival, speed, and axle spacing.
- **Prediction:** This is the process by which the data from the detectors estimate arrival patterns and generate traffic predictions for the pre-selected analysis periods and design parameters. The analysis periods may be as short as minimum vehicle headway (i.e. 2 seconds), cycle length, a 15-minute interval, a peak period, or may be left variable.
- **Optimization:** This is the process by which the predicted vehicle arrivals are used to distribute green times to the various approaches/movements of the intersection to achieve the pre-selected goals/MOEs. (Michael Shenoda, 2006)

## 2.5 History of Adaptive Control Systems

Over the course of performing the literature review, it was discovered that there were four methodologies that stand out from other attempts at adaptive signal control. They were significant due to their relative acceptance in the field, as well as the relative extent of their real-world implementation. The Optimized Policies for Adaptive Control (OPAC) methodology is a system first proposed by Nathan Gartner at the University of

Massachusetts at Lowell in the early 1980's in a study for the Federal Highway Administration. The Transport Research Laboratory in the United Kingdom also developed the Split Cycle Offset Optimization Technique (SCOOT) in the early 1980's. The Sydney Coordinated Adaptive Traffic System (SCATS) is somewhat newer, having been founded in the early 1990's by the Roads and Traffic Authority of New South Wales, Australia. The Real-time Hierarchical, Optimized, Distributed, Effective System (RHODES) is the newest of these four systems, having been developed in the mid-1990's at the University of Arizona at Tucson. SCOOT and SCATS generally use a cycle-based approach on a network, adjusting the cycle times, splits of the cycle, and offsets among cycles in the network to optimize an MOE. OPAC and RHODES vary somewhat from this, with OPAC being cycle-based and RHODES being phase-based. Both typically work on the concept of a rolling horizon approach, which optimizes (often using a dynamic approach) an MOE over a fixed prediction horizon, and then extends the horizon by a fixed time step and reiterates the optimization until an optimal split of the given cycle is found. Advancements in approaches to OPAC have allowed for some variability in network-wide cycle lengths. (Michael Shenoda, 2006) (Matt Sellinger, Adaptive Traffic Control Systems in the United States; Updated Summary and Comparison, 2010)

In|Sync's artificial intelligence is comprised of a local optimization algorithm for each intersection and global coordination between all the intersections on a corridor. The intelligent actuation and global coordination work in tandem to reduce stops and delay along the corridor. At this level, In|Sync uses its local optimization algorithm to

determine the priority for each approach to immediately adapt to real-time traffic demand. In|Sync then requests the controller to actuate the signal accordingly. Using the same algorithm, In|Sync decides in real-time how to serve all movements – through-traffic on the main corridor, side streets and left turn lanes – to minimize delay at each approach. At each intersection, In|Sync adapts signalization to demand in three different ways: in its phasing, green time allocation, and sequencing. Each of these signal control variables adapts to actual demand based on the system’s artificial intelligence. (Fehon, 2015) (Rythem Cooperation , 2017)

## 2.6 MOE Prediction Models

The topic of developing alternate prediction models for traditional MOE’s such as delay, travel time, stops and queue lengths have been the center page of a lot of research and the following provides a synopsis of said research projects.

Gartner et.al (2014) studied the dynamic traffic assignment capability that can predict future traffic conditions and a real-time traffic adaptive control system (RT-TRACS) for generation of signal control strategies that are core of ATMS/ATIS system. This research tested the integration of a dynamic traffic assignment capability that can predict future traffic conditions and a real-time traffic adaptive control system (RT-TRACS) for generation of signal control strategies into a combined system. Initially, they tested static case involving the interaction between travelers (demand) and



transportation facilities (supply) under recurrent conditions. The framework is then extended to the quasi-dynamic and the dynamic cases, which involve incorporation of advanced, ITS technologies in the form of advanced traffic management systems and advanced traveler information systems. The resultant was a dynamic traffic assignment model with future traffic conditions including user-perceived travel cost and function prediction capabilities. The researcher also concluded that their developed equations needed further research via development of ITS traffic management demonstration to test the results. (Nathan H. Gartner, 2014)

Gan et.al. (2016) proposed an alternate to the HCM model driven approach for calculating the delay and LOS using a data fusion procedure that uses vehicle counts from loop detectors and travel times from probe vehicles. The data was used to calculate Vehicle Hours Traveled (VHT) and delay; LOS is obtained using the delay-LOS lookup table provide by the HCM. The authors claim that since this process is data-driven rather than model-driven, it has the potential for a variety of scenarios including congestion and spillback. Since the research assumed travel time distribution to be stationary, additional evaluation is needed to test the applicability of this approach under actuated and adaptive signal controls. (Qijian Gan, 2016)

Comert et.al. (2008) developed a model to estimate queue lengths, in real time, for the isolated signalized intersections using data from probe vehicles (i.e. vehicles equipped with GPS and wireless communication technologies). In addition, this research also

focused on developing analytical models to evaluate the impacts of percentage of probe vehicles on the queue length estimation (accuracy). The results of this research showed that for 80% of the probe vehicles, the expected error is approx. 10% and the absolute error is roughly +/- 1% vehicle. For a normal distribution, this error rate roughly corresponds to a 95% confidence interval. One of the key findings of this research is that the location of the last probe vehicle in the traffic stream is sufficient for estimation of the queue length and the location of other probe vehicles or the total number of probe vehicles in the queue are redundant. (Gurcan Comert, 2008)

Ban et.al (2011) developed a real-time intersection queue length determination model using travel time data from mobile sensors. The process involved estimation of intersection delay pattern based on sample intersection travel times and using the estimated delay pattern to identify critical points of when the queue is maximized, minimized, or cleared within a cycle, thus enabling the researchers to develop real time queue length models using the shockwave theory and queue rear no delay arrival time (QRNAT). These models were validated via field-testing and simulation research. One of the key findings of this research is that queuing delay linearly decreases within a cycle and the critical point of the delay pattern corresponds to QRNAT. Another interesting conclusion of this research is that the arrival pattern at a location and during any given time period is not uniform; the headways changes from cycle to cycle. In conclusion, the researchers acknowledge that more work is needed in the real-time intersection queue length estimation using privacy preserving mobile sensor data. (Xuegang (Jeff) Ban, 2011)

Lv et.al. (2015) presented a unique approach, deep learning based, of traffic flow prediction using stacked auto-encoder (SAE) model. Deep learning algorithms use multiple-layer architectures or deep architectures to extract inherent features in data from the lowest level to the highest level and they can discover latent traffic flow features, such as nonlinear spatial and temporal correlations, which were not apparent or can be identified by any other evaluation model. The results of the deep learning approach with SAE model show a high degree of correlation and matches well in heavy and medium traffic flow conditions. However, the proposed model does not perform well in low traffic flow conditions, which is the same as existing traffic flow prediction methods. The reason for this phenomenon is that slight differences between the observed flow and the predicted flow can cause a bigger relative error when the traffic flow rate is small. (Yisheng Lv, 2015)

Yang (2005), in his efforts to predict arterial travel time, used the GPS test vehicle and Kalman filtering techniques. Kalman filter is the technique that uses recursive, discrete-time Kalman filter along with historic and real-time data to estimate the current state of the given system; however, it can also be used to predict future values of a variable or for improving estimates of variables at earlier times. The overall predicted travel time follows the observed travel time. One of the key findings is that the average error gets smaller as the duration time of traffic congestion lasts longer and as the number of data points increases the results became less sensitive to sudden fluctuation of actual travel time. (Yang, 2005)

Cheek et.al. (2007), in their efforts to develop queue length and delay algorithm, utilizes the data generated by Video Imaging Vehicle Detection Systems (VIVDS). The technique used in this research involve placing virtual detectors with the cone of vision of the VIVDS to produce queue length measurements which were than processed and corrected using established statistical techniques, linear regression, and Kalman filter to produce estimates of queue lengths. The results of this research were very promising; the magnitude of error produced by this technique for any 10-second interval is approximately 22 feet (close to one car length) and the plots of actual and predicted reveal that the developed algorithm can explain 86 percent of the actual queue length data. One of the key findings of this research is that the use of linear regression technique along with Kalman filter produces very reliable results in a very cost-effective way and that the technique is adaptive and self-correcting with the use of Kalman filter, which keep the estimates within set limits. (Marshall T. Cheek, 2008)

Hallenbeck et.al. (2008) published their findings on the micro-simulation tests they conducted to estimate occupancy values from the “STOP” bar sensors during the green and amber signal phases and used the occupancy values as a surrogate value for arterial congestion (as congestion grew, occupancy grew too). The design of this experiment (i.e. assessing effects of changes in sensor configuration and location on arterial monitoring capabilities) prohibits the use of actual field loops for data collection. “STOP” bar detectors are the most common sensors and are not ideal sensors to monitor traffic volume or queues; however, stop bar detector data can be used to monitor occupancy. The results of this research show that at heavier congestion levels

(slower speeds) shows noticeable fluctuations in occupancy values over time. At low to moderate congestion levels, average occupancy values per cycle tend to be more clustered, varying more smoothly over time. The general conclusion is that the use of occupancy values from a stop bar detector during the green and amber signal states is a simple and cost-effective way to estimate arterial performance; however, additional testing of the abilities of this method for different scenarios is needed. (Mark E, 2008)

EI Esawey et.al. (2009) reported results of his work on travel time estimation for an urban street system using sparse probe vehicle data and historical travel time relationship. The concept is very simple that traffic patterns/operations (travel times) of neighboring links in an urban environment are correlated with each other. Identifying those relationships and travel time data from few (or one) of those links should be sufficient to estimate travel times on other links in the network. EI Esawey tested this hypothesis on a microscopic traffic simulation model using VISSIM. Results of the developed models showed a good fit with the mean absolute percentage Error (MAPE) of travel time estimates ranged between 1.91% and 9.48% for the selected weighting schemes. (Mohamed EI Esawey, 2009)

Li et.al. (2009) developed models to estimate arterial performance measurements (Arterial travel time, number of stops and travel time reliability) using microscopic traffic simulation models using PARAMICS. The model was based on a major arterial in northern California. To mimic the data collection system (format and frequency of the

inductive loop detectors) on the real arterial, researchers wrote programs, using PARAMICS's application programming interface (API), to collect simulation data to support and evaluate their proposed model. The six-signal simulation network covers both heavily congested and light traffic intersections. The results show that the developed model works well at both the intersection level and arterial level with insignificant error in travel time, number of stops, and travel time reliability. Further research is needed to field validate the proposed model along with sensitivity analysis of the key variables. (Meng Li, 2009)

Dimitriou, I. et.al. (2007) proposed an adaptive hybrid fuzzy rule-based system (FRBS) approach for modeling and short-term forecasting of traffic flow (vehicles/hour) in urban arterial networks. The advantage of using FRBS is that it can combine linguistic and numerical information in a seamless way. The process developed in this paper constitute development and implementation of a hybrid, meta-optimized FRBS which is a fuzzy rule-based system augmented with meta-heuristic (optimization methods from operations research) optimization techniques. Dimitriou et.al used micro simulation platform developed by Federal Highway Administration (FHA) called Traffic Software Integrated System (TSIS) to develop two models, univariate and multivariate models, to forecast and compare the short-term traffic flow. The results based on the models show that the FRBS capture general trend of the traffic flow and timely reflects variations i.e. upward or downward shifts in the trend. In addition, the FRBS enabled the predicted flows to retain a more smoothed pattern, which is less sensitive to the high frequency

variations of traffic flows. The FRBS results in lower prediction errors for all performance measures too. (Loukas Dimitriou, 2007)

Barkley et.al (2010) proposed an approach that consists of two models, Hidden Markov Model (HMM) and Heuristic Signal Event Estimator (HSEE), for the estimation of signal phasing using the data from in-pavement vehicle sensors. The two developed models were tested using one years' worth of data collected from the study corridor. The HMM uses vehicle arrival data from intersection detectors to estimate green time; the Heuristic Signal event estimator uses vehicle arrival data along with timing plan parameters to develop green time estimates. Both the methods showed promising results and could estimate green times, start of green time, and cycle-by-cycle or aggregated measures of signal progression quality; however, HMM underestimates the cycle lengths as compared to HSEE. At the time of this research, these two models were not field validated. (Tiffany Barkley)

Smaglik et.al (2010) studied the use of Green Occupancy Ratio (GOR) and Volume to Capacity (V/C) ratio to estimate the efficiency of the splits and estimate of over saturated conditions. This research also evaluates the sensitivity of the GOR and V/C ratio to the detection zone lengths and vehicle speeds. This research compares the GOR and V/C ratio to the calculated delay matrix. The conclusion, using linear regression analysis, was that V/C is a more reliable indicator of the delay than GOR. For researchers and practitioners using GOR as a performance measure (ACS-Lite

users among others), it is critical to calibrate the system to observed speeds and detection zone lengths as the GOR is very sensitive to these two variables. (Edward J. Smaglik, 2011)

Day et.al. (2012) studied the impacts of adaptive traffic signal control (ACS-Lite) on travel time in a simulation environment using VISSIM microsimulation package and Econolite ASC/3 and ACS-Lite (with a preselected traffic response algorithm) as control variables and delay as response variable. The simulation model was developed to mimic traffic flow on the selected corridor before, after, and during the University of West Virginia football game. ACS-Lite showed slight improvements in reducing the delay over other strategies; however, overall, the results were inconclusive.

(Christopher M.Day)

Zheng et.al (2012) published travel time distribution model based on microsimulation (VISSIM) mimicking SCATS system. The key assumption of her work was that during peak flow conditions, dynamic traffic control systems, e.g. Scats or Scoot (this applied to other adaptive traffic control systems too) fall back to nearly fixed time control. The proposed model was validated using field data collected at another test site. The comparison of the model predicted link travel time distribution with that of VISSIM simulation and field data show that proposed model can reasonably replicate the VISSIM simulation and field data with few exceptions where prediction model estimated much higher (50%) travel time as compared to field data. Some of the discrepancies



may be attributed to small sample size and to the mid-block source and sink nodes (driveways). (Fangfang Zheng, 2012)

Songchitruka et.al. (2012) studied the use of dilemma zone detectors (no stop bar detection) to improve the prediction of required queue clearance time for through movements at the signalized intersections. This approach uses variable initial green (minimum green) function of the NEMA TS 1 and later controllers. The methodology involves developing a full factorial experimental design, to develop vehicle to actuation ratios, using VISSIM microsimulation. These ratios were used to calculate through demand and queue clearance times within the confines of minimum and maximum green controller settings. The proposed queue clearance time algorithms were field validated and found to have a strong correlation between counts on red and queue clearance times and that the predicted queue clearance time are in good agreement with the actual values, but other site-specific factors remained uncaptured through the proposed method. (Praprut Songchitruksa, 2012)

Stevanovic et.al. (2012) studied the performance of the In|Sync system, an ATCS System, in comparison to traditional time of the day signal timing plans using VISSIM microsimulation. The major concern when evaluating an ATCS in microsimulation environment is the model's ability to replicate all assumptions complexities critical to the ATCS. As reported by Stevanovic et.al. VISSIM is the only tool available to interface with the In|Sync system. The VISSIM model for the test corridor was calibrated and

validated to resemble field condition (In|Sync system). The results depict that In|Sync outperforms TOD signal timings in terms of overall network performances (delay, stops and average speed) including corridor travel time, intersection delay and stops, and main street delays. It also shows improvements in fuel efficiencies and most of the emission output. (Aleksandar Stevanovic, 2012)

## 2.7 Literature Review Summary

The purpose of the literature review conducted was to identify and report the research work done in MOEs estimation, especially with the use of field data and using ATCS. Since ATCS, technologies are fairly new and evolving, it was decided to limit the research timeframe from 2007 to 2017 and focus on urban arterial systems only. There was tremendous amount of information available on the selected topics and the synopsis included in this section represent less than 5% of the data reviewed. Due to the relatively recent (2008 - 2009) entrance of In|Sync in the ATCS market, it has not been researched thoroughly. Most of the published work on In|Sync is conducted by local and state agencies dealing with before and after traffic performance on their respective corridors. This doesn't mean there is no proprietary research going on to develop tools to better understand the In|Sync MOEs and develop interface to models for this system, however, it is not publicly available.

Most the reviewed work include development of various traffic performance MOEs for urban arterial systems. The MOEs were arrivals (volume), queue lengths, stops, delay, occupancy, signal phasing, efficiency of the splits, estimation of over saturation conditions, vehicle travel time, and distribution and queue clearance times. The input data sources include loop detectors, in-pavement vehicle sensors, "STOP" bar sensors, dilemma zone detectors, probe vehicles (i.e. vehicles equipped with GPS and wireless communication technologies), mobile sensors, radars, cameras and Video Imaging Vehicle Detection Systems (VIVDS), crowd sourcing, and mobile media. Most of the microsimulation models were developed using VISSIM software except in one case PARAMICS was used.

One of the key observation made during the literature review is that all the traffic operational models developed were either theoretical models or microsimulation based with field-testing left for validation purposes only. The use of microsimulation techniques provides a controlled environment conducive to generate high quality data at a much faster pace than real world data, which is prone to external elements and can only be collected at real time pace.

In conclusion, based on the comprehensive literature review conducted so far, no evidence was found of any research work conducted to estimate MOEs based on field data for ATCS like In|Sync. Thus, it is safe and prudent to state that this dissertation is

unique by its scope and approach. This research will be the cornerstone in the development of evaluation procedures for ATCS.

## CHAPTER THREE: FUNDAMENTALS OF MODEL DEVELOPEMNT

In this chapter, following three main tasks are discussed:

- Site selection for model development and validation, including the site selection for development of IPI
- Data collection and validation data
- Model structure

### 3.1 Model Development Data Corridor

There are currently three intersections in Marion County, Florida, with ATCS (In|Sync). These three intersections are located on SE Maricamp Road (CR464/SR464) southeast of the City of Ocala, in unincorporated Marion County. FDOT and County staff selected these three locations for ATCS installation after a detailed deliberation and they represent typical intersections in a suburban environment in terms of traffic characteristics, geometric layout, and land use, conducive for an ATCS installation. Data at all three intersections was collected. Data from these two sites were used for the model development and the third intersection was used for initial model validation.

However, during the review of the data collected it was determined that the intersection of SE Maricamp Road and SE 49th Terrace is operating at “FREE” mode all the time and cannot be used for validation purposes. Instead, the intersections in Orange County on Alafaya Trail was used for validation purposes.

- ***SE Maricamp Road (CR464/SR464):*** is a four-lane divided arterial with 31,000 veh. /day (2016) and with a 50-mph speed limit. The cross section is a rural cross section with 12 feet wide travel lanes, 40 feet wide median, and turn lanes at multiple locations. The adjacent land use consists of commercial uses near the intersection of SE 44th Avenue Road which transition to residential and light industrial land uses on the north side and institutional and preservation land on the south side. The study segment of SE Maricamp Road consists of the following three signalized intersections:

- ***SE Maricamp Road (CR464/SR464)/S E 44<sup>th</sup> Ave Road Intersection:***  
This is a four-way intersection controlled by a box span-wire traffic signal. The eastbound approach on SE Maricamp Road consists of a right turn lane, two through lanes, and a left turn lane. The westbound approach includes two through lanes and a left turn lane. The both northbound and southbound approaches on SE 44th Avenue Road consist of a right turn lane and combination through/left turn lane. The northbound right turn lane, however, is a slip lane. The phasing for both approaches on SE Maricamp Road includes protected left turns while SE 44th Avenue Road is split phased. There are no pedestrian facilities at the intersection including sidewalk or pedestrian signals.

- SE Maricamp Road (CR464/SR464)/S E 49<sup>th</sup> Terrace intersection:*** The intersection of SE Maricamp Road and SE 49th Terrace is a four-way intersection controlled by a span-wire traffic signal. The eastbound approach on SE Maricamp Road consists of a right turn lane, two through lanes, and a left turn lane. The westbound approach includes two through lanes and a left turn lane. The southbound approach consists of a single right/through/left shared use lane. The northbound approach comes out of Forest High School and consists of a left turn lane, a shared left/through lane, and a right turn lane. The phasing for both approaches on SE Maricamp Road includes protected left turns while the approaches on SE 49th Terrace/Forest High School Entrance is split phased. There are high visibility crosswalks and pedestrian signals across the eastern and southern legs of the intersection.
- SE Maricamp Road (CR464/SR464)/Baseline Road (SE 58<sup>th</sup> Ave, SR 35) intersection:*** The intersection of SE Maricamp Road at SE 58th Avenue is a four-way intersection controlled by a drop box span wire traffic signal. The eastbound and westbound approaches on SE Maricamp Road consist of a right turn lane, two through lanes, and a left turn lane. The northbound and southbound approaches consist of a right turn slip lane, two through lanes, and two left turn lanes. The phasing for all approaches includes protected left turns only. Pedestrian facilities at the intersection include sidewalks, pedestrian detectors, countdown pedestrian signals, and high visibility crosswalks.

For determining generalized roadway LOS analysis, the roadway maximum service volumes were obtained from FDOT generalized tables. The peak hour peak direction traffic volumes of the model corridor were calculated using the traffic volumes, K and D factors obtained from FDOT Florida traffic online (2016). Table 3 depicts Peak hour peak direction traffic volume and the generalized roadway LOS for the study corridor.

Table 3 – Existing Generalized Roadway LOS Summary

Roadway	# of lanes	Maximum Service Volume	Peak hour Peak Direction Volume	LOS
<b>Maricamp Road (Marion County)</b>				
47 <sup>th</sup> Avenue and Baseline (SR 35)	4	1,800	1,640	C
Baseline (SR 35) to Pine Road	4	1,800	1,847	E
<b>Alafaya Trail (Orange County)</b>				
SR 50 and Waterford lakes Parkway	6	2,970	2,400	D
Waterford Lakes parkway and Lake Underhill Road	4	2,970	3,025	F
Lake Underhill Road and Curry Ford Road	4	2,060	3,250	F
Curry Ford Road and Mark Twain Boulevard	4	2,060	1,710	C

The three signalized intersections on model development corridor are synchronized and have video detection and pedestrian push buttons on all approaches with monitoring capabilities at the Marion County Traffic Monitoring Center (TMC). For analysis purposes, Maricamp Road was considered as Major road.



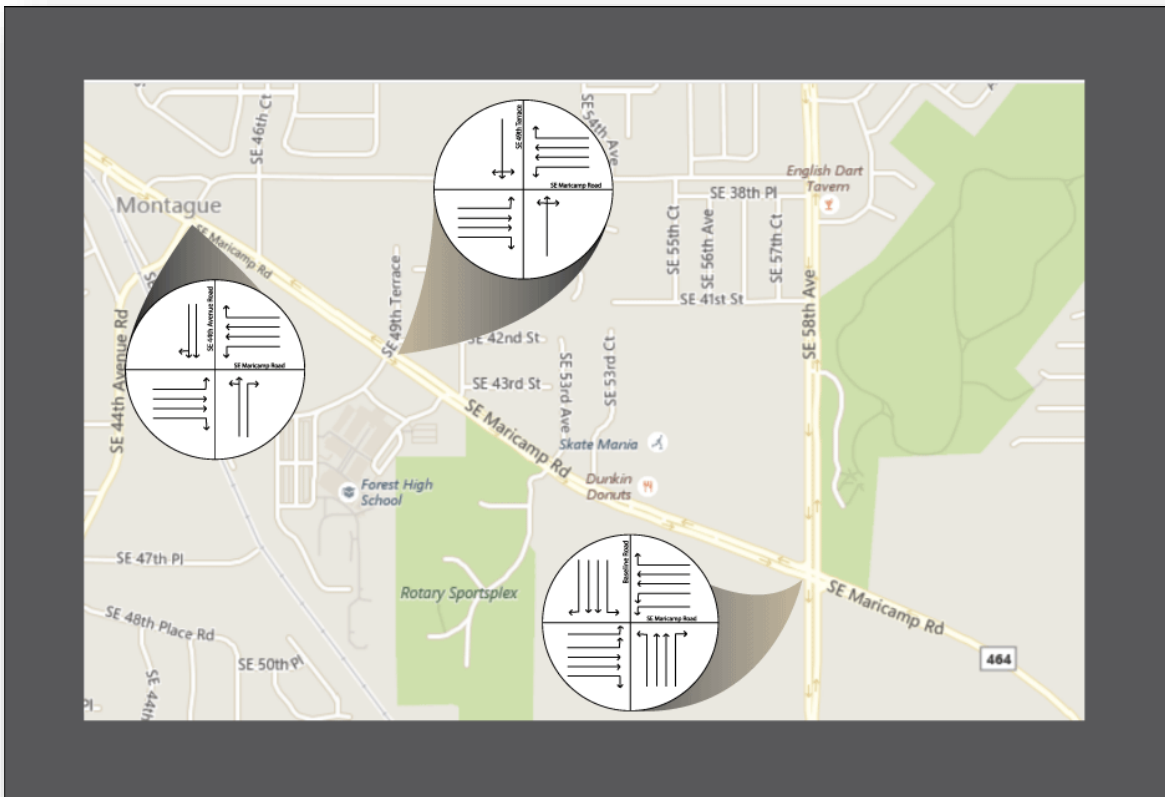


Figure 2: Intersections used for Model Development

For the three intersections, mentioned above, with In|Sync ATCS, the following traffic data was collected for 30 days (Sept. 1, 2016 through Sept. 30, 2016):

- Phase duration (seconds)
- Movement type
- Volume (vehicles/hour)
- Queue Length (number of vehicles)
- Wait time (seconds)
- Period length (seconds)

The queue length for an In|Sync ATCS represents the maximum number of vehicles waiting before the light turns green for a phase. Similarly, the wait time represents the amount of time between the arrival and release of the first vehicle in the queue for any given phase. Appendix A shows a sample data used for the model development.

### 3.2 Model Validation Data Sites

The validation process for the developed prediction models is the key step to establish the functionality of these models under different traffic volumes and operational conditions. The validation process employed for this research consists of collecting data, like the data collected for model development, but at a different location and under similar traffic controls. The data used in the final validation process was collected at the following three locations, as depicted in Figure 3, in Orange County, Florida during the week of May 10 -May 17, 2017:

- Alafaya Trail and Waterford Lakes Pkwy
- Alafaya Trail and Lake Underhill Road
- Alafaya Trail and Huckleberry Finn Drive

The model development data was collected at a semi-urban corridor (Maricamp Road, Marion County, FL) where the daily traffic volume were relatively low and peak traffic periods are not more than one hour each during the morning and evening peak periods. In addition, due to a very heavy senior citizen population in Marion County and its surrounding areas (i.e. The Villages, On Top Of World developments), the driver mix is quite different especially during off peak hours. Therefore, it was decided to select a model validation corridor in an urban environment with heavy traffic (50,000 veh. /day) and longer peaks and different driver mixes. The Alafaya Trail, Orange County Florida corridor around UCF was the perfect choice for the model validation corridor because it carries very heavy daily traffic and has peak periods extending more than one hour and is dominated by young and aggressive drivers.

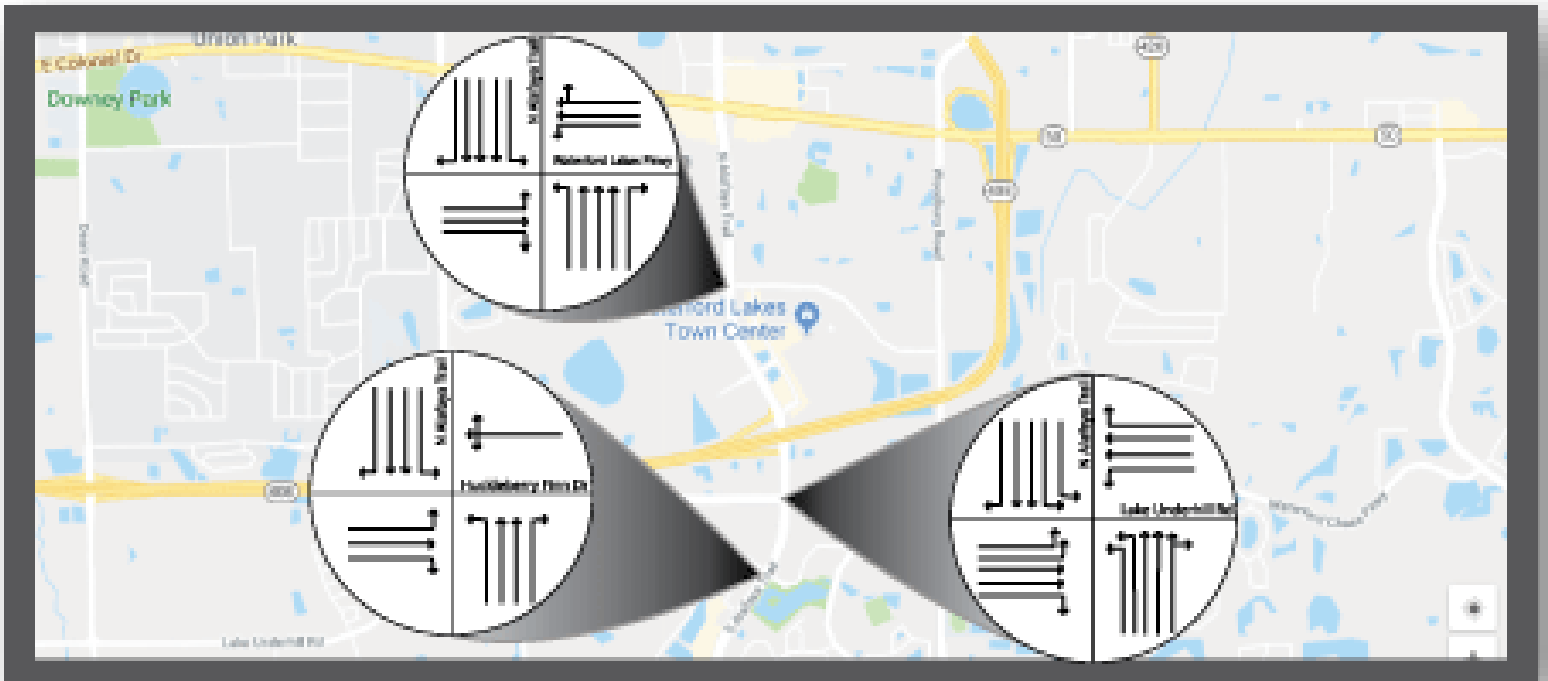


Figure 3: Model Validation Data Locations

Preliminary review of the collected data, at the above-mentioned three locations, showed that the two intersections (Alafaya Trail and Waterford Lakes Pkwy and Alafaya Trail and Lake Underhill Road) during the peak periods were severely congested with spill over queues from one cycle to another. Under these conditions, the majority of the phases were maxing-out and adaptive traffic signal controls are operating like the fixed time of the day operations. Based on these observations, data from Alafaya Trail and Huckleberry Finn Drive intersection were used for the final validation process. The validation data obtained from Alafaya Trail and Huckleberry Finn Drive intersection

consist of over 11,000 data sets and was able to provide a valid validation process. For analysis purposes, Alafaya Trail was considered as Major road.

Generalized LOS for the validation corridor along with peak hour peak direction traffic volumes are included in the Table 3 also.

### 3.3 Cleanup of Raw Data

To make sure the data collected for this research is reflective of the typical month and to minimize data corruption, the following steps were taken during data collection.

- Make sure all the video detection equipment was working properly.
- All the hardware issues were immediately identified and fixed within 2 hours of reporting.
- All the communication and data collection equipment were tested at site and remotely to minimize any feedback loops or residual errors.
- Constant communication with the vendors during the data collection month. At the intersections, which do not have “In|Sync Pedestrian Module”, every time there is a pedestrian call, the system generates an error message (it will serve the pedestrian). All those events were removed during the data cleanup process.

- Since the video detection equipment at these Marion County intersections are mounted on a span wire system, there was some momentary loss of video, which generates system errors. Those events were also taken out from the data set.
- Due to the traffic conditions, the synchronization part of the adaptive system, in Marion County, is set to run during the following hours only:
  - 6:00 am – 9:00 pm - Weekdays
  - 7:00 am – 9:00 pm - Saturdays
  - 8:00 am – 9:00 pm – Sundays

Outside those hours, In|Sync ATCS is set to run, its equivalent of “Free” mode and during those periods, it did not calculate a cycle length. For that reason, the events outside the above-mentioned periods were also not included in the data evaluation.

- In|Sync ATCS, reports traffic volume in 15-minute increments, so a 15-minute analysis period is used for this evaluation.
- In|Sync ATCS produces the two MOEs, queue length and wait time, for the major (left and through) movements for each phase of the signal cycle. Appendix A and B depicts sample data used for model development and validation purposes.

- Due to the absence of a shared right-through lane on the model development corridor, the model data does not include any data points corresponding to those conditions.

### 3.4 Development of Macros for Data Processing

Raw field data obtained from the study intersections was scrubbed to obtain workable data set. The scrubbing process eliminated noise and errors including phase information (partial data) when the system is running free; during these times, the system does not calculate cycle length. Also, the three ATCS system installed in Marion County didn't have In|Sync pedestrian module, therefore when there is a pedestrian call, the system transfer the controls to the parent controller and log that event with a message and no traffic data was reported. In addition, all the events with failed communication, with vehicle detection failure and/or traffic signal preemption need to be removed to obtain clean data for further evaluations. Due to the enormous size of the data, several macros were developed to process the data to make it ready for use in the model development. The main tasks that were completed by using macros were:

- Summarize the data into 15 minutes interval
- Calculate various tendencies (Average, 85th percentile and maximum) for the two dependent variables (Queue and Wait time).
- Develop all the fourteen-independent variable.
- Transpose the data in to two distinct databases for the development of left turn and through movement prediction models.

### 3.5 Development of Dependent and Independent Variables

In|Sync produces two measures of effectiveness (MOEs) for the major (left and through) movements for each phase of the signal cycle:

- Queue Length – is the maximum number vehicles in the queue for each phase of the cycle
- Wait Time – is the wait time for the first vehicle in the queue

The values were aggregated for the analysis period of 15-minutes and then three tendencies, Average, 85th percentile and maximum, were calculated for use in the prediction model development. The independent variables used in the development of prediction model represent two main categories;



### 3.5.1 Volume

- 15-minute Left turn volume for the movement
- 15-minute Through volume for the movement
- Total Left Turn Volume
- Total Through Volume
- Remaining Through Turn (Total Through Volume – 15-minute through volume for the movement)
- Remaining Left Turn (Total Left Turn Volume – 15-minute left turn volume for the movement)

### 3.5.2 Traffic Operation

- Total Green time the left turn phase is served during analysis period (Secs)
- Number of times left turn phase is served during analysis period
- Average amount of green each time left turn phase is served
- Ratio of (total green/analysis period) X (number of lanes)
- Total Green time the through phase is served during analysis period (Secs)

- Number of times through phase is served during analysis period
- Average amount of green each time through phase is served
- Ratio of (total green/analysis period) X (number of lanes)

The traffic operational variables were tabulated to match the analysis period of 15-minutes, which correspond to the frequency of the traffic volume provided in In|Sync’s output matrix.

### 3.6 Model Structure

Linear regression analysis is the most widely used of all statistical techniques and is the part of statistics, which deals with the relationship between two or more variables related, in a nondeterministic fashion. In a linear regression model, the dependent variable is predicted from another variable called “independent” variable. In the equation shown below Y denotes the “dependent” variable whose values we wish to predict using X1, ..., Xk denotes the “independent” variables.

$$Y = b_0 + b_1X_1 + b_2X_2 + \dots + b_kX_k \dots \dots \dots (1)$$

Equation 1 has the property that the prediction for Y is a straight-line function of each of the X variables, holding the others fixed, and the contributions of different X variables to

the predictions are additive. The slopes of their individual straight-line relationships with Y are the constants  $b_1, b_2, \dots, b_k$  (coefficients of the variables). The additional constant  $b_0$  (intercept) is the prediction that the model would make if all the X's were zero. The coefficients and intercept are estimated by least squares, i.e., setting them equal to the unique values that minimize the sum of squared errors within the sample of data to which the model is fitted and the model's prediction errors are typically assumed to be independently and identically normally distributed. (Devore, 1982) (John Neter, 1985) (Dali Wei, 2012)

### 3.6.1 F-Test (Test for Modal Utility)

This test was used to evaluate if the two-independent variables used in the development of prediction model have a linear relationship (variances are equal). This test is very useful in eliminating redundancy and excessive number of variables in the prediction model. For comparing variances of the two variables, a two-tailed test is performed to show if the variables are linearly connected with others or have unequal variance and are not connected with each other. The F hypothesis test is defined as:

$H_0: \sigma^2_1 = \sigma^2_2$  (Null Hypothesis)

$H_a:$

$\sigma^2_1 < \sigma^2_2$  for a lower one-tailed test

$\sigma^2_1 > \sigma^2_2$  for an upper one-tailed test

$\sigma^2_1 \neq \sigma^2_2$  for a two-tailed test

Test Statistic:  $F = \sigma^2_1 / \sigma^2_2$ ..... (2)

Where  $\sigma^2_1$  and  $\sigma^2_2$  are the sample variances. The more this ratio deviates from 1, the stronger the evidence for unequal population variances. Using  $\alpha$  value = 0.05 and appropriate degree of freedom and for sample size over 120, critical  $F_c$  value is established. If  $F \geq F_c$ , the presence of a relationship between any of the independent variable is indicated.

### 3.6.2 Correlation – Paired T-Test (significance of independent variables)

The t-test (student's t-test) is the most commonly used test to compare two averages (means), to calculate how significant the differences are, and to identify if the differences in the averages (means) could have happened coincidentally or not. The basic assumption for the application of t-test is that the data set comes from a standard normal distribution or a student's t-distribution. Although the normal distribution and student's t-distribution have almost the same shape (bell curve), t-distribution is more applicable for a sample of data or a small size of sample rather than the entire population.

- A level  $\alpha$  test for  $H_0 : \mu = \mu_0$

$$T = \frac{\bar{X} - \mu_0}{S/\sqrt{n}} \dots\dots\dots (3)$$

○ Rejection Zones

○  $H_a: \mu > \mu_0$        $T \geq t_{\alpha, n-1}$

○  $H_a: \mu < \mu_0$        $T \leq -t_{\alpha, n-1}$

○  $H_a: \mu \neq \mu_0$       either  $T \geq t_{\alpha, n-1}$  or  $T \leq -t_{\alpha, n-1}$

○  $\alpha$  Value used for this research is 0.05.

## CHAPTER FOUR: DESIGN OF EXPERIMENT

According to the literature, there is no related research that focuses on investigating the development of prediction models for queue, wait times for left turns, and for through movement produced by Adaptive (In|Sync) Traffic Signal Controllers. To develop prediction models, this chapter documented an experiment study based on the field data. The purpose was to develop prediction models for queue, wait time for left turns and for through movement and for intersection level of service by using the field data available from the Adaptive (In|Sync) Traffic Signal Controllers.

### 4.1 General Model Layout

The general format of the relationship used for the prediction model for estimating queue length and weight times is:

$$Y_v = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + b_7X_7 + b_8X_8 + b_9X_9 + b_{10}X_{10} + b_{11}X_{11} + b_{12}X_{12} + b_{13}X_{13} + b_{14}X_{14} \dots \dots \dots (4)$$

Where

- $Y_v$  - dependent variables (queue length or wait time for left turn and through movements)

and

- $X_1$  = 15-minute Left turn volume

- X2 = Total Green time the left turn phase is served during analysis period (Secs)
- X3 = Number of times left turn phase is served during analysis period
- X4 = Average amount of green each time left turn phase is served
- X5 = Ratio of (total green/analysis period) X (number of lanes)
- X6 = Total Left Turn volume
- X7 = Total Through volume
- X8 = Remaining left turn
- X9 = 15-minute Through volume
- X10 = Total Green time the through phase is served during analysis period (Secs)
- X11 = Number of times through phase is served during analysis period
- X12 = Average amount of green each time through phase is served
- X13 = Ratio of (total green/analysis period) X (number of lanes)
- X14 = Remaining Through movements

and

- b1, b2..... b14 – are un-standardized coefficients
- b0 – constant

The independent variables depicted in the equations above are part of In|Sync's output matrix. The independent variables, X2 through X6 and X10 through X14, were tabulated to match the analysis period of 15-minutes, which correspond to the frequency of the traffic volume provided in In|Sync's output matrix.

#### 4.2 Experimental Design - Linear Regression Model (LRM)

Initially, Linear Regression Model (LRM) development procedures were used to develop the prediction models for various tendencies (average, 85th percentile and maximum values) for queue and wait times for left turns and for through movement produced by Adaptive (In|Sync) Traffic Signal Controllers. The models were developed using JMP software and were tested using the following criterion:

- Linear relationship exists (F-test)
- R-Square test statistic = 0.70
- Identify collinearity between two variables (variable excluded)
- Level of significance at  $\alpha = 0.05$  (T-test)
- Correlation > 0.70



The prediction models were tested to ensure that the  $\alpha$  value (T-Test) for all the independent variables included in the model did not exceed 0.05. The independent variables with  $\alpha > 0.05$  were dropped from the equation (iterative process) and the process was repeated until all the variables included in the prediction model had  $\alpha \leq 0.05$ .

#### 4.3 Experimental Design - General Linear Regression Model (GLRM)

Majority of the developed models using LRM techniques were not showing good correlation between the field observed and predicted values of various tendencies (average, 85th percentile and maximum values) for queue and wait times for left turns and for through movement and were also missing key variable from the proposed prediction models. Based on that, it was determined that the Linear Regression Model (LRM) development procedures are not best suited for this analyzing this data set and that General Linear Regression Model (GLRM) development procedures to develop the prediction models. The models were also developed using JMP software and were tested using the following criterion:

- Chi-squared Prob < 0.0001
- Identify collinearity between two variables (variable excluded)

- Correlation > 0.70

The prediction models were tested to ensure that the Chi-squared Prob for all the independent variables included in the model did not exceed 0.0001. The independent variables with Chi-squared Prob > 0.0001 were dropped from the equation (iterative process) and the process was repeated until all the variables included in the prediction model had Chi-squared Prob < 0.0001.

The correlation between predicted values and the field observed values of a given dependent variable such as queue or wait time were tested using t-test (student's t-test). The critical correlation value used to pass or fail any prediction model was 0.7. All the prediction models with correlation value of 0.7 or more were advanced to validation process.

#### 4.4 Validation Process of the Prediction Models

The validation of the prediction models consists of comparing the predicted values of a given independent variable with its corresponding field measured values using t-test (student's t-test). Similar to the initial correlation test during model development phase,

the critical correction value used to pass or fail any prediction model was 0.7. All the prediction models with correlation value of 0.7 or more were considered “Validated”.

#### 4.5 Intersection Performance Index (IPI)

The proposed Intersection Performance Index (IPI) is a measure overall performance of an intersection controlled by an Adaptive (In|Sync) Traffic Signal Controllers and is calculated based on the weighted average of the product of Wait Time (W) and Queue (Q) for all the eight (four lefts and four through) movements.

$$IPI = \frac{\sum_{n=1}^8 V_n (Q_n \cdot W_n)}{\sum_{n=1}^8 V_n} \dots\dots\dots (5)$$

Where V= 15 min traffic volume for the movements 1 through 8. Movements 1, 3, 5 and 7 – left turns and Movements 2, 4, 6 and 8 are through movements. The Q and W for each movement can be calculated using the proposed prediction models. Where IPI for existing conditions should be based on the field observed Q and W values and the future IPI can be calculated based on the estimated Q and W values using the newly developed Q and W models.

The validation of the IPI is a critical element and was achieved by calculating the intersection capacity using the Intersection Capacity Utilization (ICU) method. The method sums the amount of time required to serve all movements at saturation for a given Cycle length and divides by that reference cycle length. The ICU indicates how much capacity is left (reserve Capacity) or how much overcapacity a signal is operating at a given cycle length and at a given volume level. (David Husch)

The ICU values were calculated for the peak periods of the model development data. The calculated ICU values and corresponding LOS were compared with the predicted IPI values to establish a scale and threshold for the determining LOS using the proposed methodology. GLRM techniques were used to develop a prediction model for ICU and IPI. The model was developed using JMP software and were tested using the same criterion used for the development of prediction models for ATCS MOES. For further validation of the proposed IPI, additional comparisons of the IPI values were made with the results (Delay, LOS and 95th percentile queue) of Highway Capacity Manual (2010) conducted for the same time periods.

## CHAPTER FIVE: PREDICTION MODELS

This chapter summarizes the results of the efforts employed for the development of the prediction models for various tendencies (average, 85th percentile and maximum values) for queue and wait times for left turns and for through movement produced by Adaptive (In|Sync) Traffic Signal Controllers.

### 5.1 Results of Linear Regression Modeling (LRM) Efforts

Initially, Linear Regression Model (LRM) development procedures were used to develop the prediction models for queue and wait times for left turns and for through movement.

Table 3 shows a 3X4 matrix that was initially used to develop models.

Table 4 - Matrix of the Initial Prediction Models using LRM Techniques

Tendencies	Left Turns		Through Movement	
	Queue	Wait	Queue	Wait
Average	X	X	X	X
85 <sup>th</sup> Percentile	X	X	X	X
Maximum	X	X	X	X

The above-mentioned twelve models were developed using the following general format of the relationship and the fourteen independent models discussed earlier.

$$Y_v = b_0 + b_1(X_1) + b_2(X_2) + b_3(X_3) + b_4(X_4) + b_5(X_5) + b_6(X_6) + b_7(X_7) + b_8(X_8) + b_9(X_9) + b_{10}(X_{10}) + b_{11}(X_{11}) + b_{12}(X_{12}) + b_{13}(X_{13}) + b_{14}(X_{14}) \dots \dots \dots (6)$$

Where

- $Y_v$  - dependent variables (queue length or wait time for left turn and through movements)

and

- $X_1$  = 15-minute Left turn volume
- $X_2$  = Total Green time the left turn phase is served during analysis period (Secs)
- $X_3$  = Number of times left turn phase is served during analysis period
- $X_4$  = Average amount of green each time left turn phase is served
- $X_5$  = Ratio of (total green/analysis period) X (number of lanes)
- $X_6$  = Total Left Turn volume
- $X_7$  = Total Through volume
- $X_8$  = Remaining left turn
- $X_9$  = 15-minute Through volume
- $X_{10}$  = Total Green time the through phase is served during analysis period (Secs)

- X11 = Number of times through phase is served during analysis period
- X12 = Average amount of green each time through phase is served
- X13 = Ratio of (total green/analysis period) X (number of lanes)
- X14 = Remaining Through movements

and

- b1, b2..... b14 – are un-standardized coefficients
- b0 – constant

The results of the initial model development using the LRM techniques are shown below in Table 4.

Table 5- Results of the Linear Regression Modeling Efforts

R-Square values of the Prediction Models				
Tendencies	Left Turns		Thru Movement	
	Queue	Wait	Queue	Wait
Average	0.7095	0.5139	0.7641	0.6849
85 <sup>th</sup> Percentile	0.6578	0.2828	0.7279	0.6117
Maximum	0.3148	0.1905	0.4614	0.6233

The R-square test statistic of 0.7 was used to evaluate the relationship of the basic with the dependent variables (queue and wait time) for all three (Average, 85th percentile and Maximum) tendencies. The R-square values of the majority (nine out of twelve prediction models) of the developed prediction models is below 0.7 threshold values and four of the nine prediction models have low, less than 0.5 R-square values. In

addition to having relatively lower R-square values, the majority of the LRM based prediction models were missing key independent variables, such as traffic volumes, from the prediction models. This may be because the field-based data set was not normally distributed and has a very high degree of randomness. Based on these findings, it was determined that LRM based development procedures are not best suited for this analyzing this data set and that General Linear Regression Model (GLRM) development procedures should be used to develop the prediction models for various tendencies (average, 85th percentile and Maximum values) for queue and wait times for left turns and for through movement produced by adaptive (Synch) traffic signal controller.

In addition, the four initially developed models with extremely low R-squared values were dropped from any further considerations. The four models dropped from further considerations are:

- Left Turn - Queue maximum, Wait 85th percentile and Wait Maximum
- Through Movement - Queue maximum.

## 5.2 Results of General Regression Modeling (GLRM) Efforts

The remaining eight models were developed using the above mentioned 14 basic independent variables and their cross products were used in the GLRM model



development procedures along with Poisson distribution with log link function was found to best suit the data set required to develop the above mentioned prediction models.

Table 5 depicts the evaluation matrix.

Table 6 - Matrix of the Models advanced for Further (GLRM) Consideration

Tendencies	Left Turns		Thru Movement	
	Queue	Wait	Queue	Wait
Average	✓	✓	✓	✓
85 <sup>th</sup> Percentile	✓	X	✓	✓
Maximum	X	X	X	✓

A Chi-Square (goodness of fit) test statistic of less than 0.0001 was used to evaluate the relationship of independent (basic and cross product) variables with the dependent variables (queue and wait time) at the three (average, 85<sup>th</sup> percentile and maximum) tendencies. Also, the correlation between the field observed value of a dependent variable and the corresponding predicted value of the same variable were tested using paired T-test with an acceptable minimum correlation value of 0.70. The average MOE was found to have acceptable models for both left turns and through movements. Results of the above-mentioned evaluation matrix are depicted in Tables 7 through 22 and are discussed in the following sections.

Sample of the data used in the development of the prediction models is provided in Appendix A.

### 5.2.1 Prediction Model for Left Turn Queue (Average)

Basic statistical descriptions of the experiment are shown in Tables 6 and 7. Table 6 shows that the prediction model for the left turn queue (average) consists of six independent variables having Prob > ChiSq of less than 0.0001. As expected, the prediction for the left turn queue is very depended (3 variables out of 6) on the critical traffic movements. Table 8 shows the results of the T-test (t-ratio 4.32E-07, DF 6773) conducted between the predicted and the field observed left turn queue (average) shows a correlation value of 0.8329.

Table 7 - Model Development Results of the Left Turn Queue (Average)

Term	Estimate	Std Error	L-R ChiSquare	Prob>ChiSq
Intercept	-0.429917	0.0431402	101.17966	<.0001
15-minute Left TurnVolume	0.0057681	0.0008488	46.071562	<.0001
Total Green time the phase is served during analysis period (Secs)	0.0051003	0.0003846	174.47485	<.0001
Number of times phase is served during analysis period	0.0105054	0.0023935	19.165654	<.0001
TOTAL Left Turns	0.0023005	0.0002591	78.418705	<.0001
TOTAL Thru Movement	0.000668	8.58E-05	59.787813	<.0001
(15-minute Left TurnVolume -27.3527)*(Total Green time the phase is served during analysis period (Secs)-73.7913)	-0.000118	0.0000123	93.773128	<.0001

Table 8 - Results of the T-test conducted for predicted and field observed Left turn Queue (Average)

Pred Lt_Qave	2.117149771	t-Ratio	4.32E-07	
Lt_Qave	2.117149768	DF	6773	
Mean Difference	2.87E-09	Prob >  t		1
Std Error	0.006640444	Prob > t		0.5
Upper 95%	0.01301736	Prob < t		0.5
Lower 95%	-0.013017354			
N	6774			
Correlation	0.832986186			

### 5.2.2 Prediction Model for Left Turn Queue (85th percentile)

Tables 8 and 9 depicted the basic statistical descriptions of experiment results. Table 8 shows that the prediction model consists of six variables: three of them are volume based and two variables are traffic operation based and sixth variable is a combination of volume and traffic operations. Table 9 shows the results of the T-test (t-ratio 1.58E-08, DF 6958) conducted between the predicted and the field observed left turn queue (85th percentile) shows a correlation value of 0.7999.

**Table 9 - Model Development Results of the Left Turn Queue (85th Percentile)**

Term	Estimate	Std Error	L-R ChiSquare	Prob>ChiSq
Intercept	0.5174906	0.0289027	314.0824	<.0001
15-minute Left TurnVolume	0.0052836	0.0005021	110.70478	<.0001
Total Green time the phase is served during analysis period (Secs)	0.0035913	0.0002417	218.92268	<.0001
Number of times phase is served during analysis period	0.0109017	0.0016237	44.879023	<.0001
TOTAL Left Turns	0.0011229	0.0001704	43.318044	<.0001
TOTAL Thru Movement	0.0008866	5.50E-05	255.36287	<.0001
(15-minute Left TurnVolume -29.3003)*(Total Green time the phase is served during analysis period (Secs)-76.6801)	-0.00011	7.9158E-06	197.43838	<.0001

**Table 10 - Results of the T-test conducted for predicted and field observed Left turn Queue (Average)**

Pred Lt_Q85th (Field)	4.783086651	t-Ratio	1.58E-08	
Lt_Q85th (Field)	4.78308665	DF	6958	
Mean Difference	2.27E-10	Prob >  t		1
Std Error	0.014353923	Prob > t		0.5
Upper 95%	0.028138067	Prob < t		0.5
Lower 95%	-0.028138067			
N	6959			
Correlation	0.799962004			

### 5.2.3 Prediction Model for Left Turn Wait (Average)

Tables 10 and 11 depicted the basic statistical descriptions of experiment results. Table 10 depicts that the prediction model consists of seven variables: three of them are volume based and three variables are traffic operation based and seventh variable is a combination of volume and traffic operations. Table 11 shows the results of the T-test (t-ratio 1.69E-10, DF 6971) conducted between the predicted and the field observed left turn wait (average) shows a correlation value of 0.7126.

Table 11 - Model Development Results of the Left Turn Wait (Average)

Term	Estimate	Std Error	L-R ChiSquare	Prob>ChiSq
Intercept	2.1462042	0.0171648	15606.192	<.0001
15-minute Left TurnVolume	0.0029293	0.0002263	166.95619	<.0001
Total Green time the phase is served during analysis period (Secs)	-0.005663	0.000159	1249.0247	<.0001
Number of times phase is served during analysis period	0.0462429	0.001038	1915.3494	<.0001
Average amt of green each time phase is served	0.0649423	0.0017161	1376.6797	<.0001
TOTAL Left Turns	0.0022081	7.54E-05	852.00073	<.0001
TOTAL Thru Movement	0.0002112	2.53E-05	69.625764	<.0001
(15-minute Left TurnVolume -32.2549)*(Total Green time the phase is served during analysis period (Secs)-79.5647)	-0.000046	3.37E-06	188.62305	<.0001

Table 12- Results of the T-test conducted for predicted and field observed Left Turn Wait (Average)

Pred Formula Lt_Wave (Field)	23.19823123	t-Ratio	1.69E-10	
Lt_Wave (Field)	23.19823123	DF	6971	
Mean Difference	0	Prob >  t		1
Std Error	0.059824096	Prob > t		0.5
Upper 95%	0.117273435	Prob < t		0.5
Lower 95%	-0.117273435			
N	6972			
Correlation	0.7126802			

#### 5.2.4 Prediction Model for Through Movement Queue (Average)

Tables 12 and 13 depicted the basic statistical descriptions of experiment results. Table 12 depicts that the prediction model consists of six variables: two of them are volume based and three variables are traffic operation based and variable is a combination of volume and traffic operations. Table 13 shows the results of the T-test (t-ratio 7.51E-10, DF 9879) conducted between the predicted and the field observed through movement queue (Average) shows a correlation value of 0.8485.

Table 13 - Model Development Results of the Through Movement Queue (Average)

Term	Estimate	Std Error	L-R ChiSquare	Prob>ChiSq
Intercept	-0.124955	0.0281191	19.880068	<.0001
15-minute thru Volume	0.0036976	0.0001008	1305.2805	<.0001
Total Green time the phase is served during analysis period (Secs)	0.0007596	0.0001311	33.692053	<.0001
Number of times phase is served during analysis period	0.0288166	0.0013892	421.30482	<.0001
Average amt of green each time phase is served	0.0141941	0.0012355	124.55993	<.0001
TOTAL Left Turns	0.0024928	0.0001269	382.82735	<.0001
(15-minute thru Volume -100.415)*(Total Green time the phase is served during analysis period (Secs)-161.333)	-0.000011	6.80E-07	273.35366	<.0001

Table 14 - Results of the T-test conducted for predicted and field observed Through Movement Queue (Average)

Pred Formula thru_Qave (Field)	3.63560227	t-Ratio	7.51E-10	
thru_Qave (Field)	3.63560227	DF	9879	
Mean Difference	7.75E-12	Prob >  t		1
Std Error	0	Prob > t		0.5
Upper 95%	0.020236115	Prob < t		0.5
Lower 95%	-0.020236115			
N	9880			
Correlation	0.848549508			

### 5.2.5 Prediction Model Through Movement Queue (85th percentile)

Tables 14 and 15 depicted the basic statistical descriptions of experiment results. Table 14 depicts that the prediction model consists of six variables: two of them are volume based and three variables are traffic operation based and sixth variable is a combination of volume and traffic operations. Table 15 shows the results of the T-test (t-ratio 4.39E-08, DF 10158) conducted between the predicted and the field observed through movement queue (85<sup>th</sup> percentile) shows a correlation value of 0.8089.

Table 15 - Model Development Results of the Through Movement Queue (85th percentile)

Term	Estimate	Std Error	L-R ChiSquare	Prob>ChiSq
Intercept	0.8728037	0.0183866	2139.1652	<.0001
15-minute thru Volume	0.002611	6.11E-05	1773.269	<.0001
Number of times phase is served during analysis period	0.0298206	0.0006634	2000.8864	<.0001
Average amt of green each time phase is served	0.0148695	0.000512	786.21282	<.0001
TOTAL Left Turns	0.0021759	8.97E-05	585.59308	<.0001
TOTAL remaining thru Movement	-0.000183	3.85E-05	22.576385	<.0001
(15-minute thru Volume -102.705)*(TOTAL Left Turns-84.8609)	-1.43E-05	8.31E-07	303.90023	<.0001
(15-minute thru Volume -102.705)*(TOTAL remaining thru Movement-324.061)	1.79E-06	4.99E-07	12.935808	0.0003

Table 16 - Results of the T-test conducted for predicted and field observed Through Movement Queue (85th percentile)

Pred Thru_Q85th Field	7.427896447	t-Ratio	4.39E-08	
Thru_Q85th Field	7.427896447	DF	10158	
Mean Difference	0	Prob >  t		1
Std Error	0.019020814	Prob > t		0.5
Upper 95%	0.037284554	Prob < t		0.5
Lower 95%	-0.037284552			
N	10159			
Correlation	0.808928888			

## 5.2.6 Prediction Model for Through Movement Wait (Average)

Tables 16 and 17 depicted the basic statistical descriptions of experiment results. Table 16 shows that the prediction model consists of seven variables: three of them are volume based, three variables are traffic operation based, and seventh variable is a combination of volume and traffic operations. Table 17 shows the results of the T-test (t-ratio 1.39E-07, DF 9749) conducted between the predicted and the field observed through movement queue (85<sup>th</sup> percentile) shows a correlation value of 0.8028.

Table 17 - Model Development Results of the Through Movement Wait (Average)

Term	Estimate	Std Error	L-R ChiSquare	Prob>ChiSq
Intercept	1.5164676	0.0140819	11046.199	<.0001
15-minute thru Volume	-0.002586	5.04E-05	2766.2861	<.0001
Total Green time the phase is served during analysis period (Secs)	-0.00334	7.39E-05	2024.5536	<.0001
Number of times phase is served during analysis period	0.054833	0.0007565	5105.7841	<.0001
Average amt of green each time phase is served	0.057612	0.0008763	4068.4408	<.0001
TOTAL Left Turns	0.0048604	0.0000651	5535.9936	<.0001
TOTAL remaining thru Movement	0.0004091	2.71E-05	226.84875	<.0001
(15-minute thru Volume -110.188)*(Total Green time the phase is served during analysis period (Secs)-168.164)	7.36E-06	3.13E-07	542.28475	<.0001

Table 18 - Results of the T-test conducted for predicted and field observed Through Movement Wait (Average)

Pred thru_Wave(Field)	18.15882028	t-Ratio	1.39E-07	
thru_Wave(Field)	18.15882027	DF	9749	
Mean Difference	7.07E-09	Prob >  t		1
Std Error	0	Prob > t		0.5
Upper 95%	0.099718088	Prob < t		0.5
Lower 95%	-0.099718074			
N	9750			
Correlation	0.802809993			

### 5.2.7 Prediction Model for Through Movement Wait (85th percentile)

Tables 18 and 19 depicted the basic statistical descriptions of experiment results. Table 18 shows that the prediction model consists of ten variables: three of them are volume based, three variables are traffic operation based, and four variables are combination of volume and traffic operations. Table 19 shows the results of the T-test (t-ratio 1.47E-07, DF 10045) conducted between the predicted and the field observed through movement queue (85<sup>th</sup> percentile) shows a correlation value of 0.7779.

**Table 19 - Model Development Results of the Through Movement Wait (85th percentile)**

Term	Estimate	Std Error	L-R ChiSquare	Prob>ChiSq
Intercept	2.6746614	0.0089738	80864.064	<.0001
15-minute thru Volume	-0.002705	3.23E-05	7413.5273	<.0001
Total Green time the phase is served during analysis period (Secs)	-0.00183	4.70E-05	1514.7307	<.0001
Number of times phase is served during analysis period	0.0414346	0.0004739	7532.5872	<.0001
Average amt of green each time phase is served	0.038669	0.000544	4819.2294	<.0001
TOTAL Left Turns	0.0038202	0.0000419	8322.1834	<.0001
TOTAL remaining thru Movement	0.0006027	0.0000168	1273.0656	<.0001
(15-minute thru Volume -110.684)*(Total Green time the phase is served during analysis period (Secs)-174.718)	8.03E-06	2.59E-07	945.10654	<.0001
(15-minute thru Volume -110.684)*(TOTAL Left Turns-	1.37E-05	4.97E-07	746.93936	<.0001
(Total Green time the phase is served during analysis period (Secs)-174.718)*(TOTAL Left Turns-87.9759)	-0.000014	3.38E-07	1723.8586	<.0001
period (Secs)-174.718)*(TOTAL remaining thru Movement-318.962)	-1.31E-06	1.46E-07	81.01592	<.0001

**Table 20 - Results of the T-test conducted for predicted and field observed Through Movement Wait (85th percentile)**

Pred thru_W85th(Field)	45.09799922	t-Ratio	1.74E-07	
thru_W85th(Field)	45.0979992	DF	10045	
Mean Difference	2.01E-08	Prob >  t		1
Std Error	0.115932887	Prob > t		0.5
Upper 95%	0.227251686	Prob < t		0.5
Lower 95%	-0.227251646			
N	10046			
Correlation	0.777990535			



### 5.2.8 Prediction Model for Movement Wait (Maximum)

Tables 20 and 21 depicted the basic statistical descriptions of experiment results. Table 20 depicts that the prediction model consists of nine variables: three of them are volume based, three variables are traffic operation based, and three variables are combination of volume and traffic operations. Table 21 shows the results of the T-test (t-ratio 0, DF 10528) conducted between the predicted and the field observed through movement queue (85<sup>th</sup> percentile) shows a correlation value of 0.8128.

**Table 21 - Model Development Results of the Through Movement Wait (Maximum)**

Term	Estimate	Std Error	L-R ChiSquare	Prob>ChiSq
Intercept	3.9126014	0.0060766	369870.59	<.0001
15-minute thru Volume	-0.002396	2.39E-05	10530.857	<.0001
Total Green time the phase is served during analysis period (Secs)	-0.000379	2.90E-05	171.27822	<.0001
Number of times phase is served during analysis period	0.0108022	0.0003154	1168.7104	<.0001
Average amt of green each time phase is served	0.0085549	0.0003014	785.47615	<.0001
TOTAL Left Turns	0.0017949	3.03E-05	3510.2066	<.0001
TOTAL remaining thru Movement	0.0007824	1.17E-05	4352.4145	<.0001
(15-minute thru Volume -109.976)*(Total Green time the phase is served during analysis period (Secs)-178.601)	6.44E-06	1.89E-07	1151.8005	<.0001
(15-minute thru Volume -109.976)*(TOTAL Left Turns-90.3791)	1.14E-05	3.61E-07	960.59505	<.0001
(Total Green time the phase is served during analysis period (Secs)-178.601)*(TOTAL Left Turns-90.3791)	-1.18E-05	2.31E-07	2584.3577	<.0001

**Table 22 - Results of the T-test conducted for predicted and field observed Through Movement Wait (Maximum)**

Pred thru_Wmax (Field)	76	t-Ratio	0
thru_Wmax (Field)	75.53050171	DF	10523
Mean Difference	2.93E-10	Prob >  t	1
Std Error	0.126298142	Prob > t	0.5
Upper 95%	0.247568285	Prob < t	0.5
Lower 95%	-0.247568284		
N	10524		
Correlation	0.812808172		

### 5.3 Validation of the Prediction Models

As last step of the prediction model development, all the models discussed in the previous section were validated using the In|Sync data obtained from Orange County. Details of the validation data development are discussed in Section 3.2. The newly developed models were used to predict the dependent variable and those values were compared with the corresponding field observed values using paired T-test and the results of that evaluation are summarized in the following sections.

#### 5.3.1 Validation of Left Turn Queue (Average) Model

Table 22 depicted below provide the results of the validation process for the left turn queue (average). The difference of the means for the predicted and field observed values for this variable is 0.7403 with a standard error of 0.0333. The results of the T-test (t-ratio 22.38129, DF 287) conducted between the predicted and the field observed left turn queue (average) shows a correlation value of 0.6991 (approx. 0.7) and the prediction model is validated.

Table 23 - Validation Results of the Left Turn Queue (Average)

Lt_Qave (calc)	1.86549	t-Ratio	22.38129
Lt_Qave	1.12517	DF	287
Mean Difference	0.74032	Prob >  t	<.0001
Std Error	0.03308	Prob > t	<.0001
Upper 95%	0.80542	Prob < t	1
Lower 95%	0.67521		
N	288		
Correlation	0.69915		

### 5.3.2 Validation of Left Turn Queue (85th percentile) Model

Table 23 depicted below provide the results of the validation process for the left turn queue (85<sup>th</sup> percentile). The difference of the means for the predicted and field observed values for this variable is 16.6146 with a standard error of 0.2408. The results of the T-test (t-ratio 69.0069, DF 322) conducted between the predicted and the field observed left turn queue (85<sup>th</sup> percentile) shows a correlation value of 0.5288 (less than 0.7) and the prediction model failed to be validated.

Table 24 - Validation Results of the Left Turn Queue (85th percentile)

Lt_Q85th (Calc)	5.51282	t-Ratio	28.29592
Lt_Q85th	2.65728	DF	322
Mean Difference	2.85554	Prob >  t	<.0001
Std Error	0.10092	Prob > t	<.0001
Upper 95%	3.05408	Prob < t	1
Lower 95%	2.657		
N	323		
Correlation	0.52887		

### 5.3.3 Validation of Left Turn Wait (Average) Model

Table 24 depicted below provide the results of the validation process for the left turn wait (average). The difference of the means for the predicted and field observed values for this variable is 16.6146 with a standard error of 0.24077. The results of the T-test (t-ratio 69.0069, DF 314) conducted between the predicted and the field observed left turn wait (average) shows a correlation value of 0.7033 and the prediction model is validated.

Table 25 - Validation Results of the Left Turn Queue (Average)

Lt_Wave (Calc)	20.2	t-Ratio	69.00697
Lt_Wave	3.58531	DF	314
Mean Difference	16.6146	Prob >  t	<.0001
Std Error	0.24077	Prob > t	<.0001
Upper 95%	17.0884	Prob < t	1
Lower 95%	16.1409		
N	315		
Correlation	0.70333		

### 5.3.4 Validation of Through Movement Queue (Average) Model

Table 25 depicted below provide the results of the validation process for the through movement queue (average). The difference of the means for the predicted and field observed values for this variable is 2.4446 with a standard error of 0.1108. The results

of the T-test (t-ratio 22.069, DF 1517) conducted between the predicted and the field observed through movement queue (average) shows a correlation value of 0.7719 and the prediction model is validated.

Table 26 - Validation Results of the Through Movement Queue (Average)

Calc Thru_Qave	4.49504	t-Ratio	22.06998
Thru_Qave	2.05039	DF	1517
Mean Difference	2.44465	Prob >  t	<.0001
Std Error	0.11077	Prob > t	<.0001
Upper 95%	2.66193	Prob < t	1
Lower 95%	2.22738		
N	1518		
Correlation	0.77187		

### 5.3.5 Validation of Through Movement Queue (85th percentile) Model

Table 26 depicted below provide the results of the validation process for the through movement queue (85<sup>th</sup> percentile). The difference of the means for the predicted and field observed values for this variable is 3.3932 with a standard error of 0.1272. The results of the T-test (t-ratio 26.6759, DF 1425) conducted between the predicted and the field observed through movement queue (85<sup>th</sup> percentile) shows a correlation value of 0.7562 and the prediction model is validated.

Table 27 - Validation Results of the Through Movement Queue (Average)

Calc Total Thru_85th	7.95833	t-Ratio	26.67591
Thru_Q85th	4.56515	DF	1425
Mean Difference	3.39318	Prob >  t	<.0001
Std Error	0.1272	Prob > t	<.0001
Upper 95%	3.6427	Prob < t	1
Lower 95%	3.14366		
N	1426		
Correlation	0.75617		

### 5.3.6 Validation of Through Movement Wait (Average) Model

Table 27 depicted below provide the results of the through movement wait (average). The difference of the means for the predicted and field observed values for this variable is - 0.8753 with a standard error of 0.1306. The results of the T-test (t-ratio -6.7026, DF 1469) conducted between the predicted and the field observed through movement wait (average) shows a correlation value of 0.7269 and the prediction model is validated.

Table 28 - Validation Results of the Through Movement Queue (Average)

Calc Thru_Wave	9.01772	t-Ratio	-6.70265
Thru_Wave	9.89302	DF	1469
Mean Difference	-0.8753	Prob >  t	<.0001
Std Error	0.13059	Prob > t	1
Upper 95%	-0.6191	Prob < t	<.0001
Lower 95%	-1.1315		
N	1470		
Correlation	0.72691		

### 5.3.7 Validation of Through Movement Wait (85th percentile) Model

Table 28 depicted below provide the results of the through movement wait (85<sup>th</sup> percentile). The difference of the means for the predicted and field observed values for this variable is 2.3876 with a standard error of 0.7941. The results of the T-test (t-ratio 3.0068, DF 1807) conducted between the predicted and the field observed through movement wait (85<sup>th</sup> percentile) shows a correlation value of 0.3875 and the prediction model the failed the validation process.

Table 29 - Validation Results of the Through Movement Queue (Average)

Calc Thru_W85th	32.2402	t-Ratio	3.006847
Thru_W85th	29.8527	DF	1807
Mean Difference	2.38759	Prob >  t	0.0027
Std Error	0.79405	Prob > t	0.0013
Upper 95%	3.94495	Prob < t	0.9987
Lower 95%	0.83024		
N	1808		
Correlation	0.3875		

### 5.3.8 Validation of Through Movement Wait (Maximum) Model

Table 29 depicted below provide the results of the through movement wait (maximum). The difference of the means for the predicted and field observed values for this variable is 12.2634 with a standard error of 1.1013. The results of the T-test (t-ratio 11.1356, DF

1410) conducted between the predicted and the field observed through movement wait (maximum) shows a correlation value of 0.6840 (approx. 0.7) and the prediction model the failed the validation process.

Table 30 - Validation Results of the Through Movement Queue (Average)

Calc Thru_Wmax	83.3073	t-Ratio	11.13558
Thru_Wmax	71.0439	DF	1410
Mean Difference	12.2634	Prob >  t	<.0001
Std Error	1.10128	Prob > t	<.0001
Upper 95%	14.4237	Prob < t	1
Lower 95%	10.1031		
N	1411		
Correlation	0.68401		

### 5.3.9 Conclusions of the Validation Process

The correlation values provided in Tables 22 through 29 are summarized in Table 30. The evaluation matrix provided in Table 30 with cells marked with “X” represent the scenarios that failed during initial model development phase; the cells with correlation values less than 0.7 (shown in red) symbolize the model development scenarios which failed the validation test. The prediction models for the left turns and through movements for average queue and wait passed the validation test. The other prediction model that passed the validation is through movement model for 85<sup>th</sup> percentile queue.



Table 31 - Final Validation Results (Correlation Values)

Tendencies	Left Turns		Through Movement	
	Queue	Wait	Queue	Wait
Average	0.6991	0.7033	0.7718	0.7269
85 <sup>th</sup> Percentile	0.5288	X	0.7561	0.3875
Maximum	X	X	X	0.6840

The validation of left turn and through movement models for average tendency provide complete set of variables needed for the development of IPI index. The models based on averages provide more realistic results, which are closer to the actual values. The prediction models for averages provide information about the entire range of the data set. The models predicting 85<sup>th</sup> percentile, however, do not provide any information for the 15% of the observations and they are good predictors for certain MOEs like queue and speed. The prediction models for the maximum value of MOEs are good for determining worst-case scenarios. Any evaluation and design based on worst-case scenario provides a good safety margin and is required in many engineering fields such as structural, hydrology and mechanical engineering. In traffic engineering, however, the use of maximum value of an MOE may lead to oversizing of the facility i.e. design of a parking lot or streets for Christmas season.

## 5.4 Final Prediction Models

The following models show the relationship between the selected MOEs for the dependent (Left turns and through movements) and independent variables (direct output of adaptive traffic controller).

### Left Turn

- $\text{Log (Left Turn Queue Ave)} = -0.429917 + 0.0057681 (X1) + 0.0051003 (X2) + 0.0105054 (X3) + 0.0023005 (X6) + 0.000668 (X7) + -0.000118 ((X1 -27.3527) * (X2 -73.7913)) \dots\dots\dots (7)$

- $\text{Log (Left turn Wait Ave)} = 2.1462042 + 0.0029293 (X1) + -0.005663 (X2) + 0.0462429 (X3) + 0.0649423 (X4) + 0.0022081 (X6) + 0.0002112 (X7) + -0.000046 ((X1 -32.2549) *(X2 - 79.5647)) \dots\dots\dots (8)$

### Through Movement

- $\text{Log (Through Queue Ave)} = -0.124955 + 0.0036976 (X9) + 0.0007596 (X10) + 0.0288166 (X11) + 0.0141941 (X12) + 0.0024928 (X6) + -0.000011 ((X9 - 100.415) * (X10 - 161.333)) \dots\dots\dots (9)$

- $\text{Log (Through Queue 85th percentile)} = 0.8728037 + 0.002611 (X9) + 0.0298206 (X11) + 0.0148695 (X12) + 0.0021759 (X6) + -0.000183 (X14) + -1.43E-05 ((X9 -102.705) * (X6 -84.8609)) + 1.79E-06 ((X9 -102.705) *(X14 -324.061)) \dots\dots\dots (10)$

$$\begin{aligned} \text{Log (Through Wait Ave)} = & 1.5164676 + -0.002586 (X9) + -0.00334 (X10) + \\ & 0.054833 (X11) + 0.057612 (X12) + 0.0048604 (X6) + 0.0004091 (X14) + 7.36E-06 (X9 - \\ & 110.188) * (X10 - 168.164) \dots\dots\dots (11) \end{aligned}$$

Where

- X1 = 15-minute Left turn volume
- X2 = Total Green time the left turn phase is served during analysis period  
(Secs)
- X3 = Number of times left turn phase is served during analysis period
- X4 = Average amount of green each time left turn phase is served
- X5 = Ratio of (total green/analysis period) X (number of lanes)
- X 6 = Total Left Turn volume
- X7 = Total Through volume
- X 8 = Remaining left turn
- X9 = 15-minute Through volume
- X10 = Total Green time the through phase is served during analysis period  
(Secs)
- X11 = Number of times through phase is served during analysis period
- X12 = Average amount of green each time through phase is served

- $X_{13}$  = Ratio of (total green/analysis period) X (number of lanes)
- $X_{14}$  = Remaining Through movement

The variables  $X_1$ ,  $X_6$ ,  $X_7$ ,  $X_8$ ,  $X_9$  and  $X_{14}$  are traffic demand based and can be measured directly in the field. The remaining variables, however, are based on direction and arrival patterns of traffic flow and their determination requires making initial assumptions:

- All the movements will be served each period (cycle)
- The initial cycle length should be able to accommodate all the minimum green and all yellow and red intervals.
- $X_2$  is calculated by multiplying total left turn volume during the analysis period by the 2.81sec / veh for single lane and 2.69 sec / veh for two-lane approach
- $X_3$  can be calculated dividing the analysis period (15 minutes) by the assumed cycle length
- $X_4$  can be calculated by dividing  $X_2$  by  $X_3$
- $X_5$  can be calculated by multiplying ( $X_2$ ) by number of lanes for the movement and dividing the product by analysis period (sec)

The same process should be applied for calculating  $X_{10}$  through  $X_{13}$  using through volumes and number of through lanes.

As discussed earlier the average models are good for determining planning level evaluations and calculating overall intersections operations. The use of 95<sup>th</sup> percentile queue for location of median opening is often considered too restrictive and often criticized and challenged for not being practical especially in the development review area. Therefore, having a criterion that addresses the queue buildup for 85<sup>th</sup> percent of the time is quite useful and provide a balanced approach in locating median openings (access management) on a corridor.

Since, the model development corridor does not have shared right and through lanes, therefore, it is advisable not to use these equations when such conditions, i.e. shared right and through, exists at study intersections.

## CHAPTER SIX: INTERSECTION PERFORMANCE INDEX (IPI)

This chapter discusses the following five main points:

- Development of the Intersection Performance Index (IPI)
- Intersection Capacity Utilization (ICU)
- Development of correlation between Intersection Performance Index and Intersection Capacity Utilization (ICU)
- Calibration and Validation of Intersection Performance Index
- Development of IPI Threshold

### 6.1 Development of Intersection Performance Index (IPI)

IPI is the proposed measure of effectiveness (MOE) to measure overall intersection performance at an intersection controlled by adaptive traffic systems (ATS). The IPI, as discussed previously in equation five, is developed using the basic outputs (Queue and Wait time) and the corresponding traffic demands from ATS (In|Sync) and is represented by the following equation:

$$IPI = \frac{\sum_{n=1}^8 V_n (Q_n.W_n)}{(\sum_{n=1}^8 V_n)}$$

Where  $V = 15$  min traffic volume for the movements 1 through 8. Movements 1, 3 5 and 7 – left turns and Movements 2, 4, 6 and 8 are through movements. Where IPI for existing conditions should be based on the field observed Q and W values and the future IPI can be calculated based on the estimated Q and W values using the newly developed Q and W models.

As part of validation process, IPI was calculated for the data collected for the development of prediction models. The data for Maricamp Road and Baseline Road intersection for the period (weekday only) of September 28, 2016 through October 16, 2016 was used to calculate IPI. Figures 4 through 8 shows the calculated IPI values for a typical week (Monday through Friday) at the study intersection. Figures for the rest of the data is provided in the Appendix C.

Figures 4 through 8, clearly depict the relationship and sensitivity of IPI with the traffic volume. Like the traditional letter grade LOS, the IPI values are higher during peak periods (AM, noon and PM). These figures also show consistent IPI values and patterns for the 5 days.

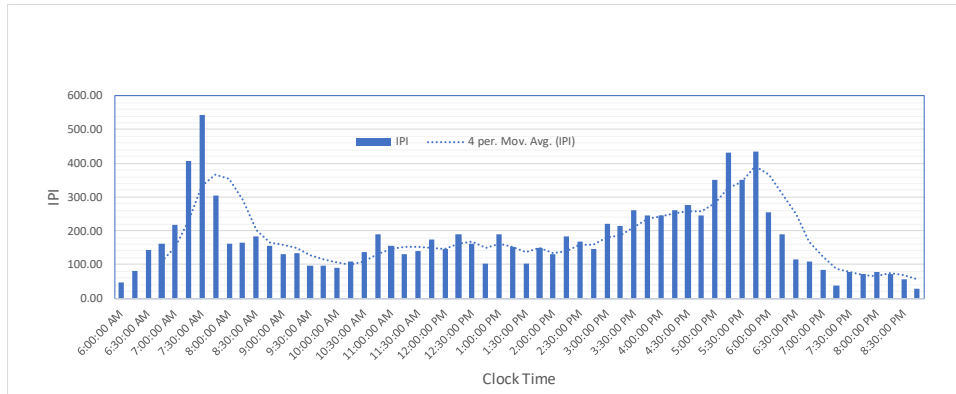


Figure 4: IPI vs 15-min traffic volume for Monday, 10/17/2017 at the study intersection

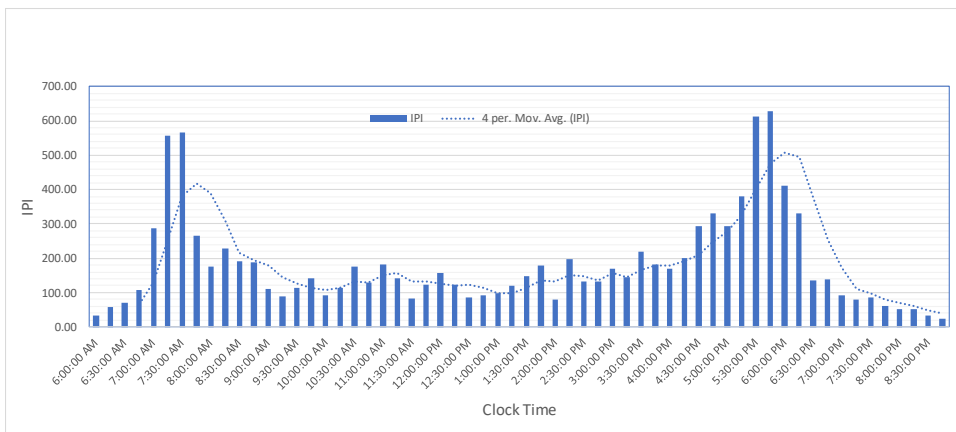


Figure 5: IPI vs 15-min traffic volume for Tuesday, 10/4/2016 at the study intersection



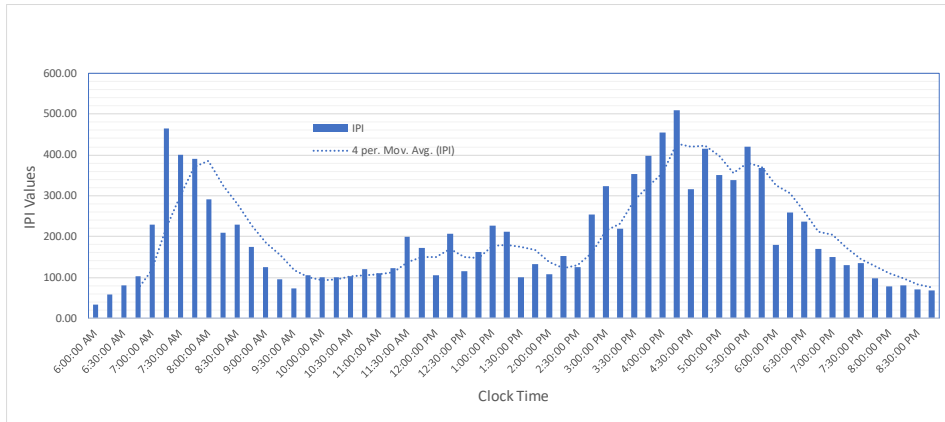


Figure 6: IPI vs 15-min traffic volume for Wednesday, 09/28/2016 at the study intersection

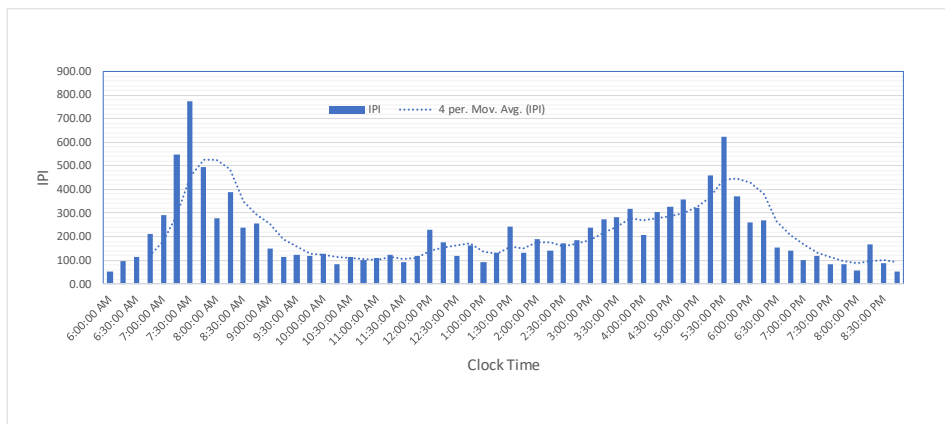


Figure 7: IPI vs 15-min traffic volume for Thursday, 10/20/2016 at the study intersection

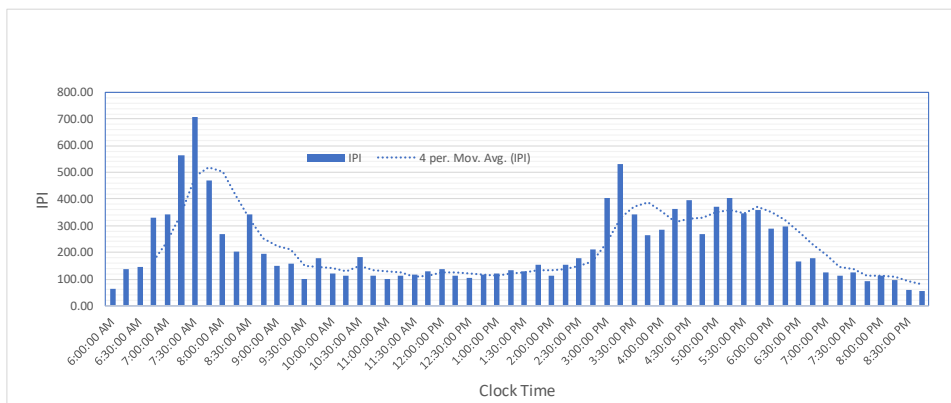


Figure 8: IPI vs 15-min traffic volume for Friday, 10/14/2016 at the study intersection

## 6.2 Internal Capacity Utilization (ICU)

Internal Capacity Utilization (ICU) methodology is a simple planning level tool, which is designed to measure capacity of signalized and un-signalized intersections. This methodology is independent of the signal timings plan; however, it considers basic signal timing parameter such as minimum cycle length. This is a good planning level tool, which provided the practitioners information about the capacity utilization and available reserve capacity for future usages. This tool is not designed for operational analysis and development of signal timing plans.

ICU is defined as the sum of the time required to serve all movements at saturation for a reference cycle length divided by the reference cycle length:

$$ICU = \sum(\max(t_{Min}, V/S_i) * CL + t_{L_i}) / CL \dots \dots \dots (12)$$

Where:

CL = Reference Cycle Length

t<sub>L<sub>i</sub></sub> = Lost time for critical movement i

V/S<sub>i</sub> = volume to saturation flow rate for critical movement i

t<sub>Min</sub> = minimum green time, critical movement i

Based on the calculated ICU, level of service (letter grade) is determined. The ICU LOS is based on field observations and it gives understanding how the intersection is functioning and how much reserve capacity is available to handle future demands. ICU LOS is different than delay-based LOS calculated using HCM. ICU LOS reports reserve capacity or lack off and HCM LOS reports average delay observed by experienced by the motorized.

Although the MOEs (reserve Capacity) produced by ICU methodology are different than HCM MOEs (delay per vehicle), the current version of the ICU methodology is developed to produce comparable MOEs and two methods are correlated. Both the methodologies use the same default saturation flow rates and volume adjustments factors. Table 31 shows the relationship of the ICU LOS and HCM LOS. (David Husch)

Table 32 - ICU vs HCM Level of Service

<b>ICU LOS</b>	<b>HCM LOS</b>
LOS F or worse	Normally will be F
	D or E with especial signal timings
E or Better	E or Better
D or Better	D or Better ( depend on cycle length) v/c ratios < 0.8

### 6.3 Correlation between IPI and Internal Capacity Utilization (ICU)

Upon review of the IPI values and corresponding time of the day in Figures 5 through 9, it was evident that the IPI methodology for ATCS intersection is similar to the approach/philosophy of the internal Capacity Utilization (ICU) methodology used for typical non-adaptive traffic control systems. As discussed in the literature review chapter, that currently there is no software or traffic operational methodology available for evaluation of projected traffic conditions at a ATCS intersections, there IPI validation was based on comparison of IPI with corresponding ICU and LOS values for the peak period (AM and PM). ICU/LOS during the peak periods were calculated using the traffic volumes, intersection geometry and optimized signal timings for the study intersection. The evaluation results (ICU/LOS and IPI) for a typical week (Monday through Friday), for the same dates as for Figures 4 through 8, is provided in Table 32. Complete summary of those efforts is provided in the Appendix D.

Table 33 - Sample ICU and IPI Data

Date	TIME	ICU - (%)	LOS	IPI
9/28/17	6:45 AM	72.0%	C	103.64
	7:00 AM	100.0%	F	229.69
	7:15 AM	92.0%	F	463.79
	7:30 AM	68.3%	C	399.31
	7:45 AM	68.0%	C	389.09
	8:00 AM	63.3%	B	290.46
	8:15 AM	73.0%	C	209.43
	3:15 PM	69.0%	C	219.93
	3:30 PM	79.0%	D	352.84
	3:45 PM	78.0%	D	396.82
	4:00 PM	97.0%	F	455.08
	4:15 PM	91.0%	E	509.72
	4:30 PM	78.0%	D	315.92
	4:45 PM	77.0%	D	414.22
9/29/17	6:30 AM	63.0%	B	115.49
	6:45 AM	67.0%	C	119.90
	7:00 AM	91.2%	F	313.62
	7:15 AM	90.0%	E	562.94
	7:30 AM	85.0%	E	485.70
	7:45 AM	75.0%	D	424.77
	8:00 AM	77.4%	D	262.80
	11:30 AM	58.4%	B	102.2868
	11:45 AM	72.0%	C	131.237
	12:00 PM	72.2%	C	438.4574
	12:15 PM	76.5%	D	646.0472
	12:30 PM	58.9%	B	87.88755

The prediction model for the IPI and ICU was developed based on the data the data provided in Appendix C. The prediction model was developed using GLRM with Poisson distribution log link function.

$$\text{Log (ICU)} = -0.51161 + (0.000683) \times (\text{IPI}) \dots \dots \dots (13)$$

Table 33 shows the model development results.

Table 34 - Model Development Results for ICU and IPI

Term	Estimate	Std Error	L-R ChiSquare	Prob>ChiSq	Lower CL	Upper CL
Intercept	-0.51161	0.245709	4.5088816	0.0337	-1.002493	-0.03868
IPI	0.000683	0.000613	1.2157583	0.2702	-0.000541	0.001864

Results of the Paired T-Test (t-ratio 6.68E-08, DF 141) between the predicted ICU values and calculated ICU are summarized in Table 34. Table 34 clearly shows that there is a definite correlation between IPI and ICU/LOS. The difference in the mean values for the predicted and field observed values for this variable is 4.30E -10 with a standard error of 0.00644 and a correlation value of 0.73527.

Table 35 - Results of the T-test for model-based ICU values and calculated ICU using traditional ICU methodology

Pred ICU	0.76715	t-Ratio	6.68E-08
ICU	0.76715	DF	141
Mean Differ	4.30E-10	Prob >  t	1
Std Error	0.00644	Prob > t	0.5
Upper 95%	0.01274	Prob < t	0.5
Lower 95%	-0.0127		
N	142		
Correlation	0.73527		

Figure 9 provide a graphical representation of relationship between ICU and IPI.

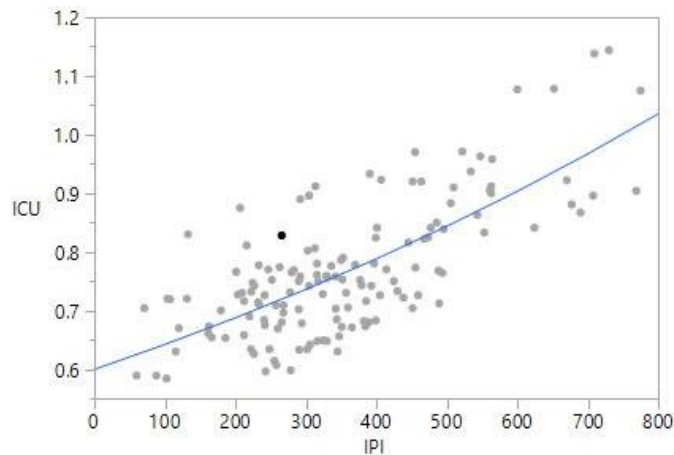


Figure 9: IPI vs ICU

Finally, IPI Thresholds based for the adapted traffic controllers (IN|SYNC) and the corresponding ICU values are shown in the Table 35 and in Figure 10 provided below.

Table 36 - IPI Thresholds vs ICU/LOS

Critical IPI	Intersection Traffic Operation	Corresponding ICU & LOS	
395	Under capacity	$\leq 0.73$	A,B,C
429	Near Capacity	$> 0.73$ to $0.82$	D
575	At Capacity	$> 0.82$ to $0.91$	E
$> 575$	Over capacity	$> 0.91$	F & Above

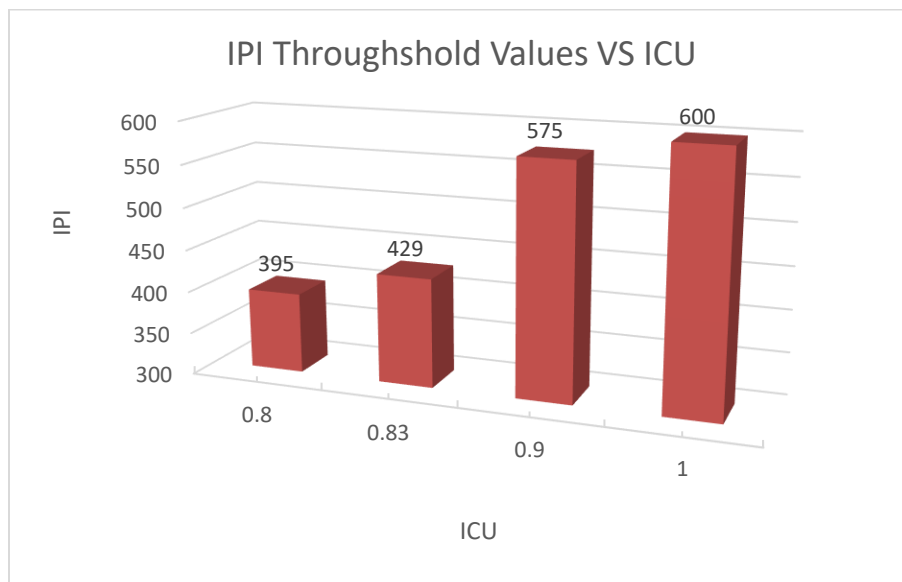


Figure 10: PI Thresholds vs ICU/LOS

#### 6.4 Comparison of HCM 2010 Delay and IPI

Table 36 depicts sample, two days only, ICU values and HCM 2010 delay/LOS for the for the data collected to evaluate the relationship between IPI and HCM 2010 delay.

Complete set of data is provided in Appendix E. Also included in Appendix E are the corresponding 95<sup>th</sup> percentile queues for the left and through movements using Synchro analysis software. The delay reported by Synchro under HCM 2010 signalized option are based on year 2010 update of HCM, which calculates delays using percentile delay calculation techniques. (Trafficware, LLC., 2017)

Lastly, the IPI and HCM 2010 delay was also developed using the data provided in Appendix E. The prediction model was developed using GLRM with Poisson distribution log link function.

$$\text{Log (IPI)} = 4.6433902 + (0.0234801) \times (\text{HCM 2010 Delay}) \dots\dots\dots (14)$$

Table 37 shows the model development results.



Table 37 - IPI and HCM 2010 Delays

Date	TIME	HCM 2010 (Delay/LOS)		IPI
9/28/17	6:45 AM	35.5	D	103.64
	7:00 AM	56.3	E	229.69
	7:15 AM	50.6	D	463.79
	7:30 AM	43.3	D	399.31
	7:45 AM	46.1	D	389.09
	8:00 AM	43.7	D	290.46
	8:15 AM	45.3	D	209.43
	3:15 PM	48.4	D	219.93
	3:30 PM	50.1	D	352.84
	3:45 PM	50.2	D	396.82
	4:00 PM	91.0	F	455.08
	4:15 PM	53.9	D	509.72
	4:30 PM	50.0	D	315.92
	4:45 PM	47.9	D	414.22
9/29/17	6:30 AM	35.0	D	115.49
	6:45 AM	35.6	D	119.90
	7:00 AM	58.7	E	313.62
	7:15 AM	58.0	D	562.94
	7:30 AM	48.8	D	485.70
	7:45 AM	37.3	D	424.77
	8:00 AM	41.7	D	262.80
	11:30 AM	36.1	D	102.2868
	11:45 AM	38.5	D	131.237
	12:00 PM	38.6	D	438.4574
	12:15 PM	40.2	D	646.0472
	12:30 PM	36.1	D	87.88755

Table 38 - Model Development Results for HCM 2010 Delay and IPI

Term	Estimate	Std Error	L-R ChiSqu	Prob>ChiS	Lower CL	Upper CL
Intercept	4.64339	0.020103	76950.27	<.0001	4.604087	4.68289
HCM 2010 (Delay/LOS)	0.02348	0.000386	3001.144	<.0001	0.02272	0.024234

Results of the Paired T-Test (t-ratio 4.089784, DF 144) between the predicted ICU values and calculated ICU are summarized in Table 38. Table 38 clearly shows that there is a definite correlation between IPI and ICU/LOS. The difference in the mean values for the predicted and field observed values for this variable is 1.99505 with a standard error of 0.48781 and a correlation value of 0.75143.

Table 39 - Results of the T-test for model-based Delay and calculated Delay using HCM 2010 methodology

HCM Predicted	50.264	t-Ratio	4.089784
HCM 2010 (Delay/LOS)	48.269	DF	144
Mean Difference	1.99505	Prob >  t	<.0001
Std Error	0.48781	Prob > t	<.0001
Upper 95%	2.95925	Prob < t	1
Lower 95%	1.03085		
N	145		
Correlation	0.75143		

Figure 11 provide graphical representation of relationship between HCM 2010 (Delay) and IPI.

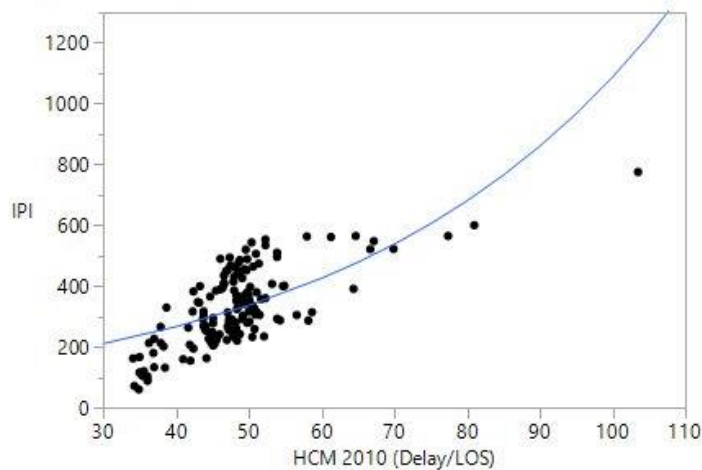


Figure 11: IPI vs HCM 2010 (Delay/LOS)

IPI values and the corresponding HCM 2010 delay/LOS are shown in the Table 39.

Table 40 - HCM 2010 delays and corresponding IPI

<b>HCM 2010</b>		<b>IPI</b>
<b>Control Delay (sec/Veh)</b>	<b>LOS</b>	
10	A	131
20	B	166
35	C	236
55	D	378
80	E	680
>= 81	F	> =696

### 6.5 Recommendations for use of IPI

As discussed in earlier sections ICU methodology is based on reserved capacity concept is suitable for planning purposes. However, the HCM 2010 methodology, based on delay, is appropriate for the operational level analysis, evaluation, and design of signal timing plan. Current research provides the practitioners a choice, which IPI threshold to use, IPI vs ICU or IPI vs Delay. The delay is calculated using HCM 2010 percentile delay method. Recommendations for the use of IPI are as follows:

Use the IPI vs ICU threshold, when:

- ✓ Evaluating traffic impact studies
- ✓ Future roadway design
- ✓ Congestion management plan development
- ✓ Access management plan development

Use IPI vs Delay threshold, when:

- ✓ Traffic Operations
- ✓ Signal timing plan development

## CHAPTER SEVEN: CONCLUSIONS

Use of Adaptive Traffic Controls Systems (ATCS) is becoming more and more common due to its abilities to handle and quickly react to unexpected changes in traffic demands. The changes in the traffic demands could be manmade (i.e. sports events, accidents, emergency road closures) or natural (i.e. natural disaster, early evening rains at the beach etc.). The result is unplanned increase in traffic volume. Traditional traffic signals with properly designed Time of the Day (TOD) works great when traffic volumes increase at fixed time every day (AM, Noon and PM peak hours). However, if the traffic fluctuation occurs outside the predetermined period, these systems cannot do much to handle changed demands. In addition, the efficiency of a fixed cycle length coordination system is decreased approx. 4% per year. (Matt Sellinger, Adaptive Traffic Control Systems in the United States - A review of the cost, maintenance and reliability of popular Adaptive traffic control technologies, 2009) (Fehon, 2015)The industry normal retiming cycle for a fixed cycle length coordination system is three years, as after this time the changes in the traffic volume, peak hours, and traffic configuration becomes significant.

On the other hand, ATCS can quickly adapt to the changes in traffic volume by changing its signal timings parameters accordingly. The performance level of an adaptive signal control, theoretically, can stay constant over a very long period as

compared to a fixed cycle length coordination system. All these advantages make the ATCS very desirable for large-scale deployment. However, currently the absence of reliable analysis tools for the ATCS to evaluate the impacts of changes in traffic flow (i.e. volume and/or direction) makes it very difficult for the practitioners to measure the magnitude of the impacts and to develop an appropriate mitigation strategy. This research is intended to provide the traffic engineers and Planners tools, which are based on sound engineering assumptions and practices. Firstly, this research uses the basic output of the ATCS to develop dataset to be used to develop prediction models for the most critical performance measures, queue and wait time. These two performance measures are most noticeable by the users. Therefore, managing these performance measures are critical not only from traffic engineering point of view but also from the user's perspective too. This research developed the variables which are vital for the development of the prediction models for the critical (left and through) movements and used them to produce a full factorial experiment design by employing volume and traffic operational factors. Secondly, this research developed Intersection Performance Index (IPI), which is tool to evaluate overall intersection performance based on the weighted average of queue and wait for the critical movements. This new tool was calibrated and validated against the Intersection Capacity Utilization (ICU) methodology. In short, this research is planned to fill the gap in the ATCS evaluation arena by producing prediction models for performance measures (queue and wait time) for the critical movements (Left and through movements) and IPI, a tool to predict overall intersection

performance. The tools may also be used for practical applications including signal retiming's, needs analysis and access management.

### 7.1 Discussion of the Results

This research was focused to develop prediction models for queue and wait time for three tendencies (average, 85<sup>th</sup> percentile and maximum) for twelve models. However, the final validation resulted in only five valid models. Four of them are based on the average values of left turn queue and wait time and through movement queue and wait time; and one (through movement queue) model on 85<sup>th</sup> percentile. The four models (based on averages) can be used to calculate queue and wait time for each critical movement and which can then be used to calculate IPI to estimate overall intersection performance measure. IPI Thresholds and corresponding intersection capacity designation can be employed to establish level of service at the intersection. This research has established a traffic operational analysis procedure for the most versatile adaptive system (In|Sync) currently in the market. The models, despite being based on field data, have shown excellent correlation and can be used stand-alone or as part of a traffic analysis package for Adaptive Traffic Control Systems.

Calculation of the queue length is always critical for traffic engineers and designers and is an important aspect of a Preliminary Engineering (PE), Project Development and Environment (PD&E) and Traffic Impact Analysis (TIA). The queue length calculation dictates the sizing of the roadway facility, impacts on Right-Of-Way (ROW), access management and overall traffic operations and safety of the facility. The 85<sup>th</sup> percentile queue model will assist the engineers and designers by providing them queue length for adaptive traffic controllers, which can be used to calculate adequacy and reserve/additional storage capacity, project impacts, mitigation and proportionate share.

## 7.2 Practical Applications

One impetus of this research was to provide tools to the practitioners to evaluate impacts of changes in the traffic volumes and operational conditions due to a development at intersections controlled by ATCS. As mentioned earlier, the Highway Capacity Manual (HCM) and other commercially available software have documented prediction models for traffic performance measures for non-adaptive traffic control systems; however, there is very little research and guidance available for the prediction MOEs such as real-time delay, queue length, queue storage ratios and wait time for adaptive traffic control systems (ATCS). Since, by design, the ATCS systems are self-adjusting to the changes in the traffic demand by taking capacity (green time) from other movements thus keeping the LOS of the impacted movement at same level. This is an



operational point of view, but it minimizes (or totally diminishes) the real impact of traffic increases due to the development. The current research has provided tool to evaluate traffic impacts at the ATCS control intersections by movement and for the whole intersection. These tools can be incorporated in the TIA methodologies for evaluating before and after conditions at the ATCS controlled intersections.

### 7.2.1 Signal Timing

To keep a traffic control system at its peak efficiency level require monitoring the health (efficiency level) on regular basis. ATCS systems are no exceptions. The only difference is the frequency of the check up and the level of fine-tuning required for keeping the system running. Currently, the only way to check performance of ATCS system is from direct output from the system or through travel time survey. Both evaluation techniques provide information about existing conditions but lack capabilities for sensitivity analysis. The models developed as part of this research provide practitioners ability to conduct sensitivity analysis and test “what if” scenarios for both volume changes and traffic operational conditions.

### 7.2.2 Needs Analysis

As mentioned in previous section, that the models developed in this research provide engineers and planners ability to conduct sensitivity analysis and test “what if” scenarios for both volume changes and traffic operational conditions at the ATCS intersections. Currently, the decision to install or replace existing traffic controllers with ATCS is based on availability of funds/grants, antidotal experience and/or politics. These models will provide a sound engineering basis to install ATCS system or replace the existing system with the ATCS system. In addition, during a PE and PD&E study phases, reserve capacities and sizing of an ATC intersections can be evaluated with and without the proposed improvements.

### 7.2.3 Access Management and Safety

A key element of an access management is the location, type and size of the median opening and need and size of storage lengths at the signalized and un-signalized intersections. Sizing, which includes number of lanes and storage capacity, of the left turn lanes at the signalized intersections is the critical aspect of an Access Management Study (AMS). Back of left turn queue exceeding the available storage have the potential to block or slowdown the traffic in the adjacent lane or cause sudden lane changes. These ripple effects can yield safety concerns. The queue length, average and 85<sup>th</sup>

percentile, models developed in this research provide much needed insight in to this critical design requirement for ATCS intersections. The through movement queue length model provides guidance for the location and type of the adjacent (first) median opening to a ATCS intersection.

### 7.3 Further Research

The current research was focused on the traffic operational analysis of isolated intersections controlled by ATCS system. The models developed in this research provided prediction capabilities for the MOEs associated with critical movements and for the entire intersection. When signals are closely spaced so that vehicles arriving from upstream intersection to downstream intersection in a platoon, then running these intersections in coordination is desirable. Same is true for ATCS intersections. Based on the literature review done for this research, there is no research or software in the market, which can evaluate LOS for a coordinated ATCS, controlled intersections.

As continuation of this work, future research can investigate developing coordination evaluation system based on the current findings and recommendations. The factors that could be part of evaluation are number of stops, stops per mile, and percentage of

platoon dispersion or served corridor travel speed. That research could be based on field or laboratory (driving simulator) data.

## APPENDIX A: SAMPLE DATA FOR MODEL DEVELOPMENT



## APPENDIX B: SAMPLE DATA FOR MODEL VALIDATION





## APPENDIX C: GRAPHICAL REPRESENTATION OF IPI DATA

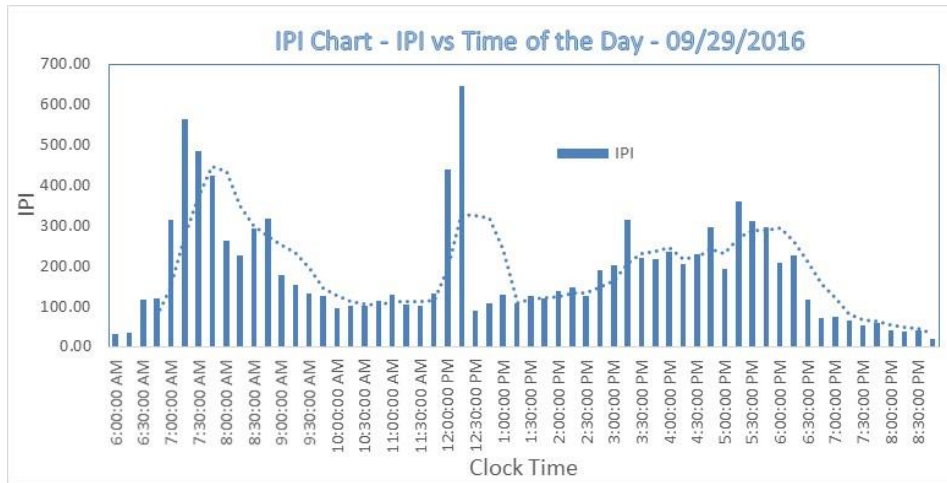


Figure 12: IPI values at study location for 09/29/2016

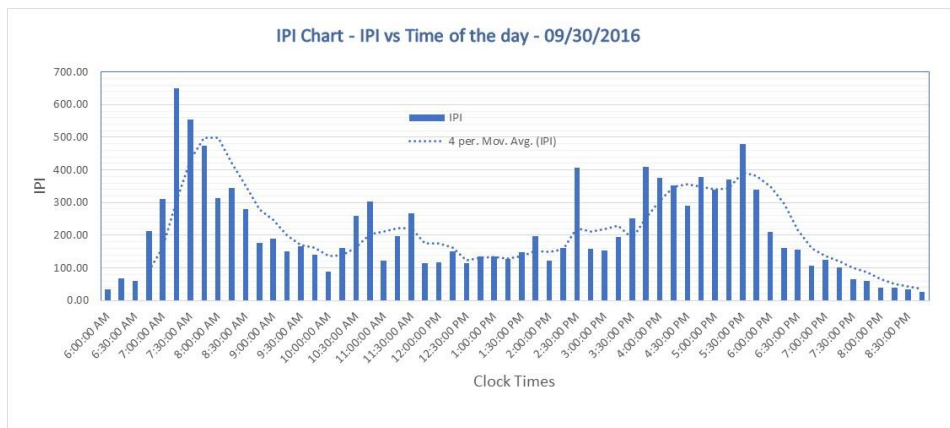


Figure 13: IPI values at study location for 09/30/2016

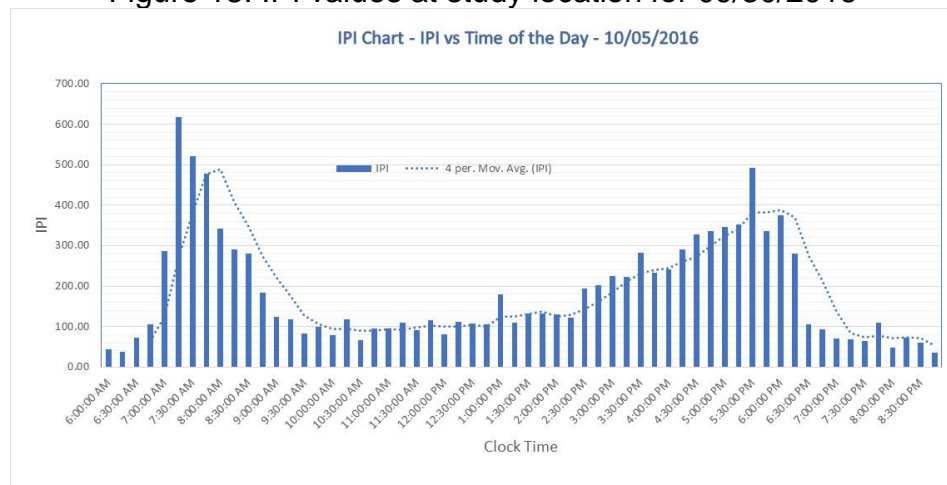


Figure 14: IPI values at study location for 10/05/2016

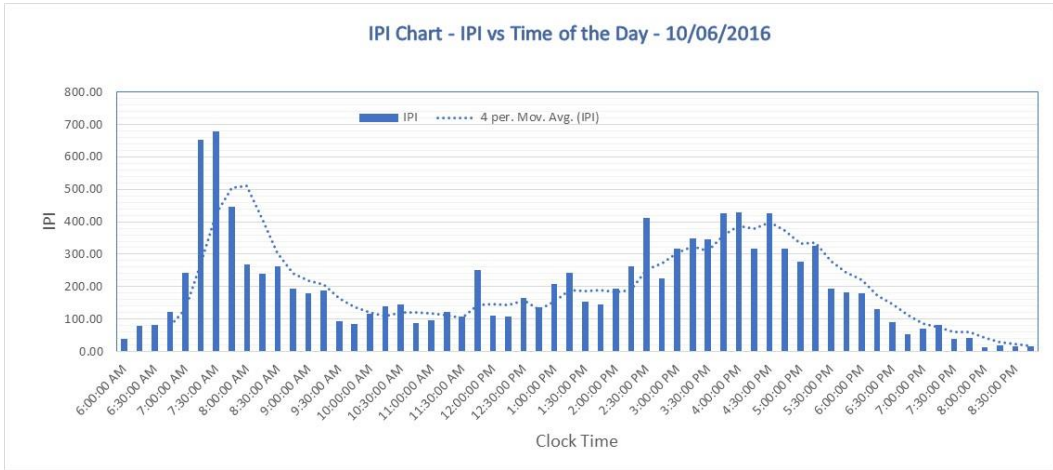


Figure 15: IPI values at study location for 10/06/2016

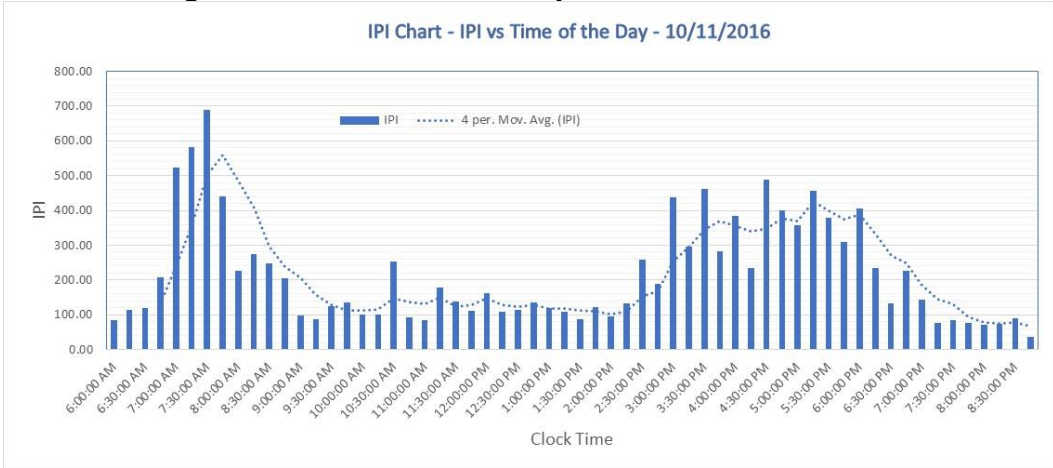


Figure 16: IPI values at study location for 10/11/2016

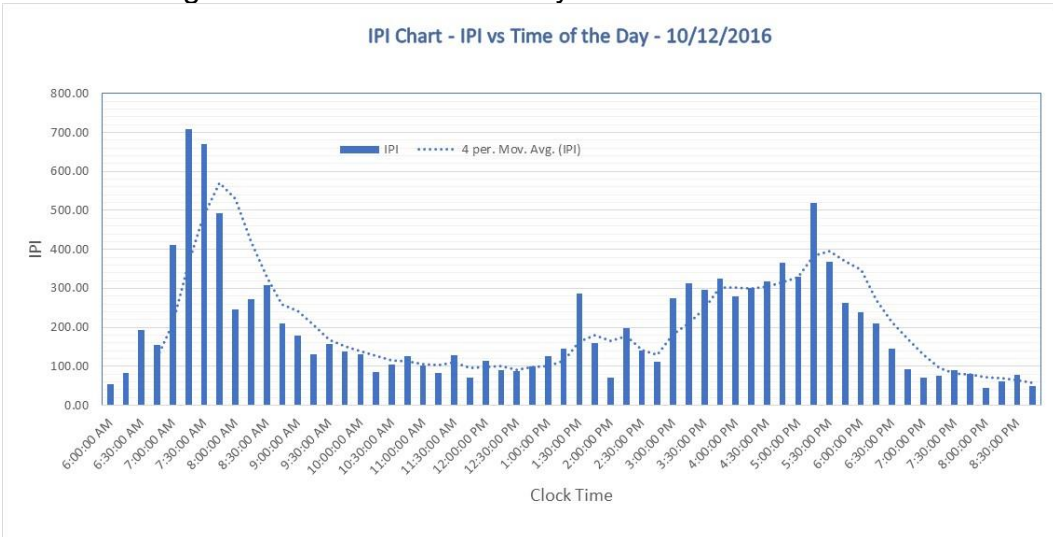


Figure 17: IPI values at study location for 10/12/2016

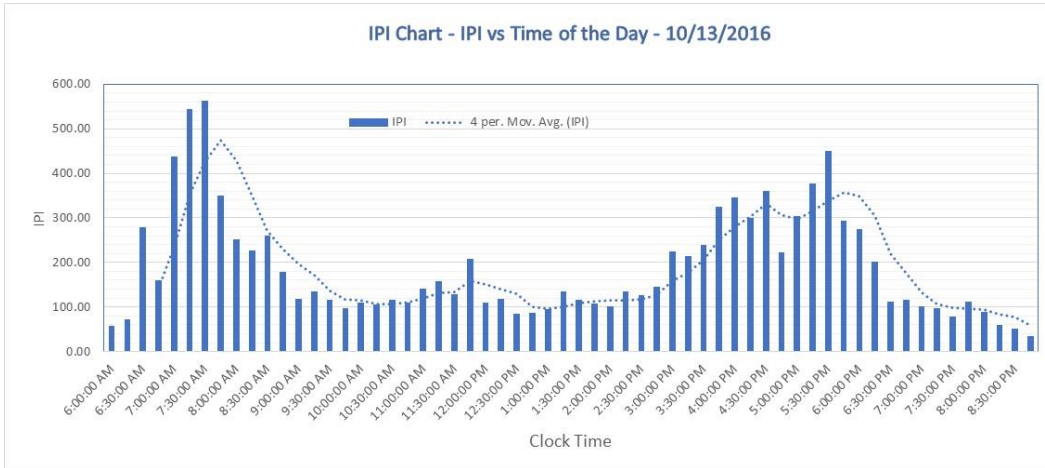


Figure 18: IPI values at study location for 10/13/2016

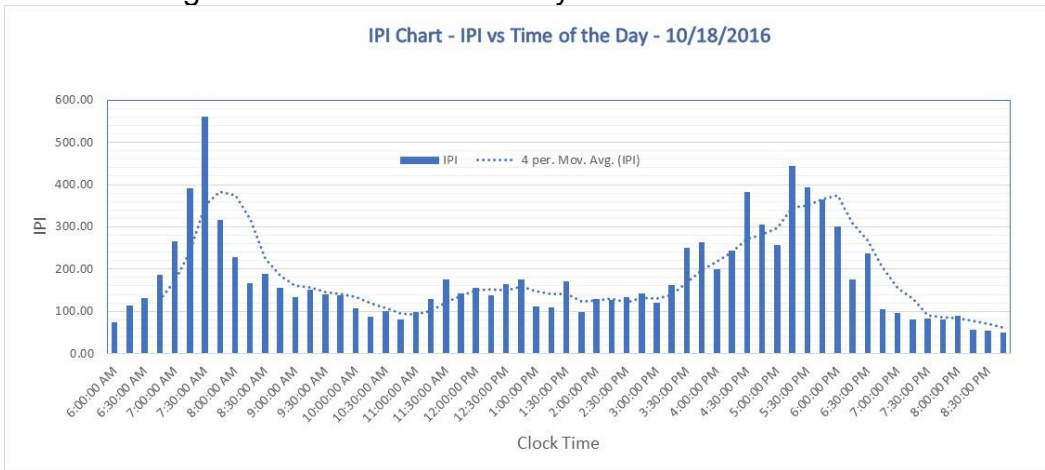


Figure 19: IPI values at study location for 10/18/2016



Figure 20: IPI values at study location for 10/19/2016

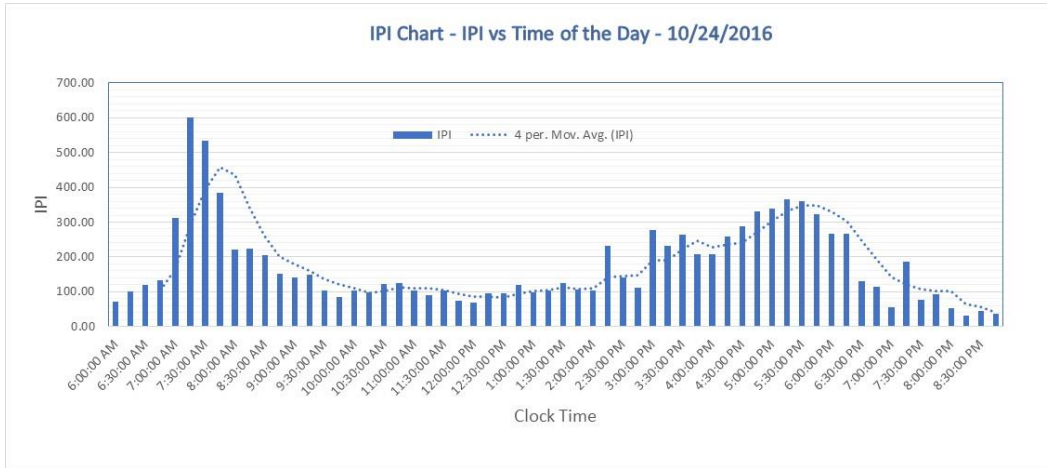


Figure 21: IPI values at study location for 10/24/2016

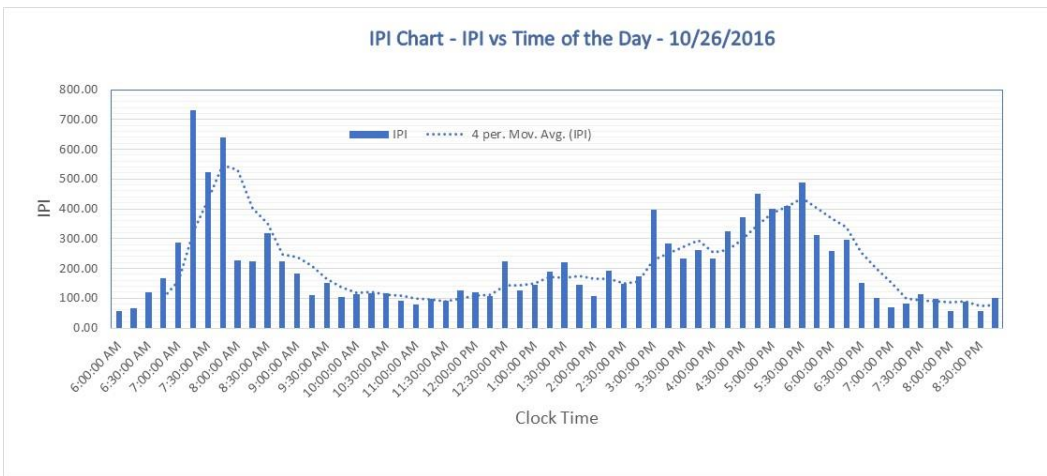


Figure 22: IPI values at study location for 10/26/2016

APPENDIX D: ICU AND CORRSPONDING LOS FOR THE PEAK  
PERIODS

Table 43 – Peak Period ICU and LOS

Date	TIME	ICU - (%) / LOS		IPI
10/4/16	6:30 AM	70.4%	C	70.84647
	6:45 AM	71.9%	D	107.4723
	7:00 AM	99.7%	F	286.0623
	7:15 AM	114.5%	H	557.6838
	7:30 AM	108.2%	G	564.6537
	7:45 AM	68.0%	C	265.8262
	4:45 PM	75.6%	D	330.4996
	5:00 PM	75.8%	D	292.0274
	5:15 PM	74.3%	D	379.1179
10/5/16	7:00 AM	95.0%	F	287.0243
	7:15 AM	118.5%	H	617.5907
	7:30 AM	104.4%	G	520.8759
	7:45 AM	84.1%	E	477.198
	8:00 AM	75.8%	D	341.8534
	8:15 AM	75.0%	D	289.9894
	3:00 PM	74.7%	D	224.3675
	3:15 PM	63.4%	B	222.1694
	3:30 PM	76.9%	D	282.9131
	3:45 PM	71.4%	C	232.2372
	4:00 PM	67.5%	C	241.9264
	4:15 PM	70.2%	C	289.971
10/6/16	7:00 AM	101.2%	G	243.4543
	7:15 AM	107.8%	G	652.0303
	7:30 AM	88.1%	E	677.2471
	7:45 AM	81.6%	D	445.4774
	8:00 AM	70.9%	C	268.1663
	8:15 AM	68.4%	C	240.7377
	2:45 PM	62.6%	B	226.2727
	3:00 PM	64.8%	C	316.4005
	3:15 PM	65.6%	C	347.3685
	3:30 PM	63.0%	B	345.0189
	3:45 PM	63.8%	B	425.8166

Date	TIME	ICU - (%)/LOS		IPI
10/11/16	6:45 AM	87.5%	E	206.7525
	7:00 AM	108.3%	G	523.0323
	7:15 AM	112.1%	H	582.4654
	7:30 AM	86.7%	E	689.7314
	7:45 AM	62.4%	B	440.457
	8:00 AM	74.2%	D	226.7434
	4:00 PM	71.6%	C	385.4596
	4:15 PM	77.7%	D	233.1113
	4:30 PM	76.8%	D	488.2188
	4:45 PM	84.1%	E	400.9682
	5:00 PM	73.0%	D	357.1349
	5:15 PM	77.3%	D	455.5433
10/12/16	6:30 AM	91.5%	F	194.3579
	6:45 AM	88.3%	E	154.0217
	7:00 AM	105.2%	G	410.5021
	7:15 AM	113.8%	H	709.2577
	7:30 AM	92.2%	F	670.2743
	7:45 AM	76.4%	D	493.8342
	3:45 PM	64.9%	C	324.9504
	4:00 PM	59.8%	B	278.4953
	4:15 PM	63.4%	B	301.8911
	4:30 PM	75.0%	D	317.639
	4:45 PM	67.1%	C	365.3811
	5:00 PM	64.8%	C	329.803
5:15 PM	65.5%	C	520.0247	
10/13/16	6:30 AM	92.0%	F	279.2949
	6:45 AM	88.2%	E	159.1941
	7:00 AM	107.9%	G	437.7087
	7:15 AM	111.6%	H	544.2335
	7:30 AM	91.2%	F	563.0396
	7:45 AM	78.6%	D	350.0223
	8:00 AM	75.2%	D	251.7442
	4:30 PM	70.5%	C	359.8979
	4:45 PM	73.2%	D	222.3759
	5:00 PM	74.2%	D	304.7472
	5:15 PM	75.2%	D	377.0107
	5:30 PM	65.2%	C	449.806
5:45 PM	67.8%	C	294.2246	



Date	TIME	ICU - (%) / LOS		IPI
10/14/16	6:30 AM	86.0%	E	145.1245
	6:45 AM	75.9%	D	329.0745
	7:00 AM	99.9%	F	342.1457
	7:15 AM	95.8%	F	564.3872
	7:30 AM	89.6%	E	707.4756
	7:45 AM	82.2%	E	467.8751
	8:00 AM	69.6%	C	268.2257
	8:15 AM	72.7%	C	203.5378
	2:30 PM	70.0%	C	179.5179
	2:45 PM	71.6%	C	212.4115
	3:00 PM	72.6%	C	405.1982
	3:15 PM	67.4%	C	529.5775
	3:30 PM	70.3%	C	342.4464
10/17/16	6:45 AM	66.1%	C	161.5949
	7:00 AM	81.1%	D	216.0172
	7:15 AM	92.3%	F	406.8368
	7:30 AM	86.3%	E	543.4161
	7:45 AM	80.2%	D	302.7481
	8:00 AM	67.3%	C	162.5578
	4:15 PM	66.9%	C	260.1909
	4:30 PM	73.1%	D	277.6575
	4:45 PM	77.0%	D	246.7112
	5:00 PM	67.2%	C	350.9229
	5:15 PM	73.3%	D	430.0485
	5:30 PM	75.3%	D	351.7552
	5:45 PM	65.2%	C	434.5496
6:00 PM	61.4%	B	255.3267	
10/18/16	6:45 AM	65.3%	C	185.8109
	7:00 AM	82.8%	E	265.7341
	7:15 AM	93.3%	F	390.7241
	7:30 AM	90.5%	E	561.0425
	7:45 AM	76.1%	D	315.8448
	4:15 PM	59.6%	B	242.886
	4:30 PM	68.2%	C	382.1065
	4:45 PM	89.6%	E	304.5946
	5:00 PM	70.9%	C	257.482
	5:15 PM	55.6%	B	444.057
	5:30 PM	74.2%	D	392.9528
	5:45 PM	60.9%	B	365.0661

Date	TIME	ICU - (%) / LOS		IPI
10/19/16	6:30 AM	76.6%	D	201.0313
	6:45 AM	65.4%	C	166.4379
	7:00 AM	92.0%	F	451.5293
	7:15 AM	90.4%	E	768.8744
	7:30 AM	88.3%	E	505.5963
	7:45 AM	112.3%	H	579.6474
	8:00 AM	63.4%	B	248.3124
	4:00 PM	71.0%	C	233.8719
	4:15 PM	72.6%	C	241.4559
	4:30 PM	77.6%	D	335.9784
	4:45 PM	68.5%	C	343.905
	5:00 PM	64.2%	C	305.9296
10/20/16	7:00 AM	89.0%	E	292.1893
	7:15 AM	96.3%	F	547.5504
	7:30 AM	107.5%	G	774.9655
	7:45 AM	83.9%	E	495.6824
	8:00 AM	76.5%	D	279.7697
	5:00 PM	72.8%	D	324.0104
	5:15 PM	72.6%	C	459.2869
	5:30 PM	84.1%	E	624.2819
	5:45 PM	58.9%	B	370.9653
	6:00 PM	60.7%	B	258.2397
10/24/16	6:45 AM	83.0%	E	132.8002
	7:00 AM	107.8%	G	310.9372
	7:15 AM	107.7%	G	600.0687
	7:30 AM	93.7%	F	533.9597
	7:45 AM	67.3%	C	384.6646
10/26/16	6:45 AM	87.2%	E	167.1792
	7:00 AM	101.2%	G	287.9358
	7:15 AM	114.4%	H	729.9894
	7:30 AM	97.1%	F	521.9478
	7:45 AM	76.2%	D	639.9613
	4:30 PM	77.8%	D	370.2429
	4:45 PM	70.4%	C	451.4607
	5:00 PM	82.4%	E	399.3344
	5:15 PM	64.0%	B	410.5274
	5:30 PM	71.2%	C	489.2923

APPENDIX E: ICU AND CORRSPONDING HCM 2010 Delay/LOS and  
95th PERCENTILE QUEUE FOR THE PEAK PERIODS





Date	TIME	HCM 2010 (Delay/LOS)		ICU - (%) / LOS		IPI/ Traffic Congestion Status		95th Percentile Queue ( ft) - Thru and Left Turns Only							
								EBLT	EB Thru	WBLT	WB Thru	NLT	NB Thru	SBLT	SB Thru
10/18/16	6:45 AM	29.4	C	65.3%	C	185.8	Under	0	0	94	453	186	105	42	125
	7:00 AM	37.9	D	82.8%	E	265.7	Under	0	0	96	971	#329	121	71	148
	7:15 AM	64.4	E	93.3%	F	390.7	Under	0	0	75	#1434	#451	220	45	138
	7:30 AM	61.3	E	90.5%	E	561.0	At Cap	0	0	77	#1392	#458	272	49	83
	7:45 AM	42.3	D	76.1%	D	315.8	Under	11	26	78	864	335	314	60	183
	4:15 PM	45.0	D	59.6%	B	242.9	Under	53	406	68	306	132	228	219	138
	4:30 PM	42.4	D	68.2%	C	382.1	Under	76	544	45	269	170	237	190	275
	4:45 PM	56.6	E	89.6%	E	304.6	Under	45	#606	#747	143	#168	266	#209	248
	5:00 PM	44.0	D	70.9%	C	257.5	Under	68	543	66	257	177	327	206	273
	5:15 PM	48.5	D	55.6%	B	444.1	At Cap	80	391	58	340	205	148	230	119
5:30 PM	46.4	D	74.2%	D	393.0	Under	89	566	93	282	182	327	276	171	
5:45 PM	44.7	D	60.9%	B	365.1	Under	92	467	54	391	145	217	179	134	
10/19/16	6:30 AM	38.3	D	76.6%	D	201.0	Under	0	0	172	#745	#217	84	63	88
	6:45 AM	35.0	D	65.4%	C	166.4	Under	0	0	153	454	203	101	55	104
	7:00 AM	49.7	D	92.0%	F	451.5	At Cap	0	0	342	#1291	#318	178	74	164
	7:15 AM	55.1	E	90.4%	E	768.9	Over Cap	0	0	197	#1287	#389	200	53	88
	7:30 AM	51.0	D	88.3%	E	505.6	At Cap	0	0	235	#1140	#383	254	79	151
	7:45 AM	94.1	F	112.3%	H	579.6	Over Cap	35	119	171	#1287	#791	182	207	#236
	8:00 AM	45.0	D	63.4%	B	248.3	Under	78	356	89	487	142	185	128	170
	4:00 PM	52.1	D	71.0%	C	233.9	Under	185	465	130	330	184	230	294	167
	4:15 PM	48.8	D	72.6%	C	241.5	Under	137	531	132	356	165	316	213	150
	4:30 PM	50.5	D	77.6%	D	336.0	Under	151	546	126	353	171	379	265	255
4:45 PM	48.8	D	68.5%	C	343.9	Under	144	431	74	368	153	362	188	127	
5:00 PM	50.9	D	64.2%	C	305.9	Under	165	440	109	330	182	254	209	121	
10/20/16	7:00 AM	53.9	D	89.0%	E	292.2	Under	18	31	246	#1077	#334	139	157	#330
	7:15 AM	67.2	E	96.3%	F	547.6	At Cap	0	25	203	#1223	#415	187	198	#402
	7:30 AM	103.5	F	107.5%	G	775.0	Over Cap	18	10	143	#1592	#418	272	#292	#445
	7:45 AM	53.9	D	83.9%	E	495.7	At Cap	0	0	176	823	#296	261	239	398
	8:00 AM	47.3	D	76.5%	D	279.8	Under	0	0	123	767	204	192	190	295
	5:00 PM	48.4	D	72.8%	D	324.0	Under	155	457	62	325	151	422	192	120
	5:15 PM	48.2	D	72.6%	C	459.3	At Cap	156	541	117	291	161	334	192	181
	5:30 PM	49.1	D	84.1%	E	624.3	Over Cap	170	671	27	142	219	421	215	190
	5:45 PM	50.0	D	58.9%	B	371.0	Under	156	354	74	342	168	232	190	113
	6:00 PM	50.8	D	60.7%	B	258.2	Under	108	392	54	376	163	157	194	92
10/24/16	6:45 AM	37.0	D	83.0%	E	132.8	Under	#51	264	125	577	#196	93	114	232
	7:00 AM	80.3	F	107.8%	G	310.9	Under	#146	309	240	#1364	#442	141	161	#413
	7:15 AM	81.0	F	107.7%	G	600.1	Over Cap	#166	250	328	#1428	#385	162	151	#397
	7:30 AM	52.3	D	93.7%	F	534.0	At Cap	#166	211	148	#1036	#373	175	152	245
	7:45 AM	45.5	D	67.3%	C	384.7	Under	100	160	95	520	167	152	150	156
10/26/16	6:45 AM	87.2	D	87.2%	E	167.2	Under	0	55	146	#641	#192	101	128	#297
	7:00 AM	79.1	E	101.2%	G	287.9	Under	0	61	303	#1392	#406	147	122	#427
	7:15 AM	126.3	F	114.4%	H	730.0	Over Cap	#58	42	266	#1757	#409	227	#246	#553
	7:30 AM	69.9	E	97.1%	F	521.9	At Cap	35	41	171	#1305	#325	#382	#242	#420
	7:45 AM	48.9	D	76.2%	D	640.0	Over Cap	35	22	158	722	295	246	191	246
	4:30 PM	48.3	D	77.8%	D	370.2	Under	107	591	111	255	171	390	219	210
	4:45 PM	47.1	D	70.4%	C	451.5	At Cap	137	482	111	310	128	349	201	257
	5:00 PM	54.7	D	82.4%	E	399.3	Near Cap	142	576	#147	464	212	391	341	152
	5:15 PM	46.6	D	64.0%	B	410.5	Near Cap	140	476	119	371	113	271	135	145
5:30 PM	46.1	D	71.2%	C	489.3	At Cap	124	526	90	224	146	180	211	194	

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