1-1-2015

Integrated Multi-Criteria Signal Timing Design for Sustainable Traffic Operations

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by

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
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Date of Approval:
March 18, 2015

Keywords: Sustainable Transportation, Clustering, Simulation Optimization, Experiment Design, Multivariate Regression, Genetic Algorithm, Dynamic Programming

DEDICATION

This dissertation is dedicated to my dearest parents, Ruicheng Guo and Yanzhen Cheng.

ACKNOWLEDGMENTS

Foremost, I would like to express my sincere gratitude to my Advisor, Dr. Yu Zhang, for her guidance, support and encouragement throughout my graduate studies. She is very responsible and knowledgeable and always helps me through my problems. I also thank her for teaching me not only typical knowledge but also for providing me with the skills needed to produce and present high quality work. For this dissertation, I also want to thank my committee members, Dr. Pei-Sung Lin, Dr. Jian John Lu, Dr. Soyoung (Sue) Ahn and Dr. Abdul Pinjari for their valuable time and sound advice.

My great thanks also goes to all the graduate students and friends in transportation area: Shu Yang, Chengcheng Xu, Shengdi Chen, Bin Yu, Qing Wang, Hongyun Chen, Nagesh Nayak, Makarand Gawade, Jacob Mirabella, Nikhile Menon, Srisri Pendem, Lukai Guo, Kai Liao and Yuan Wang. I gratefully appreciate their friendship, collaboration and support.

Finally and most importantly, I would like to thank my parents and my husband for their love and constant encouragement. This wouldn't have been possible without their love and support.

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ABSTRACT

Traffic signal systems serve as one of the most powerful control tools in improving the efficiency of surface transportation travel. Traffic operations on arterial roads are particularly complex because of traffic interruptions caused by signalized intersections along the corridor. This dissertation research presents a systematic framework of integrated traffic control in an attempt to break down the complexities into several simpler sub-problems such as pattern recognition, environment-mobility relationships and multi-objective optimization for multi-criterial signal timing design.

The overall goal of this dissertation is to develop signal timing plans, including a day plan schedule, cycle length parameters, splits and offsets, which are suitable for real traffic conditions with consideration of multi-criterial performance of the surface transportation system. To this end, the specific objectives are to: (1) identify appropriate time-of-day breakpoints and intervals to accommodate traffic pattern variations for day plan schedule of signal timing; (2) explore the relationship between environmental outcomes (e.g., emissions) from emission estimators and mobility measures (e.g., delay and stops) for different types of intersections; (3) optimize signal timing parameters for multi-criteria objectives (e.g., minimizing vehicular delay, number of stops, marginal costs of emissions and total costs), with the comparison of performance metrics for different objectives, at the intersection level; (4) optimize arterial offsets for different objectives at the arterial level and compare the performance metrics of different objectives to recommend suitable objectives for integrated multi-criteria signal timing design in arterial traffic operations.

An extensive review of the literature, which covers existing tools, traffic patterns, traffic control with environmental concerns, and related optimization methods, shows that both opportunities and challenges have emerged for multi-criteria traffic signal timing design. These opportunities include large quantities of traffic condition data collected by system detectors or non-intrusive data collection platforms

as well as powerful tools for microscopic traffic modeling and instantaneous emission estimation. The challenge is how to effectively deal with these big data, either from field collection or detailed simulation, and provide useful information for decision makers in practice. Methodologically, there's a tradeoff between the accuracy of objective function values and the computational efficiency of simulation and optimization. To address this need, in this dissertation, traffic signal timing design that systematically enables the use of integrated data and models are investigated and analyzed in the four steps/studies. The technology of identifying time-of-day breakpoints in the first study shows a mathematical way to classify dynamic traffic patterns by understanding dynamic traffic features and instabilities at a macroscopic level on arterials. Given the limitations of using built-in emissions modules within current traffic simulation and signal optimization tools, the metamodeling-based approach presented in the second study makes a methodological contribution. The findings of the second study on environment-mobility relationships set up the base for extensive application of two-stage optimization in the third and fourth studies for sustainable traffic operations and management. The comparison of outputs from an advanced estimator with those from the current tool also addresses improving the emissions module for more accurate analysis (e.g., benefit-cost analysis) in practical signal retiming projects. The third study shows that there are tradeoffs between minimizing delay and minimizing marginal costs of emissions. When total cost (including cost of delay, fuel consumption and emissions) is set as a single objective function, that objective clears the way for relatively reliable results for all the aspects. In the fourth study, the improvements in marginal cost of emissions and total cost by dynamic programming procedure are obvious, which indicates the effectiveness of using total link cost as an objective at the corridor level. In summary, this dissertation advocates a sustainable traffic control system by simultaneously considering travel time, fuel consumption and emissions. The outcomes of this integrated multi-criteria signal timing design can be easily implemented by traffic operators in their daily life of retiming signal timing.

CHAPTER 1: INTRODUCTION

1.1 Background and Motivation

Traffic signal systems serve as one of the most powerful control tools in overcoming the conflicts between different directional traffic flows and improving the efficiency of surface transportation travel. The basic premise behind traffic signal control is the development of signal timing plans (e.g., cycle length, splits and offsets) that are best suited for expected traffic conditions for particular dates or times. Generally, a transportation system is complex, and this complexity stems from the pluralism of its hardware (infrastructure and vehicles) and from the people and organizations involved. The complexity is multiplied by the existence and roles of different modes, regulatory and legislative bodies, technologies, land-use patterns, and, most importantly, human behavior. This is particularly true for traffic operations on arterial roads because of traffic interruptions caused by signalized intersections along the corridor. To tackle the complex problem of surface traffic operations, it is important to break down the complexities into several simpler sub-problems (e.g., the basic fundamentals for traffic flow at arterials) in a systematic way.

One of the challenges of traffic signal design is the identification of appropriate time-of-day (TOD) breakpoints, where different signal timings can be implemented during the time periods between two consecutive breakpoints. To ensure the effective operation of traffic signal systems, different signal timings (for different times of day) are widely used in practice to accommodate traffic pattern variations. The experience of traffic engineers and an imprecise analysis of traffic volume data usually determine current day plan schedules. This traditional method contains many subjective factors and can easily lead to unreasonable divisions. In many cases, the signal system does not operate very efficiently. Though optimization tools are available to assist traffic engineers in developing timing plans, few tools exist to

help them determine appropriate TOD breakpoints. This deficiency has motivated researchers to develop an improved procedure for assisting in the determination of TOD breakpoints for traffic signal systems.

A substantial opportunity to address the need for more efficient signal timing plans (or determination of TOD breakpoints) lies in the fact that the application of advanced communications, electronics, and information technologies, commonly referred to as intelligent transportation systems (ITS), have been widely deployed and play an increasingly important role in improving the efficiency, safety, and reliability of transportation systems (Smith, 2005). ITS has the ability to record large quantities of traffic condition data collected by existing system detectors or non-intrusive data collection platforms. To illustrate the potential of advanced data collection techniques, a cluster analysis-based procedure is developed in this dissertation to determine TOD breakpoints for coordinated traffic systems using continuous traffic data samples obtained from an advanced ITS data collection platform.

Another greater challenge of traffic signal design is a sustainable traffic signal control, which not only increases mobility and safety, but also simultaneously addresses the energy consumption and the environmental impacts (e.g., greenhouse gas emissions and different pollutants) that transportation systems pose. Traditionally, transport planning and operations mainly aimed to improve access, mitigate traffic congestion, and assure smooth traffic flow. Transportation planners in the past rarely saw the need for a detailed analysis of how transportation impacts the environment or connects to sustainable development. However, statistics have shown that the transportation sector is becoming increasingly linked to environmental concerns such as energy consumption, greenhouse gas (GHG) emissions, and other environmental pollutants that can cause serious human health issues. For instance, transportation accounts for between 20 and 25% of the total energy consumed among developed countries (WEC 2007) and it accounts for 27% of GHG emissions in the U.S., which is the second largest source after electricity generation (34%) (EPA, 2013; DOT, 2013). The details about GHG emissions and different pollutants can be found in Appendix A.

Among the many elements of the surface transportation system, signalized intersections along urban arterials are often “hot spots” for fuel consumption and air pollution because of higher traffic density, longer vehicle idling time, and deceleration and acceleration of the driving cycles through the intersections. Certainly, mitigating negative impacts could include smart growth with transit-oriented development, more fuel efficient vehicles, vehicles with alternative energy and improved infrastructure, etc. But, from the operational point of view, the most cost-effective way to save energy is to improve traffic system management with sustainable traffic control strategies. Studies around the country show that the benefits of investing in signal timing improvements outweigh the costs by 40:1, which can result in benefits totaling as much as $45 billion per year. Improperly timed signals contribute to increased delays, wasted fuel and negative impacts on the environment. It is estimated that poor traffic signal timing accounts for 5 to 10 percent of all traffic delays or 295 million vehicle-hours of delay on major roadways alone. The urban mobility report points out that congestion causes the average urban resident to spend an extra 34 hours of travel time and use 14 extra gallons of fuel, which amounted to an average cost of $713 per commuter in 2011 (Schrank et al., 2012).

Existing signal timing optimization tools, including fixed-time, coordinated actuated, traffic responsive and adaptive control (FHWA, 2008) (Appendix B), mainly focus on capturing an optimal cycle length and green-time split to improve mobility (i.e., reducing delays and stops or similar measures) (Sun et al., 2003; Lv, 2012). However, there is a shortage of studies investigating the comprehensive relationship between different objectives (e.g., environmental factors and traffic metrics) at different intersections and differences in the various types of emissions. To better understand the environmental factors associated with different traffic conditions and control strategies, the ability to adequately model and quantify fuel consumption and emissions at a microscopic level is of high importance. Moreover, it is not clear whether improving overall mobility (i.e., reducing control delays) would naturally lead to less energy consumption and result in reductions in all types of engine emissions. Although some existing tools have built-in emission estimation modules when calculating measurements of effectiveness after

optimization, they are imprecisely estimated by total delay, stops, or queue length without considering different levels of acceleration, cruise, deceleration, and idling. Therefore, to obtain a sustainable traffic control system, fuel consumption and emissions should all be considered in an objective function in addition to the traditional vehicular delay. In other words there's a need for a framework that systematically incorporates and balances the effects of greenhouse gas emissions and different pollutants to achieve a sustainable traffic control system.

1.2 Objectives and Organization of the Dissertation

The goal of this study is to develop signal timing plans (e.g., day plan schedule, cycle length, splits and offsets) that are suitable for the actual traffic conditions with the consideration of multi-criterial performance of the surface transportation system (e.g., vehicular delay, fuel consumption and various emissions). The primary objectives of this study are:

- Identifying appropriate TOD breakpoints/intervals to accommodate traffic pattern variations for day plan schedule of signal timing at macroscopic level;
- Exploring the relationship between environmental outcomes (e.g., fuel consumption and emissions) from emission estimators and mobility measures (e.g., control delay and number of stops) for signalized intersections;
- Optimizing signal timing parameters for different objectives (e.g., minimizing delay, stops, marginal costs of emissions and total costs) at the intersection level;
- Optimizing arterial offsets for different objectives (e.g., minimizing delay, stops, marginal costs of emissions and total costs) at the arterial level;
- Comparing the performance metric of different objectives to recommend the suitable objective for integrated multi-criteria signal timing design in arterial traffic operations.

This research aims to present a new integration of existing traffic operation, emissions estimation, and signal optimization models for the multi-criteria signal timing design. The research work consists of the following components: (1) literature survey and review so as to construct a systematic methodology;

(2) determination of key issues to be resolved that occur in current studies; (3) proposing research approaches and performing case studies to evaluate the effectiveness of the proposed framework; and (4) summary of research work and dissertation composition.

The basic idea of this research is to present a systematic framework of sustainable traffic control in an attempt to break the complexities down into the basic fundamentals which are necessary to design and implement signal timing plans and coordination. The following figure illustrates the steps to fulfill the above objectives in this research.

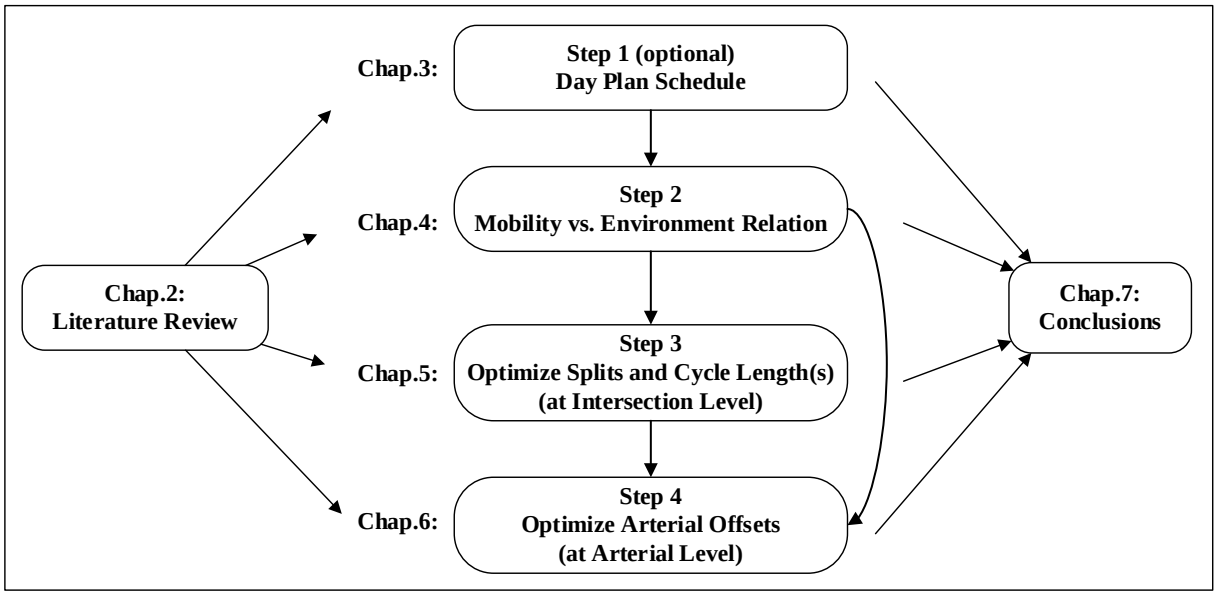


Figure 1.1 Organization of the Dissertation

As shown in Figure 1.1, the remainder of this dissertation is outlined as follows. The outline provides the organization along with the connections between different chapters in the dissertation.

Chapter 2 summarizes existing literature on identification of traffic patterns at arterials, signal control with environmental concerns and related optimization methods. Among the various gaps in literature identified thus far, summaries of the most notable omissions to be addressed in this dissertation research are discussed at the end of this chapter.

Chapter 3 presents a sub-study on identifying time-of-day breakpoints of traffic variations on arterial roads. The essential elements of traffic system and traffic flow features will be analyzed and

simulated. The dynamic traffic patterns on urban arterial roads can be investigated at both the macroscopic level and at the microscopic level. In the macroscopic level, one of the greatest challenges in the signal timing design is to identify appropriate time-of-day (TOD) breakpoints, where different signal timings can be implemented during time periods between two consecutive breakpoints. The operability of this proposed method is demonstrated in a case study of a corridor located in Tampa, Florida. The traffic simulation results reported in this chapter reveal that this novel procedure performs better than existing TOD signal timing plans.

Chapter 4 explores the macroscopic relationship between mobility and environmental externalities at signalized intersections. A metamodeling-based method involving experimental design, simulations, and regression analysis is developed. The simulations, involving microscopic traffic modeling and emission estimation with an emerging emission estimator, provide the flexibility of generating cases with various intersection types, vehicle types, and other parameters. A multivariate multiple linear regression analysis is applied to determine the relationship between environmental and mobility measurements. Given the limitations of using the built-in emissions modules within current traffic simulation and signal optimization tools, the metamodeling-based approach presented in this chapter makes a methodological contribution. Based on the relationship study in this chapter, the two-stage optimization problem (including intersection level and arterial level) can be solved more efficiently in terms of computation loads in chapter 5 and chapter 6, respectively.

Chapter 5 optimizes cycle lengths and green splits for an individual intersection. This study adopts the delay calculation method in Highway Capacity Manual (2010), which considers terms of both uniform delay and incremental delay. At the intersection level, the multi-criterial signal timing optimization problem is formulated with the objective function considering delay and emissions simultaneously (i.e., in terms of money value). The genetic algorithm method is adopted to find the optimal cycle length and effective green ratio for each approach group. Moreover, optimal signal plans

with respect not only to traffic mobility performance but also other important measures for sustainability are compared and evaluated.

Chapter 6 solves the optimization problem at the arterial level by using the dynamic programming-based method. At the corridor level with multiple signalized intersections, mobility-environment relationships are extended to the entire intersection spacing (i.e., link between two adjacent intersections) in the coordinated direction. Then based on the mobility-offset relationship considering the platoon dispersion for each link, the optimization problem is formulized with the intersection offsets as decision variables, given the cycle length and effective green ratios determined at the intersection level. Dynamic programming procedure is adopted to minimize the total costs of delay and emissions in an arterial signal optimization. The improvements in marginal cost of total emissions and total cost after execution of the dynamic programming procedure are obvious, which indicates the effectiveness of using total link cost as an objective at the corridor level.

Chapter 7 concludes the dissertation study by summarizing the findings and conclusions for each of the above chapters and providing recommendations/directions for future research.

CHAPTER 2: LITERATURE REVIEW

Traffic signals have evolved considerably since they were first introduced to prevent collision in London in 1868 (Hensher et al., 2001). Signal timing offers the opportunity to improve the mobility of a transportation system and also prevent environmental deterioration. Generally, traffic signals are operated in three modes: fixed-time, actuated, and adaptive control (as detailed in Appendix A). During the early stage of traffic signal development, methods to determine the fixed signal timings were developed assuming that traffic arrival from every intersection approach had a constant headway, which is not realistic in the field (Matson et al., 1955). Webster (1958) recognized the uncertain nature of traffic arrivals and developed an analytical delay equation and applied differential calculus technique for delay minimization. Since then, a significant amount of research effort has been dedicated to enhancing analytical delay models and the development of computerized software (Zhang, 2010). In the United States, the Highway Capacity Manual (HCM) delay equation is widely used to determine the level of service at signalized intersections (HCM, 2010).

Traffic signal timing design is a typical multi-objective optimization problem because for a signalized system, an optimal timing plan is usually required to meet several typical objectives (Leonard et al., 1998): Minimizing delay, minimizing stops, minimizing fuel consumption, minimizing emissions, and maximizing progression. In the area of traffic signal optimization, most previous work has focused on capturing an optimal cycle length and green time split which takes into account only the minimization of system delay (Sun et al., 2003; Lv, 2012). Detailed information about related existing tools and software (e.g., macroscopic signal optimization, micro-simulation and emission estimators) can be found in Appendix C. Although delay-based optimization methods prevail in signal timing design, optimized cycle

[1]Portions of this chapter were previously published in Guo and Zhang (2014 a,b&d). Permission is included in Appendix D.

lengths and green splits are subject to change depending on other factors such as fuel consumption or emissions.

Traffic phenomena are complex and nonlinear, depending on the interactions of a large number of vehicles, drivers and infrastructure. Traffic flow features are especially complicated at the signalized intersections as they typically involve a higher traffic density, longer vehicle idling time, and excessive stop-and-go driving cycles caused by traffic interruptions. This chapter aims to provide a synthesis of the extant literature on traffic signal timing design and to position our research within the overall context of related literature. Specifically, traffic patterns identification at arterials, signal control with environmental concerns, and optimization methods will be reviewed and summarized, along with related gaps in the following subsections.

2.1 Review of Identifying Traffic Pattern with Arterial Traffic Variations

It is widely observed that traffic patterns (i.e., flow, density and speed) on arterials vary significantly throughout a day, between weekday and weekend, and also within weekdays. Since timing plans are developed for specific sets of traffic conditions, it is important to define the times of day when those traffic conditions exist, and therefore, the times of day when each plan should be used (FHWA, 2008). Transition costs will occur when changing timing plans or entering into coordinated timing plans, because it takes time for controllers to operate transition algorithms and shift local offset reference points (FHWA, 2008). Therefore, the determination of TOD breakpoints needs to balance the efficiency of signal timing and the consequent transition costs.

The typical approach used to identify intervals for TOD signal plans is to plot aggregate traffic volumes over the course of a day for representative sample intersections. The significant changes in traffic volume, which indicate a need for different timing plans, are then manually determined based on engineering judgment (FHWA, 2008; Smith, 2002). These intervals rely heavily on the existing traffic conditions at typical intersections throughout the arterial. As Abbas (2005) pointed out, unless traffic

patterns change at certain times of the day and remain constant until the next change—which is highly unlikely—it is very difficult to determine the optimal breakpoints.

The dynamic traffic features play an important role in the determination of traffic control strategies (Hua and Ardeshir, 1993; Gartner and Chronis, 1998; Erman et al., 2006). Considering the intrinsic variation of traffic volumes, several researchers have proposed methodologies for selecting TOD breakpoints and have demonstrated the benefits of doing so in traffic operations (Hauser et al., 2001; Smith et al., 2002; Park et al., 2003; Wang et al., 2005; Abbas, 2005). The majority of these studies can be categorized into two groups: a heuristic search algorithm-based approach and a cluster analysis-based approach.

Searching for the best TOD breakpoints can be constructed as a mathematical optimization problem. Park et al. (2003) adopted a Genetic Algorithm (GA) into an intervals identification process to find the best TOD breakpoints. In a follow-up study, they presented a developed procedure for determining optimal breakpoints on TOD-based coordinated actuated traffic signal operations that used a feature vector of optimal cycle length per time interval instead of traffic volume itself (Park and Lee, 2008; Lee et al., 2011). Nevertheless, their studies were only conducted for hypothetical arterial networks and the GA technique is relatively time-consuming. The performance of their GA-based optimization needs to be verified in real traffic situations. At the 84th Transportation Research Board (TRB) Annual Meeting, Abbas (2005) introduced a multi-objective evolutionary algorithm, non-dominated sorting GA, with Degree of Detachment (DOD). However, this algorithm does not ensure the global optimal solutions for all cases. Similarly, Yang et al. (2006) developed an Artificial Immune Systems (AIS)-based data analysis algorithm. At a certain level, the algorithm reduces redundant information of sample traffic data and overcomes the irrationality of the artificial method. However, there are too many adjustable parameters in the algorithm and it is very difficult to select the proper parameters to illustrate objective functions or rationally add constraints.

The other approach for identifying TOD breakpoints is to apply a cluster analysis. Hauser et al. (2001) and Smith et al. (2002) studied the possibility of period division by employing a hierarchical cluster analysis to identify optimal TOD breakpoints. Their studies demonstrated the feasibility of cluster analysis through a single intersection case study. However, traffic data falling into two time intervals far away from each other along the time axis was clustered into one group. This would cause some clusters to jump around adjacent intervals and signal timing plans would have to be changed frequently, leading to high transition costs. In 2005, Wang et al. (2005) proposed a nonhierarchical cluster analysis called K-means clustering. This technique provides several benefits including simplicity, reduced data storage, and user-defined clusters (Lee et al., 2011). Their study applied the K-means clustering algorithm to identify optimal TOD breakpoints, which was based on a very limited data resource. Therefore, the treatment of the frequent transitions issue remained unresolved. Xia and Chen (2007) also used a data-clustering technology to define flow phases based on site-specific historical traffic data obtained through detectors. However, the imprecise method for determining the number of clusters was inadequate. Ratrout (2010, 2011) demonstrated his most recent research results of determining optimum TOD breakpoints based on the K-means technique. Concerned by cyclic traffic along arterials with pre-timed controllers, he considered 24-hour volumes twice to form continuous traffic data spreading over 48 hours. His research, though promising, did not take into account the coordination effect of intersections because he focused on developing timing plans for pre-timed signal controllers.

Although the cluster analysis-based studies have shown the feasibility of identifying TOD breakpoints, none of them has explicitly incorporated the time of traffic occurring as a feature in a clustering analysis. However, treating time series data as an unordered collection of events and ignoring its temporal information leads to excessive transitions, scattered outliers, and consequent high operational costs and traffic delay. Recent theoretical studies in cluster analysis have demonstrated the effectiveness of using background information at the instance level to create must-link and cannot-link constraints (Everitt et al., 2011). A must-link constraint enforces two instances to be included in the same cluster

while a cannot-link constraint enforces two instances not to be placed in the same cluster. Thus, must-link and cannot-link constraints should be implicitly defined in the cluster analysis for this particular research problem.

2.2 Review of Traffic Signal Control with Environmental Concerns

As detailed in Appendix C, existing signal timing optimization tools, including fixed-time, coordinated actuated, traffic responsive, and adaptive control (Appendix A)(FHWA, 2008), mainly focus on capturing an optimal cycle length and green-time split to improve mobility (i.e., reducing delays and stops) (Sun et al., 2003; Lv, 2012). Although some of these tools have built-in emission estimation modules when calculating measurements of effectiveness, they are imprecisely estimated by assuming a drive cycle that consists of constant fractions of free-flow and congestion conditions rather than realistic traffic characteristics.

The built-in emission estimation modules within current traffic simulations and signal optimization tools are relatively under-developed and have a very limited function. Table 2.1 summarizes current practice in traffic signal optimization. The available macroscopic optimization software for traffic signal timing includes SYNCHRO (Husch and Albeck, 2006), TRANSYT-7F (Hale, 2008), PASSER (Chaudhary and Messer, 1993) and SIDRA INTERSECTION (Akcelik, 1984). Delay and its derivatives are commonly used as objective functions in most optimization software. For example, SYNCHRO optimizes signal settings using a percentile delay, which considers cycle-by-cycle traffic variations. TRANSYT-7F optimizes signal settings using a disutility index, which is based on a combination of delay and stops (Hale, 2008). However, mobility-based optimization is usually insufficient to characterize the fuel consumption and emission levels of real-world driving behavior due to the nature of the macroscopic simulation model. Estimation of fuel consumption in Synchro and TRANSYT-7F is a linear combination of total travel distance, total delay, and total stops, without explicit considerations such as traffic congestion, vehicle type mix, and geometric and environmental factors. Only three types of emissions (i.e., carbon monoxide, nitrogen oxides, and Volatile Organic Compounds) in SYNCHRO are

roughly estimated based only on fuel consumption with fixed rates. There is no component of emission estimation in TRANSYT-7F. Besides macroscopic optimization tools, microscopic traffic simulation tools such as TSIS-CORSIM, VISSIM, and Transportation Analysis and Simulation System (TRANSIMS) have been developed to model and evaluate transportation networks in various traffic conditions (PTV, 2011; Stevanovic et al., 2009). Microscopic simulation modeling is a faster, safer, and cheaper way to test actual field implementations. Basic input parameters for microscopic simulation models, such as geometry, number of cars, and traffic signal setting, are easily obtained. However, similar to signal optimization tools, microscopic simulation software cannot adequately estimate environmental impacts of a traffic network. Although VISSIM has an add-on module related to emissions, the estimation method of the emission module is simplified without detailed considerations.

Table 2.1 Current Practice in Traffic Signal Optimization

<table>
<tr><th colspan="2">Current Practice</th><th>Main Features</th><th>Limitations</th></tr>
<tr><td rowspan="2">Macro-Signal Optimization</td><td>TRANSYT-7F</td><td>--User-selected performance index (PI);
--Linear combination of total travel, delay and stops;
--No component of emission estimation.</td><td rowspan="2">--macroscopic
--delay-based
--rough way to estimate fuel and emissions</td></tr>
<tr><td>SYNCHRO</td><td>--Delay-based optimization;
--Linear combination of total travel, delay and stops;
--Emissions are based on fuel usage only.</td></tr>
<tr><td rowspan="2">Traffic Micro Simulation</td><td>TSIS-CORSIM</td><td>--Car following logic;
--Ten user-definable driver types;
--Gap acceptance.</td><td rowspan="2">--Model Calibration & Validation
--NGSIM</td></tr>
<tr><td>VISSIM</td><td>--Psycho-physical driver behavior model;
--User-definable and location specific gap acceptance;
--User-definable vehicle types.</td></tr>
<tr><td rowspan="3">Emission Estimation Models</td><td>MOVES</td><td colspan="2">--Latest emission model release by EPA
--Second-by-second speed profile of vehicles</td></tr>
<tr><td>CMEM</td><td colspan="2">--Developed by Univ. of California
--Power demand-based emission models</td></tr>
<tr><td>VT-Micro</td><td colspan="2">--Developed by Virginia Tech
--From experimentation with various speed & acceleration levels</td></tr>
</table>

As air pollution problems attract more and more attention around the world, many researchers have attempted to incorporate traffic emission factors into traffic control strategies. Dating back to the 1970s, concerns with energy considerations and emissions at intersections were proposed (EPA, 1975; Christian, 1975), and there have been many studies on intersection emissions since then (Patterson, 1976; Tarnoff and Parsonson, 1979; EPA, 1992; Rouphail et al., 2001; Frey et al., 2001). The major limitation of most of these early studies is the lack of a sophisticated way of estimating energy consumption and emissions. Recently, several advanced emission estimation models have been developed, such as Comprehensive Modal Emission Model (CMEM) (Barth et al., 2001), the VT-Micro model (Ahn et al., 2002), and Motor Vehicle Emission Simulator (MOVES) (EPA, 2012). These microscopic models estimate vehicle pollutants at a second-by-second level of resolution using either vehicle engine or vehicle speed/acceleration data. In particular, the emerging model MOVES surpasses previous emission estimation tools. This new emission modeling system is the most sophisticated to date and is being applied at a number of different modeling scales, from the micro-scale (project-level, e.g., parking lot) to the macro-scale, where national-scale inventories are being generated for precursor, criteria, and GHG pollutants from on-road mobile sources (EPA, 2012). The embedded database and project level emission analysis in MOVES provide great opportunities for more accurate emission estimations in the traffic performance analysis.

Recent research and studies also have noted the importance of integrating traffic simulation modeling and advanced emission estimators (Li et al., 2004; Chen and Yu, 2007). For example, Coelho, Farias, and Rouphail (2005a, 2005b, 2009) explored the relative impact of traffic interruptions (e.g., pay tolls, roundabouts, and traffic signals within the corridor) on traffic performance and emissions (in terms of ratios or percentages).In their study, the research priority was given to relative values of emissions based on European driving behaviors of vehicle fleets. Park et al. (2009) proposed an optimization approach by integrating a CORSIM microscopic traffic simulation, the VT-Micro model, and a Genetic Algorithm (GA). Their study demonstrated that the proposed framework is effective in minimizing fuel

consumption and emission with moderate trade-offs in delay and stops. Similarly, Stevanovic et al. (2009) presented an integration of VISSIM, CMEM, and VISGAOST to optimize signal timings. Findings of these studies show that a formula commonly used to estimate fuel consumption in traffic simulation tools inadequately estimates fuel consumption and cannot be used as a reliable objective function in signal timing optimizations. Kwak, Park and Lee (2012) quantified the impact of direct traffic signal timing optimization aimed at minimizing fuel consumption based on TRANSIMS, the VT-Micro emission estimator, and a GA-based traffic signal optimizer. Although the GA worked well in these studies, the GA-based optimization consumed significant time and computational loads. More efficient computational techniques should be sought and implemented in the direct optimization way.

Table 2.2 Related Previous Research about Traffic Signal Control with Environmental Concerns

	Early Studies	**Recent research and studies**	
		Direct Optimization	**Surrogate model-based**
Representative references	Proposing concerns with energy and emissions for traffic control (Christian, 1975; Patterson, 1976; Tarnoff, 1979; EPA, 1992; Rouphail et al., 2001; Frey et al., 2001)	Incorporating the emission factors into traffic control strategies via direct optimization (Chen and Yu, 2007; Park et al., 2009, Stevanovic et al., 2009; Kwak et al., 2012)	Surrogate model-based optimization for multi-objectives (Lv , 2012; Zhang, Yin and Chen, 2013; Carolina, 2014)
Major limitations	The lack of a sophisticated way of estimating energy consumption and emissions	Consuming significant time and computational loads; not suitable for large-scale problem	Not clear about the correlation between environmental factors vs. mobility and different relationships for various types of emissions

Lately, Lv (2012) investigated the relationship between emissions and control delay to formulate the optimization problem. Although his study demonstrated the air quality benefit by reducing vehicle emissions under different scenarios, the dataset of vehicle trajectories is quite small, and he considered only control delay as mobility measurement when exploring the relationship between mobility and emissions, with the selection of the parabolic function. Similarly, Zhang et al. (2013) and Osorio &

Nanduri (2014) developed a surrogate model or metamode for the traffic signal optimization with environmental concerns. However, there is short of studies investigating the comprehensive relationship between different objectives (e.g., environmental factors and traffic metrics) at different intersections and different relations for various types of emissions. The summary of related previous research about traffic signal control with environmental concerns is shown in Table 2.2.

2.3 Review of Optimization Methods in Traffic Signal Control

As reviewed above, powerful tools and software have been used in the field of urban transportation to provide insights into the design and operation of complex transportation systems. Macroscopic signal optimization tools are still using some underdeveloped modules (e.g., emission estimation) with very limited function; furthermore, microscopic simulations with most detailed traveler/vehicle behavior information are mainly used to evaluate a set of predetermined strategies (i.e., what-if-analysis). Thus, there are challenges and opportunities to develop computationally efficient optimization procedures and techniques that enable the use of these integrated models to design sustainable traffic signal timings. This integrated optimization method belongs to the category of simulation-based optimization, which consists of a simulation model (or system) that provides objective function values and an optimization method that searches for the best set of parameter values for the simulation model. Generally, simulation optimization may require extensive computational time when the number of optimization variables is large or the simulation model is complex. Therefore, there is a tradeoff between the accuracy of objective function values (i.e., the opportunity) and the computational efficiency of simulation (i.e., the challenge). In this sub-section, the multi-objective optimization and coordination strategies are reviewed at intersection level and arterial level, respectively.

2.3.1 Multi-Objective Optimization

As a real-world optimization problem, several goals must be satisfied simultaneously in order to obtain the preferred solution in traffic signal timing optimization. A common difficulty with the multi-objective optimization problem is the appearance of an objective conflict where none of the feasible

solutions allow simultaneous optimality for all objectives (Sun et al., 2003). Many past research efforts were conducted to examine various signal timing optimization methods (Kesur, 2009). Park et al. (1999) developed a genetic algorithm-based signal optimization program, which consists of a genetic algorithm optimizer and a mesoscopic traffic simulator to handle oversaturated signalized intersections. Abu-Lebdeh & Benekohal (2000) and Girianna & Benekohal (2001) proposed dynamic signal control optimization algorithms. Their algorithms were constructed to find optimal control with robust queue management for oversaturated arterial and integrated multiple criteria into one objective function. Besides the studies with only one objective function, some classical optimization methods are widely used in multi-objective optimization problems, such as the objective weighing method, distance function method, and min-max formulation etc. They take advantage of some problem-specific knowledge and, thus, combine multiple objectives into one objective so that the resulting solution depends mainly on the underlying weight vector or demand level (Srinivas and Patnaik, 1994; Ma et al., 2014).

As pointed out by the researchers (Ropke, 2005; Han et al., 2012), there are two distinguished optimization procedures in general: (1) exact approaches, such as integer programs and branch-and-bound method, which guarantee that the optimal solution is found if the method is given sufficient time and space; and (2) heuristic approaches, such as those developed with genetic algorithms and fuzzy logic, which typically find a feasible solution with reasonable quality by balancing explorations within their search space. Among these heuristic approaches, the most commonly-used optimization method is the genetic algorithm, which makes up a family of computational models inspired by evolution (Kesur, 2009). The genetic algorithm encodes a potential solution for a specific problem into simple chromosome-like data structures and applies recombination operators to the structures so as to preserve critical information. It has been used to solve problems with objective functions that are difficult to work out with a closed-form function (Park et al., 1999; Kesur, 2009; Ma et al., 2014). The genetic algorithm manipulates a population of potential solutions and implements a “survival of the fittest” concept to search for better solutions (global solutions). This provides an implicit as well as explicit parallelism (Sun et al., 2003).

Explicit parallelism allows for the exploitation of several promising areas of the solution space at the same time through generations. The genetic algorithm has been shown to solve linear and nonlinear problems by exploring all regions of search space and exponentially exploiting promising areas through selection, crossover and mutation operations (MathWorks, 2014). Moreover, genetic algorithm methods search for optimal solutions based on a population of points instead of a single point, so that multiple Pareto-optimal solutions can be found in a single run (Sun et al., 2003). Multi-objective genetic algorithms provide alternative approaches for simultaneous multiple Pareto-optimal solutions from which to choose the most appropriate solution in all possible situations (Zhang et al., 2013).

2.3.2 Coordination Strategies

The efficiency of a coordinated system of traffic signal control depends largely on the timing parameters, not only including those for each individual signal, but also the system-generated ones such as common cycle length and offset settings. Signal offset is a signal-timing parameter that has a substantial impact on arterial travel times. Offsets are generally determined so that, to the extent possible, traffic can flow through a number of signals without stopping. The traditional technique is to optimize offsets with an offline software package, implement the settings, and then possibly observe field operations. It is not uncommon for a traffic engineer to fine-tune the settings by observing the arrivals of platoons at an intersection and making adjustments to the offset from the qualitative visual analysis. Traditionally, offset optimization for coordinated traffic signals is based on average travel times between intersections and average traffic volumes at each intersection without consideration of the stochastic nature of field traffic.

Generally speaking, there are two approaches of generating coordination plans (or optimizing offsets) to synchronize signals along arterials and grid networks. One aims at bandwidth maximization, e.g., MAXBAND (Little et al., 1981) and PASSER-II (Change et al., 1988). Bandwidth is the time between the first and last vehicle that can travel at the determined progression speed without impedance. It is not directly tied to actual traffic performance as it is oriented in time and space (without accounting

for the effect of traffic). Bandwidth is commonly used to describe capacity or maximized vehicle throughput (e.g., Little's formulation), but it is only a measure of progression opportunities (FHWA, 2008). Another major strategy is flow profile-based optimization, synchronizing signals to minimize the disutility measures by using delay-offset relationships. For example, TRANSY-7F is a well-known disutility-minimizing procedure based on a macroscopic traffic model (Day et al., 2011). For real-time applications (e.g., adaptive control), a simplified objective for offset optimization is to maximize arrivals on green, which is a simple calculation requiring fewer assumptions than delay models.

The flow profile approach emerged in the United Kingdom back to 1960s. Originally, Pacey (1956) described the evolution of vehicle platoons as they departed a traffic signal. In 1967, Hillier and Rothery (1967) used vehicle flow profiles to develop arrival curves and estimated the delay from a theoretical signal operation plan. This led to a delay-offset relationship that could be used to seek a delay-minimizing offset. The combination method (Huddart and Turner, 1969; Gartner and Little, 1975) and TRANSYT emerged from this research and used delay-offset relationships to design offsets for arterial roads with coordinated signalized intersections. The combination method leverages information about the network topology to optimize offsets (Huddart and Turner, 1969). Recently, Day and Bullock (2011) compared the computational efficiency of five algorithms (i.e., quasi-exhaustive search, Monte Carlo selection, genetic algorithm, hill climbing and the combination method) for arterial offset optimization and found that the combination method yielded the most optimal solutions with approximately the same level of computational effort as hill climbing. As an offshoot of the combination method, the dynamic programming method has demonstrated its effectiveness for signal offset optimization in conjunction with link performance functions (Gartner and Rahul, 2009 & 2013; Meng Li et al., 2014).

2.4 Summary

In this chapter, we summarized and synthesized evidence from relevant literature on sustainable traffic control systems at signalized intersections. An overview of current practices of signal control systems with general concepts are provided in Appendices B and C, which serve as a supplement to this

chapter and also work to support the three sections. The first section reviewed studies of identifying TOD breakpoints with dynamic traffic features at arterials roads. The second section reviewed traffic signal control and how environmental concerns have become a part of their management problems. The third section reviewed the multi-objective optimization methods and coordination strategies at the intersection level and arterial level, respectively. In addition, this chapter is supplemented by Appendix C, which compares the features and limitations of macroscopic signal timing optimization tools, the widely used microscopic traffic simulation models and the recently developed emission estimation models. Based on this thorough literature review and the supplemental information in Appendices B and C, we can conclude some findings as shown in Table 2.3.

Table 2.3 Summary of Literature Review

Issues	**Opportunities**	**Challenges**
• Insufficient method for day plan schedule • Inaccurate emission estimation in existing tools • Not clear about the environment-mobility relation • In need of a more balanced and sustainable traffic signal control	• Advanced data collection devices for big data with high quality • Powerful simulation tools and emerging emission estimators • Advanced algorithms and powerful computation tools	• How to effectively deal with these big data for decision makers in practice? • How to balance the tradeoff between the accuracy of objective function values and the computational efficiency of simulation and optimization?

An extensive review of the literature shows that both opportunities and challenges have emerged for multi-criteria traffic signal timing design. First, much work on TOD breakpoint determination has been undertaken. Although the effectiveness of previous techniques has been demonstrated due to insufficient methodologies for coordinated control modes, there are still obvious shortcomings. The major challenges of applying a cluster analysis-based approach to identify TOD breakpoints include accurate traffic data resources, adequate consideration of time-space traffic data features, and a systematic

framework that can be easily implemented. Our study aims to fill in the gaps and tackle the challenges by proposing an improved cluster analysis and a framework for practical implementation.

Second, traditional signal timing optimization tools were used to reduce vehicular delay and stops or similar measures. However, it is not clear whether minimizing only vehicular delay and stops could achieve an eco-friendly traffic signal system. In other words, a traffic signal timing plan that can minimize vehicular delay and stops may not be optimal in terms of fuel consumption and emissions or vice versa. We also have limited understanding of potential tradeoffs between greenhouse gas and different pollutants known for negative health impacts. Thus, for a sustainable traffic control system, accurate modeling of fuel consumption and emissions should all be considered in the objective function as well as traditional vehicular delay.

Third, existing emission estimation methods used in connection with current traffic signal optimization and micro simulation tools are grossly inaccurate. They assume a drive cycle consisting of constant fractions of free flow and congestion travel rather than actual traffic characteristics. Moreover, the existing signal timing programs are unable to fully consider the important aspects of traffic behavior due to the nature of the macroscopic simulation model, while the micro simulation models are mainly used to evaluate a set of predetermined strategies. Most microscopic simulation models require many different types of parameters to describe traffic flow characteristics, traffic control systems, driving behavior, and so forth. Simulation-based optimization usually requires extensive computational time when the number of optimization variables is large or the simulation model is complex. Therefore, there is a need for computational efficiency when solving optimization problem.

Last but not the least, powerful tools and high resolution analyses for traffic modeling, fuel consumption, and emissions modeling have been developed in recent years. Microscopic simulation tools, including VISSIM, CORSIM and TRANSIMS, have been used for more than a decade to model individual traffic behavior (Stevanovic et al., 2009). Similarly, emissions models, such as MOVES, were developed to estimate second-by-second emissions of individual vehicles. These models can be integrated

to estimate instantaneous emissions based on second-by-second activities of individually behaved vehicles (Chen and Yu, 2007; Park et al., 2009, Stevanovic et al., 2009; Lv 2012). Researchers have reported that these integrated methods can provide signal timings that minimize fuel consumption and some selected emissions. However, no research has been performed to investigate the comprehensive relationship between control delay and different emissions or the tradeoffs between different objectives, and there is no fine scale framework that integrates all of these components. There is a tradeoff between the accuracy of objective function values (i.e., the opportunity) and the computational efficiency of simulation (i.e., the challenge). Since it is not possible to address all of these issues in a single research effort, this research focuses mainly on the following issues:

- Investigating traffic pattern variations at arterial intersections for day plan scheduling by identifying TOD breakpoints, where different signal timings can be implemented during time periods between two consecutive breakpoints;
- Investigating the comprehensive relationship between control delay and different emissions or the tradeoffs between different objectives;
- Developing a framework that can achieve a sustainable traffic signal control system by minimizing a few selected unsustainable impacts of the surface transportation system such as, vehicular delay, fuel consumption and emissions.

CHAPTER 3: IDENTIFYING TIME-OF-DAY BREAKPOINTS OF ARTERIAL TRAFFIC

To ensure the effective operation of traffic signal systems, different signal timings should be designed to accommodate traffic pattern variations. One of the greatest challenges is the identification of appropriate time-of-day (TOD) breakpoints, where different signal timings could be implemented during the time periods between two consecutive breakpoints. This chapter presents an advanced cluster analysis aimed at identifying TOD breakpoints for coordinated, semi-actuated modes when it is necessary for multiple intersection operations to be considered simultaneously. Different from previous studies, this proposed methodology considers the time of traffic occurring as one dimension in clustering and uses continuous traffic data obtained through innovative, non-intrusive data collection techniques, which significantly improves this method's performance. The operability of this proposed method is demonstrated in a case study of a corridor located in Tampa, Florida. The traffic simulation results reported in this chapter reveal that this novel procedure performs better than existing TOD signal timing plans.

3.1 Cluster Analysis-based Procedure

This study aims to develop a cluster analysis-based procedure to identify TOD breakpoints for a coordinated semi-actuated traffic signal system using continuous traffic data obtained through innovative non-intrusive data collection techniques. An effective procedure for the development of the TOD signal timing plans formed in this research is shown in Figure 3.1. Each of the key components of the proposed procedure is described in detail after Figure 3.1.

[2]Portions of this chapter were previously published in Guo and Zhang (2014 a). Permission is included in Appendix D.

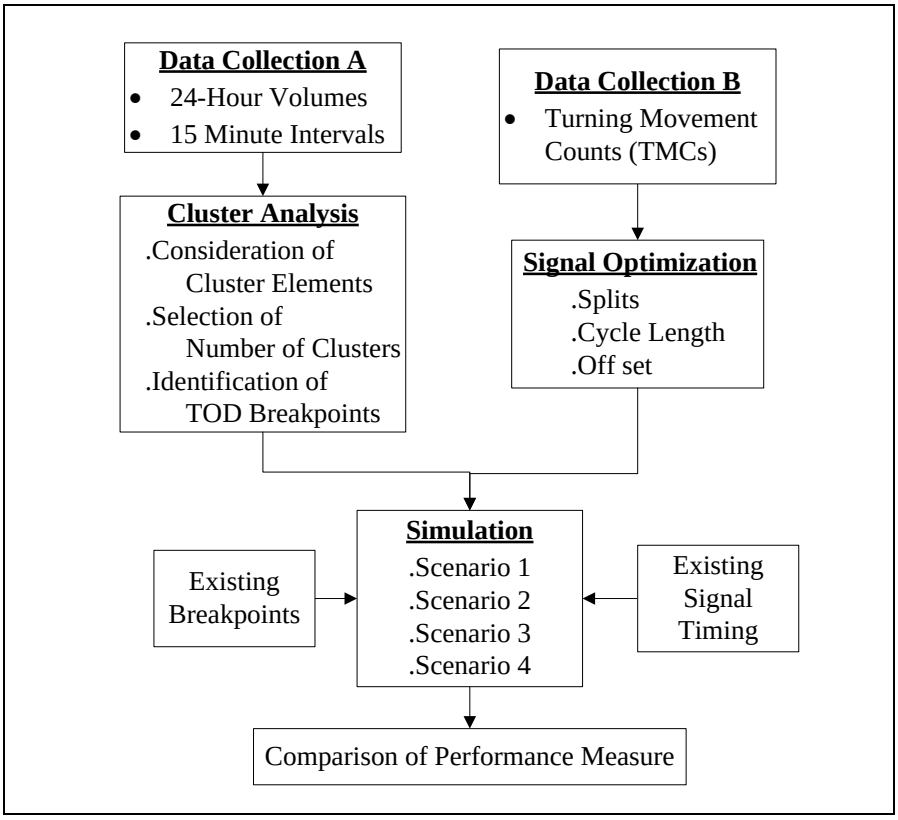


Figure 3.1 Proposed Procedure for Determining TOD Breakpoints Plans

(1) Data Collection

Two kinds of traffic volume data involved in this study are shown in Figure 1. The first is 24-hour volumes, which were collected every 15 minutes in representative segments through the entire corridor. The 24-hour volumes can be used in cluster analysis to determine TOD breakpoints. Another kind of data is turning movement counts (TMCs), which can be collected for 24 hours but are generally collected for 6 to 8 hours in different 2- to 3-hour time blocks of a day to reduce the cost. TMCs are important inputs in both signal timing optimization and performance evaluation with simulation software. Besides the traffic volume data, information related to current breakpoints and existing signal timings was collected and used to create the scenario in simulation for demonstrating the performance of different breakpoints plans.

(2) Enhanced Cluster Analysis

Based on the 24-hour volume data, enhanced cluster analysis was conducted with the following steps. Firstly, proper cluster elements were selected. With consideration of the coordination of a corridor, 24-hour volume samples for both travel directions from representative segments were selected as cluster elements. More important, a time variable was introduced as one dimension to remove certain outliers in the cluster analysis. Then, the Silhouette measure and Gap-statistic measure were used to find the appropriate number of clusters in this study. Based on the results of previous step, the K-means procedure was adopted to actually form the clusters. Given a certain threshold, all elements were assigned to the nearest cluster seed, and new seeds were computed. Elements were reassigned in successive steps, if necessary.

(3) Signal Timing Optimization

During the signal timing optimization process, SYNCHRO was used to determine macroscopic level of service (LOS) and delays of intersections along the corridor. In the context of signal timing plans, the following three parameters were of particular importance and were the focus of our optimization efforts: cycle length—the time required for a complete sequence of signal indications and signals in an actuated coordinated system, which should all operate under the same background cycle length; splits—the time assigned to a phase (green and the greater of the yellow plus all-red or the pedestrian walk and clearance times) during coordinated operations, which may be expressed in seconds or percentages; and offset—the time relationship between coordinated phases at subsequent traffic signals (FHWA, 2008). The optimization of these parameters was performed by using standard optimization techniques. Once the signal timings were developed for each of the TOD intervals, the timing parameters were entered into an Excel spreadsheet for the use in the final step, simulation and validation.

(4) Simulation and Validation

A microscopic traffic simulation tool was used to simulate and identify issues that may not have been fully realized with a macro-level model, such as SYNCHRO. Simulation, using CORSIM, requires

three types of information: roadway geometry, traffic volume, and signal timing. Geometric information was collected from Google Earth and field notes. Data for 15-minute TMCs from each time interval during selected periods supported the traffic volume requirement. A spreadsheet storing the signal timing parameters in the previous section was used to provide the third type of information. To validate enhanced cluster analysis, four different scenarios were created, as described in section 3.3.4. The existing breakpoints and existing signal timing plans were both collected to perform as the baseline scenario. Comparison of performance measures of different scenarios was conducted to evaluate the performance of our method in this final step.

3.2 Data Collection

Traffic data is the backbone of transportation analysis. To identify TOD breakpoints under various traffic conditions, continuous, stable, and accurate samples are needed to cover all traffic conditions in a sequential fashion for the study sites. Loop detectors are the most used detection technologies for collecting traffic data. However, the installation and replacement of loop detectors requires construction work on the road, which blocks lanes and disrupts traffic. In addition, it is difficult to determine the turning movement counts at intersections from the loop data. Historically, those movement counts were obtained manually by having observers at various spots of the intersections. In this study, traffic data were collected based on non-intrusive data collection platforms, which offer significant reduction in risk exposure over traditional segment count methods and moderate reductions in risk exposure for traditional turning movement count methods.

(1) 24-Hour Volumes (Segments Counts)

Given the reduced risk exposure to personnel, the flexible installation options, and the high degree of accuracy, Wavetronix Smartsensor HD units were selected to be used in this study to collect 24-hour approach counts. It is a portable, non-intrusive platform that uses dual-radar technology to detect traffic and has a patented auto-configuration process to define the roadway cross-section and direction of vehicles in each lane. Traffic counts were collected at nine segments along a local major east–west

arterial, Hillsborough Avenue in Hillsborough County, Florida, from March 9–15, 2010. The corridor, which is approximately 15 miles in length, is primarily a six-lane divided arterial.

(2) Turning Movement Counts (TMCs)

TMCs at intersections were obtained with Miovision Video Collection Units (VCU), which use digital video recording to capture all vehicle turning movements. TMCs were recorded and stored on a Secure Digital (SD) card, then uploaded via office computer to the Miovision web server (bandwidth dependent). The additional benefits of easy deployment, reduced requirements for trained staff, and the unique aspect of an audit trail make Miovision a viable alternative to traditional manual turning movement counting. In this study, TMCs were collected in the same corridor from March 23–30, 2010.

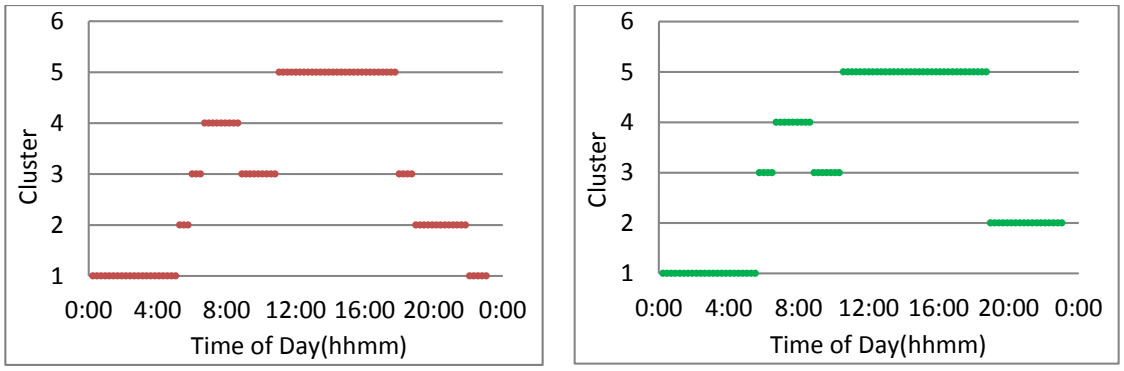
(3) Existing Breakpoints and Traffic Signal Timings

Existing data of breakpoints and traffic signal timings were obtained from the ATMS.now server of Hillsborough County and from City of Tampa traffic engineering personnel. Only weekday (Monday–Friday) signal timing plans and traffic conditions are compared in this study.

3.3 Case Study Results

3.3.1 Consideration of Cluster Elements

Different from previous studies, this proposed methodology considers the time of traffic occurring as one dimension in clustering, which allows advanced clustering to operate successfully on temporal data sets that are available in metric spaces. Specifically, time variables numbered from 1 to 96, corresponding with 96 sets of 15-minute volume data over a 24-hour period, were considered as one dimension of inputs in advanced cluster analysis. To account for the difference in scale between volumes and the time variable, the values were standardized prior to the cluster analysis so as to make original traffic data dimensionless. By following the proposed procedure in Figure 3.1, the cluster membership value for each state exported from SAS outputs was plotted against TOD in Excel, as exemplified in Figure 3.2, to determine the TOD intervals.



(a) Without consideration of time (b) With consideration of time

Figure 3.2 TOD Breakpoints with or without Consideration of Time

Figure 3.2 shows a sample clustering outcome with the time of traffic occurring as one dimension (b) vs. without (a). The clustering with the time consideration demonstrates a refined TOD timing plan scheme and the outliers are significantly reduced. In the particular case shown in Figure 3.2, the number of transitions with the consideration of time of traffic occurring is six, while it is nine without consideration of the time. Adding the dimension of the time of traffic occurring refines the cluster analysis and leads to a lower transition cost.

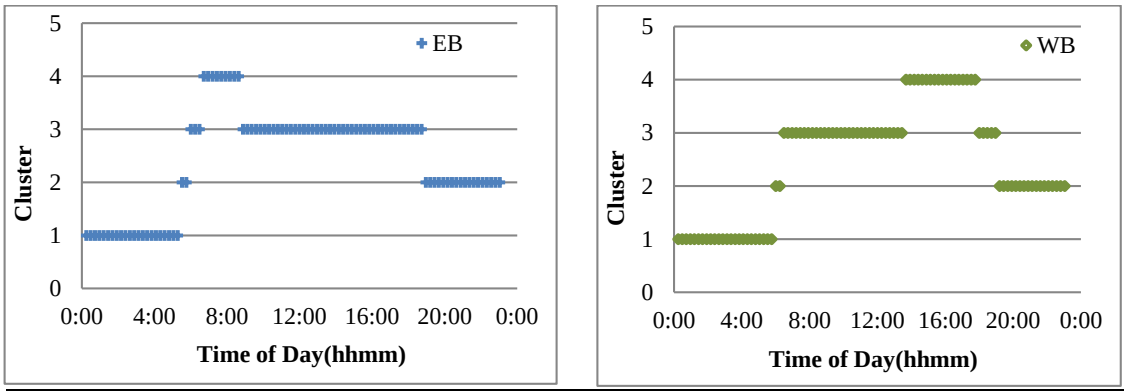
3.3.2 Selection of Cluster Numbers

To determine the optimal number of clusters, Silhouette Coefficient and Gap values were calculated by using MATLAB and R codes, respectively. Traffic samples of eastbound and westbound are considered separately because of the directional characteristics of local traffic, where the AM peak occurs in the eastbound approach and the PM peak occurs in the westbound approach. The results show that both the largest Silhouette Coefficient and Gap occur when the number of clusters is four. This is indeed consistent with existing knowledge on daily traffic where free-flow traffic, peak-hour traffic (congestion), and mid-day traffic (transition) are among the most commonly observed traffic phenomena.

3.3.3 Identification of TOD Breakpoints

The K-means clustering successfully identifies the traffic patterns based on the average weekday 15-minute traffic volumes and the time that traffic is occurring, as displayed in Figure **3.3**. Four clusters,

as determined in the previous section, were conducted to find appropriate representation of natural volume groupings over a 24-hour period. Clusters 1 and 2 both represent the free (uncoordinated) operation of each intersection in the corridor over the night time, cluster 3 represents the mid-day period, and cluster 4 represents the AM/PM peak periods.



Cluster (K=4)	TOD Classification	Interval of Eastbound	Interval of Westbound
Cluster 1+2	Free Flow	19:30-6:00	19:45-6:30
Cluster 3	Mid-Day	6:00-6:45,9:00-19:30	6:30-14:00,18:30-19:45
Cluster 4	AM/PM Peak	6:45-9:00	14:00-18:30

Figure 3.3 TOD Breakpoints and TOD Interval Classifications

3.3.4 Simulation and Improvement

It is important that the clusters obtained from the K-means clustering be validated. We developed the traffic operation modeling of the corridor to evaluate the overall performance of our new method in comparison to the performance of existing signal plans. Four scenarios were generated for the simulation analysis to fully investigate the effectiveness of the improved method and procedure. The first scenario represents a baseline situation, where simulations were performed according to the existing breakpoints and existing signal timings. The second scenario kept existing signal timings but adopted new breakpoints from the previous section, while the third scenario kept existing intervals but used new signal timings from the Synchro optimization. These two hybrid scenarios were conducted to compare measures of performance with baseline scenario by adopting new TOD breakpoints and new signal timings, respectively. The last scenario resulted from the application of the proposed procedure, wherein both

TOD intervals identified from advanced cluster analysis and the optimized signal timings were applied. CORSIM simulations for different scenarios were all conducted in multiple time periods with 15-min duration in each period in this study.

The comparison of mean performance measures of four scenarios is listed in Table 3.1. Additionally, paired samples T-test is conducted to test if there is a significant difference between the mean performance measures. According to the results of the paired samples T-test, the mean performance measures under different scenarios are statistically significantly different. The higher average speed in the second scenario (compared with the baseline of Scenario 1) demonstrates that in this case study, the new TOD breakpoints obtained from the proposed method leads to better performance of the corridor. The comparison also demonstrates the benefit of refining signal time plans given new TOD breakpoints. The combined effect leads to a nearly 8% increase in average traffic speeds throughout the corridor. The percentage changes of performance measures in different scenarios are depicted in Figure 3.4, with scenario 1 as the base.

Table 3.1 Comparisons of Performance Measures

Measures of Performance	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
	Existing TOD breakpoints & existing signal timing plans		New TOD Breakpoints & existing signal timing plan		Existing TOD Breakpoints & new signal timing plan		New TOD Breakpoints & new signal timing plan	
	Mean	STD	Mean	STD	Mean	STD	Mean	STD
Ave Speed (mph)	21.63	0.275	22.32	0.320	22.73	0.271	23.28	0.320
Move/Total (%)	52.58	0.646	54.26	0.759	55.26	0.640	56.59	0.758
Delay (min/mile)	1.32	0.035	1.23	0.038	1.18	0.031	1.12	0.035
Delay (sec/vehicle)	19.50	0.511	18.22	0.564	17.51	0.461	16.58	0.520
Fuel Usage (gallons)	243.52	1.823	242.61	1.847	240.67	1.965	240.62	1.834

As shown in Figure 3.4, the significant increase in average speeds and the Move/Total ratio (the ratio of the theoretical move time to the actual travel time for vehicles in the network) indicates that the developed signal system effectively services more vehicles through the corridor. Furthermore, delay times in minutes per mile and in seconds per vehicle are both significantly reduced in the fourth scenario. Table

3.1 also shows that the fuel consumption decreases slightly with new plans. It should be noticed that fuel consumptions of all scenarios do not make much difference because CORSIM ignores fuel usage of vehicles that are denied or queued at the entry points of the corridor. The technology of identifying time-of-day breakpoints shows a mathematical way to classify the dynamic traffic patterns and has the great potential to be further implemented on the purpose of sustainable traffic control that assimilates mobility, climate and health exposure.

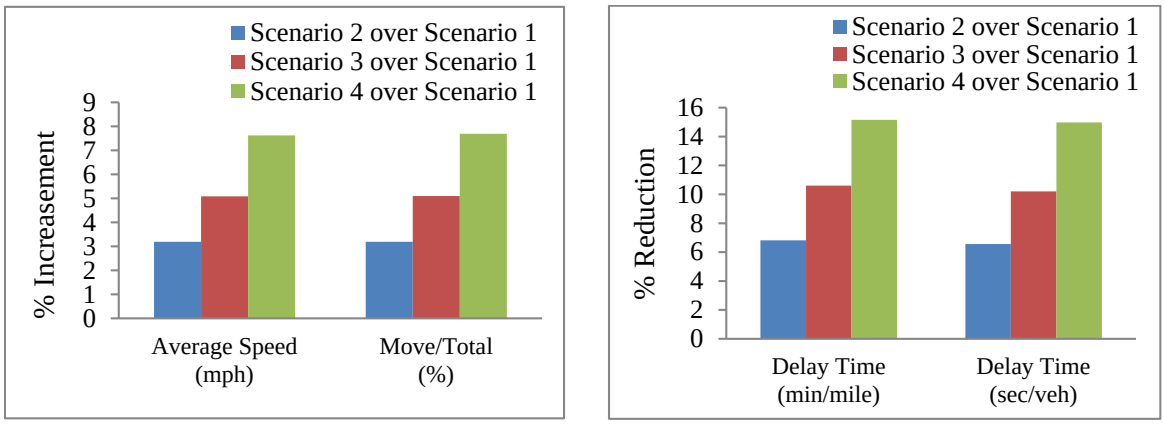


Figure 3.4 Percentage Changes of New Breakpoints and Signals over Existing Ones

3.4 Summary

In this chapter, a cluster analysis-based procedure was developed to identify TOD breakpoints for coordinated traffic signal systems using continuous traffic data obtained through innovative, non-intrusive collection techniques. A novel modification, which proposes that time of traffic occurring be taken into account as a dimension, addresses the shortcomings of previous clustering approaches. The signal timing plans for the recommended TOD intervals were developed and evaluated in the simulation analysis. The results of a case study for a corridor located in Tampa, Florida, demonstrated that the proposed method significantly improves the performance of the corridor.

CHAPTER 4: RELATIONSHIP BETWEEN MOBILITY AND ENVIRONMENTAL FACTORS

Characterizing the relationship between environmental factors and mobility is critical for developing a sustainable traffic signal control system. In this chapter, the correlation of the environmental impacts of transport and mobility measurements at signalized intersections is investigated. A metamodeling-based method involving experimental design, simulations, and regression analysis is developed. The simulations, involving microscopic traffic modeling and emission estimation with an emerging emission estimator, provide the flexibility of generating cases with various intersection types, vehicle types, and other parameters such as driver behavior, fuel types, and meteorological factors. A multivariate multiple linear regression (MMLR) analysis is applied to determine the relationship between environmental and mobility measurements. Given the limitations of using the built-in emissions modules within current traffic simulation and signal optimization tools, the metamodeling-based approach presented in this chapter makes a methodological contribution. The findings of this chapter set up the base for extensive application of simulation optimization (in next chapter) for sustainable traffic operations and management. Moreover, the comparison of outputs from an advanced estimator with those from the current tool recommend improving the emissions module for more accurate analysis (e.g., benefit-cost analysis) in practical signal retiming projects.

4.1 Metamodeling-based Procedure

This chapter focuses primarily on exploring how environmental externalities are related to mobility measurements at signalized intersections. Although some of the mobility and environmental measurements (e.g., travel time, emission rates) can be collected in the field, it is difficult to collect all factors associated with traffic management operations practically (Golob and Recker, 2004), especially

[3]Portions of this chapter were previously published in Guo and Zhang (2014b&d). Permission is included in Appendix D.

when considering different traffic demand levels with various geometric types and driver behaviors. However, the powerful simulation tools and emerging emission estimator provide the flexibility of using various intersection types, vehicle types, and other characteristics such as driver behavior, fuel types, and meteorological factors.

Thus, in this sub-study, a framework based on a metamodeling technique is developed to analyze the comprehensive relationship between mobility and environmental externalities at signalized intersections. A metamodeling technique involves experimental design, simulation modeling, and regression analysis (Kelton and Law, 2000; Wang and Shan, 2007). The experimental design is used for sampling, and the regression model is developed from the outcomes of simulation modeling. In the existing literature, some studies applied simulation optimization to simultaneously optimize the mobility and environmental impacts of traffic signal timing at intersections (Stevanovic et al., 2009; Kwak et al., 2012). However, due to complicated on-line simulation and tedious computations, the direct optimization method consumes significant time and computational loads. Given the popular coordinated traffic control of corridors and major arterials, methods that can solve multiple intersection problems in an efficient way are urgently needed. The metamodeling-based method proposed in this sub-study will provide a tool for use in simulation optimization and can reduce the complexity and computation load such that it can be used to solve large-scale sustainable traffic management problems.

As shown in Figure 4.1, a traffic signal optimization tool is used to provide optimal signal timing for some basic inputs. With the timing and basic inputs, traffic micro-simulation software is applied to generate the detailed information needed for MOVES. Given the mobility and emission measurements, econometrics tools are used to unveil the relationship. The same process is applied to different intersection types. The details of each step of the framework are discussed in the subsections below.

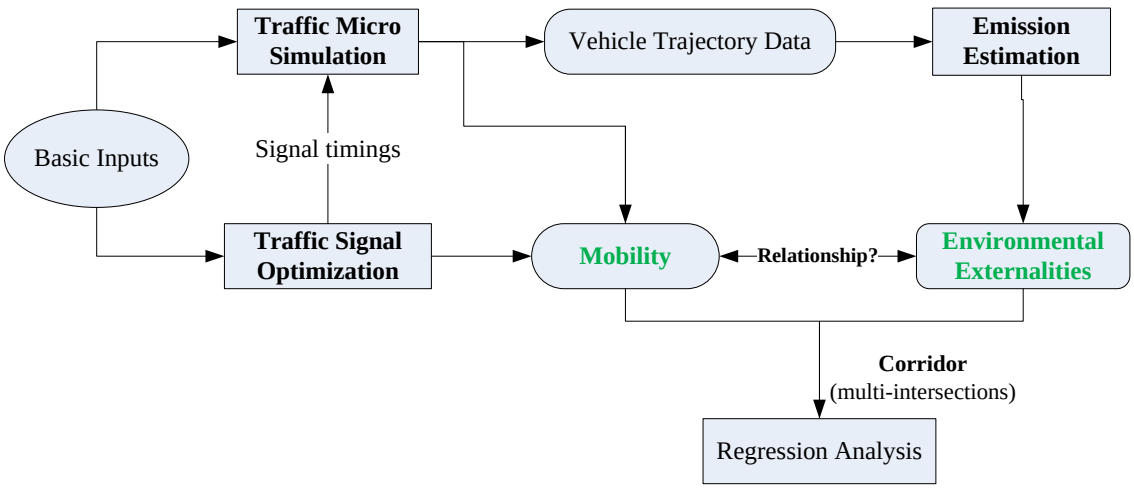


Figure 4.1 Proposed Framework for the Correlation Study

(1) Traffic Signal Optimization

The traffic signal optimization tool SYNCHRO, which is used by more than 4000 agencies and consultants throughout North America and the world, was selected to develop mobility-based signal timings for different levels of traffic demand. Three types of data are required for optimization and calculation: geometric information, traffic volumes, and initial signal timings. Measures of effectiveness that are calculated by SYNCHRO software after the optimization process include vehicle delay, fuel consumption, and emissions.

(2) Traffic Micro Simulation

Micro simulation models generate a significant amount of detail on vehicle performance that is critical for determining emissions and air quality impacts. In this study, VISSIM was used to develop second-by-second resolutions of individual vehicular data (speed/acceleration profiles). The accuracy of a traffic simulation model is mainly dependent on the quality of modeling driver behavior, such as car following and lane changing. In contrast to less complex models that use constant speeds and deterministic car-following logic, VISSIM applies the psychophysical driver behavior model developed by Wiedemann (PTV, 2011). Two kinds of data are required for establishing a VISSIM network: (1) static data, representing the roadway infrastructure, and (2) dynamic data, required for traffic simulation

applications, which include (a) traffic volumes for all links, (b) vehicle routing, departure times, and dwell times, and (c) priority rules and signal timing plans at intersections. All of these data can be collected from the field. Note that a multi-run for each scenario was conducted in this study to reflect different driver behaviors.

On the other hand, the microscopic simulation program (e.g., VISSIM) provides various link-level and network-level performance measures such as average delay time (sec/vehicle), number of stops, throughput (vehicles), queue lengths, travel time and delay along the corridor etc. Each evaluation value is the average/median value, attained from n random-seeded micro-simulation runs in an attempt to reduce stochastic variability inherent in stochastic microscopic traffic simulations such as VISSIM. Note that the Measure of Effectiveness (MOEs) in microscopic simulation, such as queue length, travel time and delay time, are based on links. If there's any approach to the intersection consisting of several links due to the changes in the attributes of the road section (e.g., the number of lanes), users need to pay attention to the MOEs calculation.

(3) Emission Estimation

The emission estimator MOVES was used to model project-level emissions. There are three approaches/options for describing vehicle activity in MOVES: (1) link average speed, (2) link drive schedules, and (3) operating mode distribution. The link drive schedules and the operating mode distribution approaches are more accurate and widely used in project-level modeling. One of the most important parameters in MOVES is Vehicle Specific Power (VSP), the primary metric used to determine operating modes and estimate emissions. VSP is an estimation of engine load based on vehicle type, vehicle speed and acceleration, and road grade:

$$VSP = (A/M)*v + (B/M)*v^2 + (C/M)*v^3 + (a + g*\sin\theta)*v \quad (4\text{-}1)$$

where: v: velocity; a: acceleration; g: road grade; M: weight; A: rolling resist; B: rotating resist; C: aerodynamic drag. The coefficients A, B, C, and M vary among vehicle types. For example, for a passenger car, A=0.1565kW-s/m, B=2.002*10^{-3} kW-s^2/m^2, C=4.926*10^{-4}kW-s^3/m^3, and M=1.479 tons.

The outputs from VISSIM provide the necessary details to calculate the operating mode distribution of the simulated traffic volume. Except for braking and idling, the operating mode bins are stratified by speed ranges (<25mph, 25–50 mph, and >50mph) and by VSP. The operating mode bins are weighted by time spent in each bin to represent any driving cycle. Note that one advantage of the emission estimator MOVES is the default data of the contributing factors in the simulator database. MOVES can adjust the default emission rates to represent user-specific values of these factors. Therefore, default data were used for generating the emission rate look-up tables, with the exceptions of link drive schedules, meteorology, vehicle types, and emission types.

(4) Multivariate Regression Analysis

Regression analysis is commonly used in the field of air pollution (Vlachogianni et al., 2011). After the complex simulation modeling, correlation and regression analyses were conducted to approximate the environmental responses given microscopic simulation databases. The outcomes of the traffic simulation and the advanced emission estimator are two training sets consisting of Set 2, the evaluations of the environmental response vector $\{y^m; m=1, 2, \cdots, n\}$ corresponding to Set 1, the mobility measurements $\{x^m; m=1, 2, \cdots, n\}$ (detailed comments are included later in the illustrative example on forming a database). Suppose we have p variables in Set 1, $X \in R^{n*p}$ indicating mobility measurements, and q variables in Set 2, $Y \in R^{n*q}$ indicating environmental externalities:

$$\text{Set1: } \mathbf{X} = [X_{m1}, X_{m2}, \cdots, X_{mp}]^T \quad \text{Set2: } \mathbf{Y} = [Y_{m1}, Y_{m2}, \cdots, Y_{mp}]^T \qquad m = 1,2,\cdots n \tag{4-2}$$

In this study, the first data set (Set 1) related to mobility was measured by delay (e.g., control delay, total delay), stops, average speed, total travel time, and total distance traveled. A dummy variable was used to test if there is a significant difference between two intersection types. The second data set (Set 2), related to environmental factors, includes carbon dioxide (CO_2) (major GHG emission), CO, NO_x, particulate matter (PM), and sulfur dioxide (SO_2) from the U.S. Environmental Protection Agency (EPA) criteria pollutants. Considering the multidimensional characteristics of both sets of variables, a multivariate multiple linear regression (MMLR) was conducted to determine a formula that can describe

how elements in a vector of variables respond simultaneously to changes in others. Multivariate statistics encompass the simultaneous observation and analysis of more than one outcome variable. This regression is "multivariate" because there is more than one outcome variable and a "multiple" regression because there is more than one predictor variable (SAS, 2009). Compared to the outcomes from conducting linear regression separately for each response variable on the common set of predictor variable, MMLR can provide large gains in expected prediction accuracy by taking the correlations between the response variables into account (Breiman and Friedman, 1997). The hypothesis being tested by a multivariate regression is that there is a joint linear effect of the set of independent variables on the set of dependent variables. Hence, the null hypothesis is that the slopes of all coefficients are simultaneously zero. The statistical model for MMLR is:

$$\left[y_1 \cdots y_q \right] = \left[x_1 x_2 \cdots x_p \right] \left(\beta_1 \cdots \beta_q \right) + E_{n \times q} \tag{4-3}$$

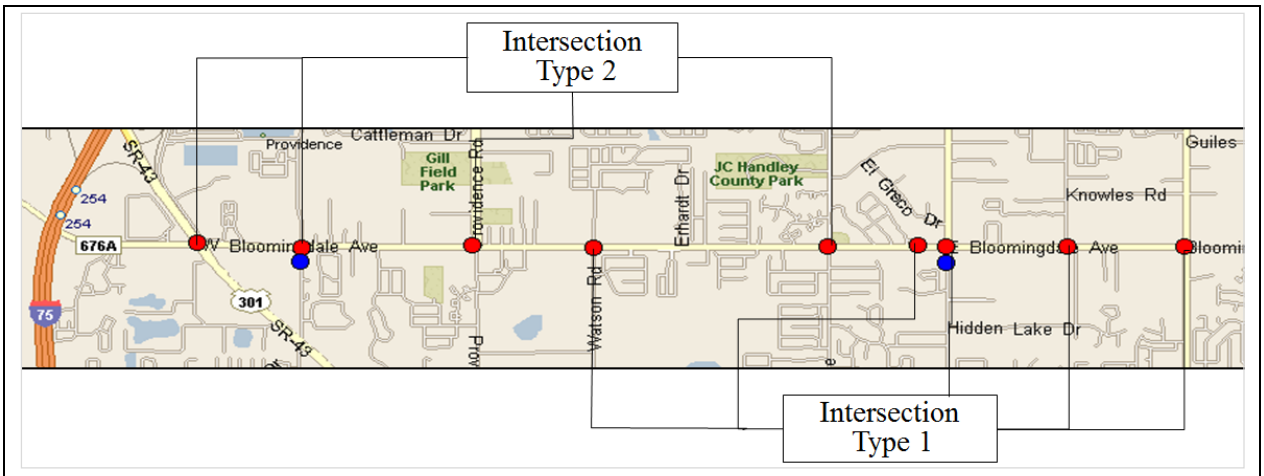
$$\mathbf{Y}_{n \times p} = \mathbf{X}_{n \times q} \mathbf{B}_{p \times q} + \mathbf{E}_{n \times p} \tag{4-4}$$

where **Y** represents n observations of a q-dependent variable, **X** represents the design matrix of rank p with its first column being the vector 1, **B** is a matrix of parameters to be estimated, and E represents the matrix of residual.

4.2 Illustrative Example and Results

This illustrative example explores the relationship between mobility and environmental externalities at signalized intersections. Based on the proposed framework, two typical intersection types along the sample corridor were examined with different levels of traffic volume. The sample corridor, Bloomingdale Avenue, is a four-lane, divided roadway in Hillsborough County, Florida. The Average Annual Daily Traffic (AADT) volumes range from 29,100 vehicles per day (vpd) (east end) to 42,600 vpd (west end) for weekday travel.

Figure 4.2 illustrates the locations of traffic signals (red) and the placement of BlueTOAD™(blue) units along the corridor. The field travel time data were collected by the BlueTOAD™ units, which is very useful in the model calibration and validation.



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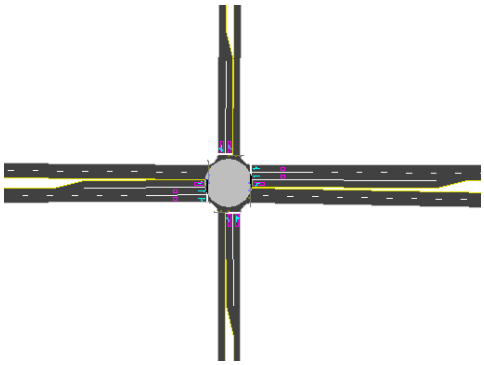
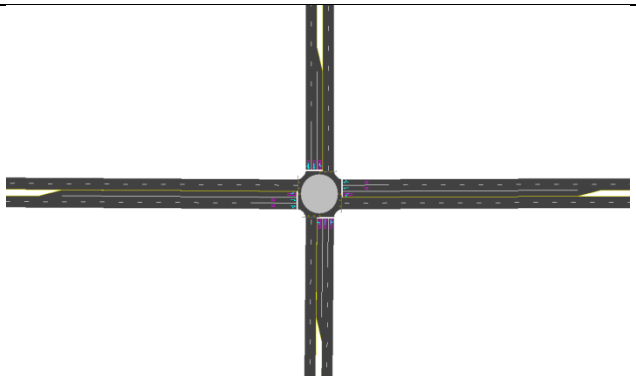
	
Lanes: 2*1 Signal control: actuated Numbers along corridor: 5	Lanes: 2*2 Signal control: actuated Numbers along corridor: 4

Figure 4.2 Map of Sample Corridor, Bloomingdale Avenue in Tampa, FL

4.2.1 Sampling for High-Fidelity Simulation

The illustrative intersections in the traffic simulation models were developed based on the two intersection types along the sample corridor, as shown in Figure 4.2. They are both four-leg intersections with actuated signal control and urban unrestricted access links. The major difference in these two types of intersections is the number of lanes on the minor street, which determines the capacity of the approaches on the minor street. The speed limits are 45mph for major roads and 30mph for minor streets. For turning vehicles, the speeds are reduced to 15mph for a left-turn movement and 9mph for a right-turn movement, respectively.

Thirty scenarios for each type of intersection were designed to input into the traffic simulation models and emission estimator. The high-fidelity outputs were then used for the purpose of multivariate regression analysis. Thirty scenarios for each type are reasonable, given that a sample size of 25–30 is generally considered sufficiently large for most situations in statistical analysis (Howell, 2011). To assess the impact of various levels of traffic demand, different scenarios were generated based on five groups, as shown in Table 4.1. Group 1, with five scenarios, was based on the collected turning-movement traffic data from the field. Groups 2, 3 and 4 were developed based on the flow ratios with the consideration of different geometric configurations, with or without exclusive turning lanes. It was assumed that the base saturation flow rate was 1900 pc/h/ln in this study. The flow ratio of critical lane groups was calculated by *v/s*, where *v* is adjusted flow rate in lane group and *s* is adjusted saturation flow. The last group was developed to represent various percentages of turning vehicles on major and minor roads.

Table 4.1 Traffic Scenarios for Different Levels of Traffic Volume Demand

Scenario Groups	Group Feature	Number of Scenarios
1	Base (average real traffic volume)	Scenarios 5: (0.5,0.75,1,1.25,1.5)*Base
2	Major Rd: exclusive-left, shared-right lanes Minor St: exclusive-left, shared-right lanes	Scenarios 6-10: (0.1,0.15,0.2,0.25,0.3)*Saturated Flow
3	Major Rd: exclusive-left, exclusive-right lanes Minor St: exclusive-left, exclusive-right lanes	Scenarios 11-15: (0.1,0.15,0.2,0.25,0.3)*Saturated Flow
4	Major Rd: exclusive-left, shared-right lanes Minor St: exclusive-left, exclusive-right lanes	Scenarios 16-20: (0.1,0.15,0.2,0.25,0.3)*Saturated Flow
5	Different Left and right turn percentages	Scenarios 21-30

Note: Scenarios 4, 5, 9, 10, 13, 14, 15, and 20 represent congested conditions.

4.2.2 Quantification of Mobility and Environmental Measurements

Based on the proposed framework and developed scenarios, the traffic signal optimization software Synchro was used to develop mobility-based signal timings for different levels of traffic volume. Two vehicle types, a typical passenger car and a heavy vehicle, were modeled, which corresponds to MOVES vehicle types 21 (passenger car) and 62 (combination long-haul truck with diesel engine). Based

on heavy vehicles percentages in the AADT dataset along the studied area, heavy vehicles were set to be 5 percent on major roads and 2 percent on minor roads in all models. Measures of effectiveness, including mobility, fuel consumption, and emissions, were calculated and exported as SYNCHRO outputs.

Within the VISSIM model, exclusive turning lanes were coded with appropriate storage lengths obtained from Google Earth, and vehicle reports were generated for a specified start and end time. Trajectory files generated in VISSIM were configured to output vehicle speed, acceleration, and location within the network on a second-by-second basis. The data were stored in an .FZP file. Note that 10 model runs for each scenario were conducted for this analysis to reflect the stochastic nature of traffic flow and driving behaviors. Calibration issues accompany the use of any microscopic traffic simulation models. Here, calibration means the process of adjusting and fine-tuning some parameters to match local traffic conditions. Since a link in the macroscopic software usually comprises several links in a microscopic simulation network, the links in VISSIM were matched with links in SYNCHRO first. Then, the calibration for basic parameters was conducted to match the real situation. In the base model, the average travel time from SYNCHRO and VISSIM was compared with that from field data collected by the BlueTOAD^{TM} units through the studied corridor. A good agreement was found between measured and simulated travel times. Following previous literature, we determined to keep the default parameters for further analysis. Moreover, the quality of the vehicle trajectory data collected by VISSIM is verified with extensive error checking, which flags any data values outside of conventional ranges (e.g., acceleration greater than $3ms^{-2}$ or deceleration greater than $-5ms^{-2}$). For congested scenarios, the inputs and outputs of vehicles in the simulation were checked and the missing vehicles were treated as unserved vehicles.

The detailed micro simulation outputs enabled a direct quantitative linkage with MOVES. All links were modeled with zero percent gradients, as no nominal grade changes exist at the intersection. Within MOVES, the vehicle operating modes are stored as an operating mode distribution, which is the percent of all vehicle-hours for a specific link, pollutant, and vehicle type that fall within each operating mode. In our study, links were defined by each segment, including links for traffic approaching and

departing at the signalized intersections. In addition, the connections for different turning movements in the center of the intersection were designed as small links. The link drive schedule approach, using user-defined drive cycles in MOVES, was adopted in this research. Based on the user-defined input and default data in the MOVES model, the emission rates were generated after running the MOVES.

In existing macro and micro simulation software (e.g., SYNCHRO, TRANSYT-7F, CORSIM, and VISSIM), the fuel usage and emissions of the unserved vehicles—vehicles that are denied entry (essentially queued at the entry points to the intersections) in the over-saturated/congested scenarios—are ignored. These vehicles use fuel, so in our study they were treated as vehicles idling on the off-network link with appropriate assumptions in MOVES. The start fraction and parked vehicle fraction parameters were both set to zero, which means no vehicle is restarted or parked during congestion. The extended idle parameter was set to 0.95, which reflects the fact that 95 percent of the total vehicle-hours (only 1 hour by definition) in the off-network link are spent in an extended idle mode. As in SYNCHRO, the time domain for the emissions estimation is one hour.

4.2.3 MMLR Analysis for Model Fitting

After the microscopic simulation modeling, statistics software, SAS, was used for MMLR analysis to explore the relationship between environmental externalities and mobility measurements. The data to be analyzed came from the quantification of the last step, with a sample of n=60. Two collections of variables were measured, as listed in Table 4.2. There were seven mobility performance variables in the first group and seven environmental externality variables in the second group. A dummy variable, indicating two comparable intersection types, was used to test if the environmental-mobility relationship statistically depends on intersection types. Arguably, differences in locations, road geometries (capacities), and land-use policies can help explain demographic dissimilarities in mobility and environmental performance.

Table 4.2 Summary of Descriptive Statistics

Variable	Mean	Standard deviation	Min	Max
Dependent variables (Environmental measure)				
Y1: CO_2 (ton)	1.00	0.578	0.263	2.92
Y2: CO (kg)	9.23	4.35	2.514	22.249
Y3: NO_X (kg)	3.72	5.08	0.422	21.987
Y4: PM_{10} (kg)	0.13	0.09	0.028	0.434
Y5: $PM_{2.5}$ (kg)	0.12	0.09	0.024	0.426
Y6: SO_2 (kg)	0.01	0.01	0.002	0.03
Y7:Total energy (Gigajoule)	13.83	7.96	3.64	40.30
Explanatory variables (Mobility measure)				
X1: Control delay (*s/veh*)	64.06	73.57	8.9	320.3
X2: Total delay (10^2h)	1.03	1.58	0.04	6.67
X3: Stops (*/veh*)	0.68	0.08	0.5	0.8
X4: Total stops (#)	2798.27	1252.20	698	6072
X5: Average speed (*mph*)	14.42	7.59	2	29
X6: Total travel time (*h*)	121.57	164.81	10	711
X7: Total distance traveled (*veh-mi*)	807.55	373.06	245	1985
Type: Dummy variable for intersection type	0.50	0.50	0	1

To avoid the multicollinearity problem, the interrelationship among independent variables was computed first, as shown in Table 4.3, with the bold values indicating the strong relations. Table 4.3 shows that X3 *(Stops/vehicle)* has relatively weak relation to all other X values (mobility measurements). X5 *(Average speed)* shows negative relation to other variables and not as strong as others' relation. X1(*Control delay*), X2 *(Total delay)*, X4(*Total stops*), X6 *(Total travel time)* and X7(*Total distance traveled*) are strongly related, which means only one of them will be selected for regression. Thus, X2, X3, X5 and Type are selected for MMLR analysis. To test if the relationships are statistically non-linear, $(X2)^2$ and $(X3)^2$ are also included in the model.

Table 4.3 Correlations for Independent Variables-Mobility Measurements

	X1	X2	X3	X4	X5	X6	X7
X1	1.00						
X2	**0.97**	1.00					
X3	0.32	0.20	1.00				
X4	**0.88**	**0.87**	0.49	1.00			
X5	-0.83	-0.76	-0.48	**-0.89**	1.00		
X6	**0.97**	**1.00**	0.21	**0.88**	-0.77	1.00	
X7	**0.83**	**0.86**	0.33	**0.95**	-0.78	**0.87**	1.00

The results of multivariate statistics and F approximations for MMLR, shown in Table 4.4, indicate that all of the equations, taken together, are statistically significant. The F-ratios and p-values for four multivariate criteria are given, including Wilks' Lambda, Pillai's Trace, Hotelling-Lawley Trace, and Roy's Greatest Root (SAS, 2009). The tests for the overall model for our study indicate that the model is statistically significant, regardless of the type of multivariate criteria used.

Table 4.4 Multivariate Statistics and F Approximations

Multivariate Statistics and F Approximations					
S=7 M=-0.5 N=22					
Statistic	Value	F Value	Num DF	Den DF	Pr>F
Wilks' Lambda	0.00004365	30.23	49	237.96	<.0001
Pillai's Trace	3.15511872	6.10	49	364	<.0001
Hotelling-Lawley Trace	228.28867490	207.97	49	139.57	<.0001
Roy's Greatest Root	207.73050599	1543.14	7	52	<.0001
NOTE: F Statistic for Roy's Greatest Root is an upper bound.					

Table 4.5 summarizes the regression results for MMLR. The adjusted R square values, adopted to test how good the model fit to the sample data, show that all models are appropriate and good fits. The signs of the coefficients show if the mobility measurements have the positive or negative impact on the environmental factors. The t-values show if the coefficients of independent variables are statistically significant. The regression results and t-values demonstrate the following: (1) For Y1(CO_2), Y2(CO), Y3(NO_x), Y4 (PM_{10}), Y5($PM_{2.5}$) and Y7(*Fuel*), the coefficients of X2(*Total delay*) are significant at 1% level and the coefficients of X3(*Stops per vehicle*) are significant at 5% or 1% level; (2) While for SO_2, the dataset is more scattered, and other models may be needed to find a better-fitting curve (the adjusted R square value is relatively smaller); (3) Y3(NO_x), Y4 (PM_{10}) and Y5($PM_{2.5}$) show strongly relationships with not only X2 (*Total delay*), but also with the quadratic term $(X2)^2$, statistically showing that they are not just linearly related. Moreover, the negative signs of quadratic terms indicate that the Y-X2 linear slope is getting less positive as X2 increases; (4)Similarly, Y1(CO_2), Y2(CO), Y3(NO_x), Y4 (PM_{10}), Y5($PM_{2.5}$) and Y7(*Fuel*) show the significant relations with the quadratic term $(X3)^2$, with the Y-X3 linear slope getting less positive as X3 increases; (5) For X5(*Average speed*), only the coefficients for

model Y4 (PM_{10}) and Y5($PM_{2.5}$) are not significant at 5% level, and the sign of the coefficient for Y3 (NO_x) is different from the others, which needs detailed investigation (e.g., eco-driving study); (6)For the dummy variable (i.e., intersection type), the coefficients for model Y1(CO_2), Y2(*CO*), Y4 (PM_{10}), Y5($PM_{2.5}$), Y6(SO_2) and Y7(*Fuel*) are also significant at 5% level, which means these six environmental factors would be statistically different for different signalized intersection types. On the other hand, the coefficient of Type for nitrogen dioxide is not significant, meaning that the relationship between NO_x with mobility would be statistically similar for different signalized intersection types.

Table 4.5 Results of MMLR with Coefficients and t-values

	Environmental Factors						
	Y1 (CO_2)	Y2 (CO)	Y3 (NO_x)	Y4 (PM_{10})	Y5 ($PM_{2.5}$)	Y6 (SO_2)	Y7 (Fuel)
Adj. R^2	0.911	0.924	0.990	0.977	0.978	0.774	0.910
Constant	-1.737 (-1.17)	-14.004 (-1.35)	-11.417 (-2.57)[b]	-0.275 (-2.26)[b]	-0.282 (-2.41)[b]	-0.015 (-0.62)	-23.939 (-1.16)
X2 (*Total delay*)	0.321 (3.57)[a]	2.025 (3.23)[a]	4.061 (15.11)[a]	0.069 (9.34)[a]	0.064 (9.13)[a]	0.0008 (0.54)	4.410 (3.53)[a]
X2*X2	-0.014 (-1.17)	-0.080 (-0.94)	-0.113 (-3.10)[a]	-0.003 (-2.87)[a]	-0.002 (-2.48)[b]	0.00002 (0.09)	-0.198 (-1.17)
X3 (*Stops per vehicle*)	9.312 (2.18)[b]	77.163 (2.59)[b]	31.705 (2.49)[b]	1.091 (3.12)[a]	1.094 (3.25)[a]	0.116 (1.67)	128.768 (2.17)[b]
X3*X3	-7.388 (-2.32)[b]	-58.085 (-2.62)[b]	-24.050 (-2.53)[b]	-0.814 (-3.12)[a]	-0.808 (-3.22)[a]	-0.094 (-1.80)	-102.192 (-2.31)[b]
X5 *(Average speed)*	-0.021 (-2.60)[b]	-0.189 (-3.38)[a]	0.069 (2.87)[a]	-0.0008 (-1.22)	-0.0008 (-1.28)	-0.0005 (-3.59)[a]	-0.290 (-2.61)[b]
Type (*Intersection type*)	-0.236 (-4.60)[a]	-2.222 (-6.23)[a]	0.139 (0.91)	-0.014 (-3.45)[a]	-0.014 (-3.56)[a]	-0.004 (-5.18)[a]	-3.273 (-4.61)[a]

N-60; [a] Significant at1%; [b] Significant at 5%

4.2.4 Comparisons of Results from MOVES and SYNCHRO

The developed model was compared with the model used in present practice. Currently, VISSIM, TRANSYT, and SYNCHRO share the same fuel consumption formula, which is based on a linear combination of total travel, delay, and stops, as shown in Equation (4-5).

$$F = K_{i1} * TT + K_{i2} * D + K_{i3} * S \quad (4\text{-}5)$$

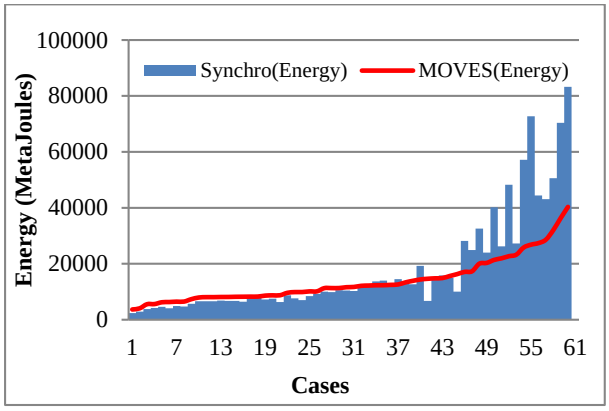
where, F = fuel consumed in gallons per hour; TT = total travel in vehicle miles (veh-mi) per hour; D = total delay in veh-h/h; S = total stops per hour; K_{i1}= 0.075-0.0016* V_i +0.000015* V_i^2; K_{i2}= 0.7329; K_{i3}= 0.0000061* V_i^2; V_i =cruise speed on each link i (mph). Note that gallons were converted to MetaJoules in the comparison (1 gallon automotive gasoline= 131.76 Metajoules).

It is worth pointing out the limitations of the current model. First, the model parameters were determined from studies conducted with only one test vehicle; second, no explicit consideration was given to factors such as traffic congestion, vehicle type mix (i.e., trucks and diesel engines), and geometric and environmental factors such as road gradient, curvature, surface quality, temperature and other factors; third, the model coefficients have not been adjusted for vehicle fleet mix since 1983 (Hale, 2008). In contrast, the proposed metamodel developed from the microscopic simulation database is based on various intersection types, traffic volume levels, vehicle types, driver behaviors, and detailed environmental factors.

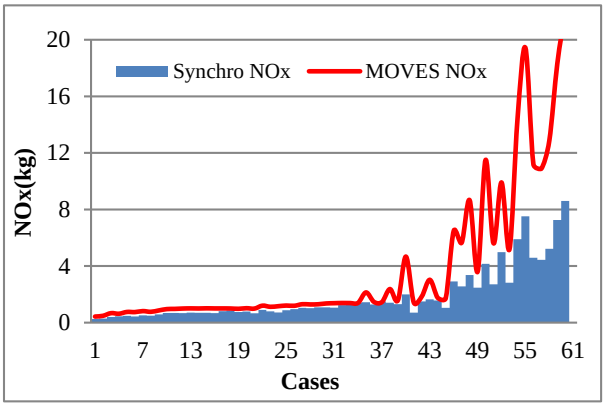
Currently, Synchro calculates only CO, NO_x, and VOCs emissions as the environmental performance measurements. When this study was conducted, at the MOVES project level, it could not model evaporative emission processes yet. It is indicated that such a capability will be added to future model upgrades (EPA, 2012). Thus, the comparison conducted in this study only look into energy consumption, CO, and NO_x emissions, as shown in Figure 4.3. Different from the scenarios' sequence in Table 1, the cases' sequence in Figure 4.3are re-ordered according to congestion conditions. Specifically, the 60 cases (sample size =60 for two intersections) are ranked based on low to high energy consumption estimated by MOVES.

From Figure 4.3 (a) and (c), it is clearly shown that SYNCHRO overestimates energy consumption and CO emission in most cases. For over-saturated scenarios, SYNCHRO significantly underestimates energy consumption and CO emission. From Figure 4.3 (b), for almost all scenarios, SYNCHRO significantly underestimates NO_x emission, which could be because SYNCHRO has no way of calculating the emission from the un-served vehicles. Figure 4.3 (d) also tells us that in most

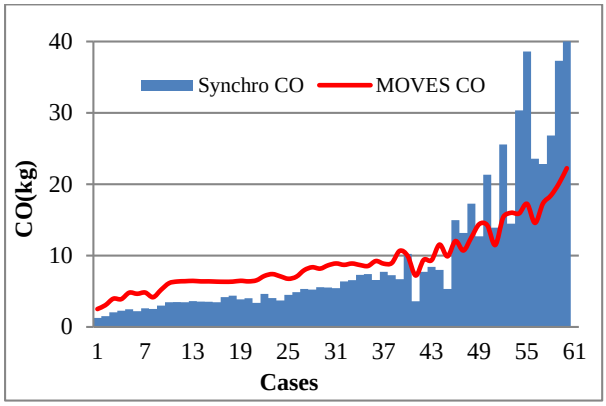
uncongested scenarios, the percentage difference of CO between two tools is the highest, and in over-saturated situations, the percentage difference of NO_x is the highest. Thus, it is recommended that the current signal optimization tool, SYNCHRO in this study, should improve its evaluation methods of environmental impacts from transport to get a more accurate analysis (e.g., benefit-cost analysis) in practical signal re-timing projects.



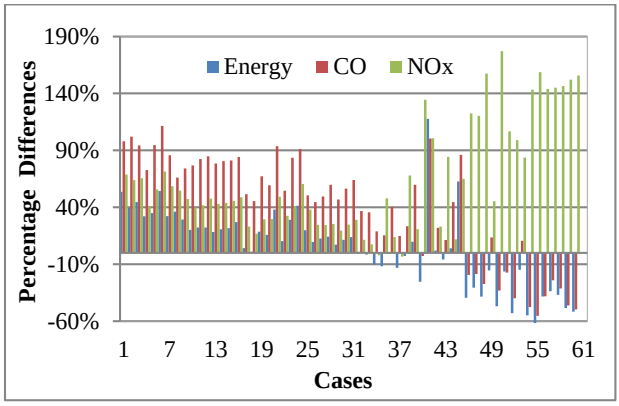
a) Comparison of energy from MOVES & SYNCHRO



b) Comparison of NO_x from MOVES & SYNCHRO



c) Comparison of CO from MOVES & SYNCHRO



d) % Diffs of results from MOVES over SYNCHRO

Figure 4.3 Comparisons of Energy, CO, and NOx from MOVES and SYNCHRO

4.3 Summary

Characterizing the relationship between environmental impacts from transport with mobility is critical for sustainable development. In this study, a framework was developed to determine how environmental externalities are related to mobility measurements during the same time period at signalized intersections. A metamodeling-based framework, involving experimental design, microscopic

simulation (i.e., a traffic signal optimization tool, a microscopic simulation model, and an instantaneous emission estimator), and multivariate regression analysis were developed to explore the environment-mobility relationship at signalized intersections. Given the microscopic simulation databases, MMLR analysis was conducted to approximate the environmental responses to the mobility measurements. The results showed good fits for multiple-responses. However, t-values, which indicate if the coefficients of independent variables are statistically significant, showed varied conclusions for different response variables (i.e., energy and emissions).

This chapter highlights the following findings: (1) the regression outcomes show that the mobility- SO_2 relationship is not clear; (2) the relationships for certain pollutants (e.g., NOx, PM_{10}, and $PM_{2.5}$) are not just linear; (2) carbon emissions, particular matters, sulfur dioxide and fuel show different distributions at various types of signalized intersections; (3) SYNCHRO overestimates energy consumption and CO emission in non-congested cases; (4) SYNCHRO underestimates energy consumption and CO emission in over-saturated cases; (5) For almost all scenarios, SYNCHRO significantly underestimates NOx emission. Thus, it's recommend to improve the current emissions module in the tool for more accurate analyses (e.g., benefit-cost analysis) in practical signal retiming projects. The findings of this chapter set up the base for extensive application of two-stage optimization (in next two chapters) for sustainable traffic operations and management.

CHAPTER 5: MULTI-CRITERIAL SIGNAL TIMING AT INTERSECTION LEVEL

To achieve a sustainable traffic signal control system, different optimization objectives (e.g., to minimize delay, stops, fuel consumption or emissions) will be formulated and examined to minimize the unsustainable impacts of the surface transportation system. This chapter extends the study about the relationship between mobility and environmental externalities at signalized intersection in several ways. Starting at the intersection level, based on the developed relationship between mobility and environment factors in chapter 4, the multi-criterial signal timing optimization problem is formulated with the objective function considering delays and emissions simultaneously (i.e., in terms of money value). Then a stochastic optimization engine-genetic algorithm method is implemented to find the optimal cycle length and effective green ratio for each approach group. Moreover, tradeoffs between different objectives are discussed, and optimal signal plans with respect not only to traffic mobility performance but also other important measures for sustainability are compared and evaluated. Based on the relationship study in the previous chapter, the surrogate model-based optimization in this chapter saves much time by relieving computational loads when compared to direct optimization.

5.1 Decision Variables for Signal Control Settings at Intersection Level

As mentioned earlier, the basic premise behind traffic signal control is to develop signal timing plans, essentially comprised of cycle lengths and phase splits at intersections and offsets between adjacent intersections to facilitate coordination that are best suited for expected traffic conditions for particular dates or times. For each individual signal, the decision variables (timing parameters of signal control settings) include cycle length (seconds), green time interval/splits for each movement group, phase sequences and others (e.g., the minimum green, green extension and maximum green for the minor phases in semi-actuated control). Usually, yellow/amber and red clearance times can be adopted from the manuals such as the Florida Department of Transportation (FDOT) Traffic Engineering Manual (FDOT,

2012), which are conditionally fixed with a given speed. When coordinated, the common cycle length and offsets for signalized intersections in a corridor are optimized variables (the details will be discussed in chapter 6).

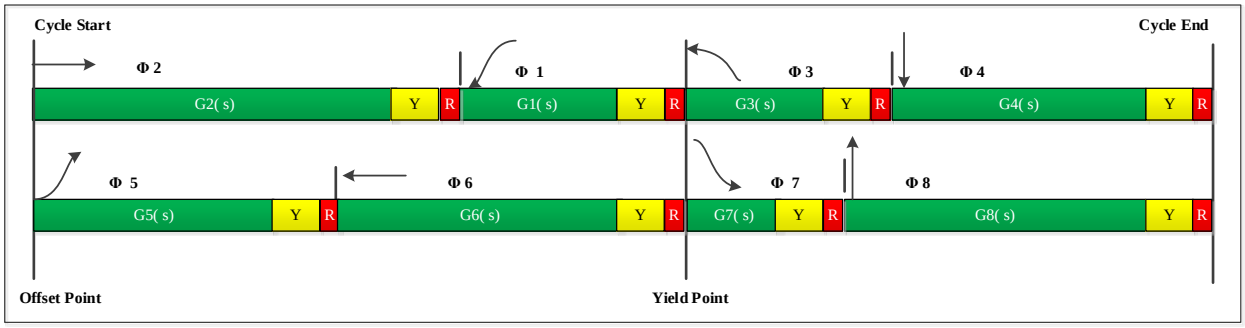


Figure 5.1 NEMA Phasing for a Four-way Signalized Intersection

Figure 5.1 shows an example of the signal timing for a four-way intersection under National Electrical Manufacturers Association (NEMA) phasing structure. Under the dual-ring control, the interval durations of the movements on the arterial (Phases 1, 2, 5, and 6) could be longer, while those for the movements in the minor streets (Phases 3, 4, 7, and 8) could be shorter. Presently, many traffic signals are still operated in fixed control modes while some in actuated modes or coordinated semi-actuated modes, where the split for each phase is at least partially controlled by detector actuations (Appendix B). However, for semi-actuated signals on an arterial, there are still many practices that consider only the phases of the pedestrian movements as the actuated (minor) movements. The interval durations of the major movements are set as deterministic values. Moreover, for the grid networks with short block spacing, particularly in downtown environments, traffic signals are frequently timed using fixed settings and no detection (FHWA, 2008). Thus, in this study, the signal control logic and strategy is based on the fixed time control at the intersection level. The decision variables in our optimization problem (chapter 5 and 6) include three important signal timing parameters: cycle length, effective green interval and offset.

(1) Cycle Length

The cycle length, one of the most important elements in signal timing, is the total time to complete one sequence of signal indications at an intersection. Many existing packages or tools do not

specify the criteria of choosing cycle length and this decision involves additional calculation and adjustment. Most widely used approximation for minimum delay cycle length is the Webster equation. The cycle length in Webster equation for minimum delay cycle lengths at an isolated pre-timed location is as follows:

$$C_o = \frac{1.5Lost + 5}{1.0 - \sum Y_i} \quad (5\text{-}1)$$

where C_o is the optimum cycle length in seconds; *L*ost is the lost time per cycle, generally the sum of the total yellow and all red clearance per cycle, in seconds; and Y_i is degree of saturation (volume divided by saturation flow) for phase *i*.

The equation above indicates that cycle length in the range of $0.75\,C_o$ to $1.5\,C_o$ do not significantly increase delay (MnDOT, 2013). This equation is for isolated pre-timed signal locations only and is usually used as the initial cycle length, especially in a coordinated system. A detailed network analysis is usually performed using a software package (e.g., TRANSYT-7F or PASSER) or computer model allowing for multiple iterations of varying cycle combinations to determine the optimum signal timing parameters. For example, in PASSER, the objective function of green bandwidth model is the ratio between total green bandwidth and cycle length while the range of the cycle length is user-specified. Too short cycle length will cause the capacity at large intersections to decrease since the yellow and red time are fixed and the smaller cycle will yield smaller green time. On the other side, too long cycle length would not be appropriate if the links presented in the corridor are short because a larger green time will yield longer queue and queue spillback may happen in peak hour.

Since coordinated signal system requires same cycle length for the whole corridor, it is much different than choosing cycle for isolated intersection. If there is large intersection, longer cycle length would help increasing the capacity. If there is short links within the corridor, shorter cycle length would help avoiding long queues. Through intensive simulation may help choosing an optimal cycle length for the whole corridor, but fluctuated traffic flow may still cause problem in peak hour. Another option to

balance the needs is allowing different cycle lengths in the same network by partitioning the large network into small zones or adding a half-cycle function for some intersections in the corridor (e.g., SYNCHRO).

(2) Green Time Interval and Effective Green

Green time interval is the segment of cycle length allocated for each phase to serve traffic with a green indication. The green percentage is less than total split for a phase because split percentages typically include the yellow and all-red associated with the phase. There are several commonly termed intervals: minimum green, maximum green, pedestrian clearance, yellow change and all red clearance. A green phase usually begins due to actuation or recall and has the following parts: minimum green/minimum initial, vehicle extension, clearance interval: all these should sum up to be equal to or less than the maximum allowable green time for a phase.

Effective green time is the time during which a given traffic movement or set of movements may proceed. It is equal to the cycle length minus the effective red time. The effective green time or green ratio will be determined by solving the optimization problem and minimum/maximum green can be used as the constraints in the optimization process.

The usable amount of green time, that is, the duration of time between the end of the start-up lost time (commonly assumed to be approximately 2 seconds) and the end of the yellow extension, is referred to as the effective green time for the movement. The unused portion of the yellow change interval and red clearance interval is called clearance lost time.

$$g = G + Y + R - (l_1 + l_2) \tag{5-2}$$

where g is the effective green time; G is the actual green interval; Y is the actual yellow change interval; R is the actual red clearance interval; l_1 is the start-up lost time, and l_2 is the clearance lost time (all values in seconds).

(3) Yellow Change Interval

To provide a safe transition between two conflicting traffic signal phases, yellow change interval is used to warn traffic of an impending change in the right-of-way assignment. In our study, the yellow change interval is taken from the FDOT Traffic Engineering Manual (FDOT, 2012) Section 3.6, as shown in the following table:

Table 5.1 Florida Yellow Change Interval Standards*

Speed (mph)	25	30	35	40	45	50	55	60	65
Yellow time (s)	3.4	3.7	4.0	4.4	4.8	5.1	5.5	5.9	6.0

* using ITE Formula with a perception-reaction time of 1.4 seconds and a grade of 0%.

(4) All-Red Clearance Interval

All-red clearance interval is the additional time following the yellow change interval to clear the intersection before conflicting traffic is released. Providing adequate red clearance intervals can significantly impact intersection safety by reducing the probability of occurrence of right angle crashes, even if drivers run the red signal indication. Engineering practices suggest that the minimum red clearance interval shall be 2.0 seconds and the maximum should normally not exceed 6.0 seconds (FDOT, 2012). The all-red clearance interval is typically computed using the formula (*from ITE's Traffic Engineering Handbook*) based upon approach speed and intersection geometry, as follows.

$$R = \frac{W + L}{1.47v} \tag{5-3}$$

where R is the length of red interval in second; W is the width of the intersection, in feet, measured from the near-side stop line to the far edge of the conflicting traffic lane along the actual vehicle path; L is the length of vehicle (with default value of 20 ft.); and v is the speed of approaching vehicles, in mph.

5.2 Optimization Model Formulation at Intersection Level

At intersection level, the objective of our optimization problem is to minimize the total costs (or maximize total benefits), in terms of dollar value by considering both mobility and environmental factors.

For a single objective function, an optimization problem can be formulated with its objective function (total cost) as a linear combination of total delay, total fuel consumption and the total emissions of five emissions at the intersection namely carbon dioxide (CO_2), carbon monoxide (CO), nitrogen oxides (NO_x), particulate matter(PM) and sulfur dioxide(SO_2), denoted as E^{CO_2}, E^{CO}, E^{NO_x}, E^{PM} and E^{SO_2} respectively, and given by:

$$Min \quad TC = w^T \times TD + w^{Fuel} \times Fuel(TD,TS) + \sum_j w^j \times EM_j(TD,TS) \tag{5-4}$$

subject to:

$$C_{min} \le C \le C_{max} \qquad \text{for lane group } i, \tag{5-5}$$

$$g_{min} \le g_i \le g_{max} \qquad \text{for lane group } i, \tag{5-6}$$

$$\sum i(g_i + l_i) = C \qquad \text{C-cycle length, } \boldsymbol{l_i}\text{-lost time} \tag{5-7}$$

where $TD = \sum_i d_i(g_i, C)$ represents the total delay function and $TS = \sum_i Stop_i(g_i, C)$ represents the total stops function of g_i and l_i. g_i and l_i represents effective green time and lost time, respectively. $w^j = \left\{w^{CO_2}, w^{CO}, w^{NO_x}, w^{PM}, w^{SO_2}\right\}$ are economic weighting parameters for five pollutants CO_2, CO, NO_x, PM, and SO_2, respectively. $EM_j = \left\{E^{CO_2}, E^{CO}, E^{NO_x}, E^{PM}, E^{SO_2}\right\}$ represents different types of emissions. This study adopts the delay calculation method in the Highway Capacity Manual (2010) that considers terms of both uniform delay and incremental delay, so $TD = \sum_i d_i(g_i, C)$ or $TS = \sum_i Stop_i(g_i, C)$ are also a function of only effective green time and the cycle length when the traffic condition (i.e., traffic volume and saturation flow) is given. For all critical movements during a cycle, the summation of their effective green time plus lost time is equal to the cycle length.

For multi-objective signal optimization, the objectives and their mathematical functions are shown in Table 5.2.

Table 5.2 Multi Objectives and their Mathematical Functions for Signal Timing

Objective		Fitness Function
Minimize Total Delay		$Min \quad TD = \sum_i d_i(g_i, C)$
Minimize Total Stop		$Min \quad TS = \sum_i Stop_i(g_i, C)$
Minimize Total Fuel Consumption		$Min \quad Fuel(TD, TS)$
Minimize Different Types of Emissions	CO_2	$Min \quad E^{CO_2}(TD, TS)$
	CO	$Min \quad E^{CO}(TD, TS)$
	NOx	$Min \quad E^{NO_x}(TD, TS)$
	PM(PM_{10} and $PM_{2.5}$)	$Min \quad E^{PM}(TD, TS)$
	SO_2	$Min \quad E^{SO_2}(TD, TS)$
Minimize Marginal Costs of Total Emissions		$Min \quad MTE = \sum_j w^j \times EM_j(TD, TS)$

(1) Control Delay and Percentile Delay at Signalized Intersections

Control delay is the portion of the total delay for a vehicle approaching and entering a signalized intersection that is attributable to traffic signal operations (Gartner & Deshpande, 2009). The HCM 2010, which is widely used for analyzing urban street performance, propounds that control delay at a signalized intersection be computed using the following Equations.

$$d_i = d_{i1}(PF_i) + d_{i2} + d_{i3} \tag{5-8}$$

$$d_{i1} = \frac{0.5C[1-(g_i/C)]^2}{1-(g_i/C)[min(X_i, 1.0)]} \tag{5-9}$$

$$d_{i2} = 900T[(X_i - 1) + \sqrt{(X_i - 1)^2 + \frac{8kIX_i}{c_i T}}] \tag{5-10}$$

$$d_{i3} = \frac{1800Q_{bi}(1+\mu)t}{QT} \tag{5-11}$$

where d_i is control delay for lane group i (sec/veh); d_{i1} is uniform delay for lane group i (sec/veh); d_{i2} is incremental delay for lane group i (sec/veh); d_{i3} is initial queue for lane group i (sec/veh) (defined in HCM Appendix 9-VI, *not considered*); PF_i is progression factor, the uniform delay adjustment for quality of progression for lane group i; C is cycle length (sec); g_i is effective green time

for lane group i (sec); $\lambda_i = g_i/C$ is effective green ratio for lane group i; $\beta_i = v_i/s_i$ is flow ratio for lane group i; c_i is capacity of lane group i (veh/hr), calculated from saturation flow rate, effective green time, & cycle length ($c_i = s_i(g_i/C) = s_i\lambda_i$); s_i is saturation flow rate for lane group i (veh/hr); X_i is degree of saturation for lane group i, also known as the $(v/c)_i$ ratio for lane group with v_i representing demand flow rate for lane group i (veh/hr) $X_i = (v/c)_i = v_i/(s_i\lambda_i) = \beta_i/\lambda_i$; T is duration of the analysis period (hr); k is incremental delay adjustment for actuated control (o.5 for pre-timed signals); I is incremental delay adjustment for filtering and metering by upstream signals (1 for isolated intersection); Q_{bi} is the initial queue at the start of period T (veh); t is the duration of unmet demand in T (h); and μ is the delay parameter.The simplified equation for unsaturated condition is (a constrained non-linear optimization problem):

$$d_i = \frac{C(1-\lambda_i)^2}{2(1-\beta_i)} + 900\,\mathrm{T}[(\frac{\beta_i}{\lambda_i} - 1) + \sqrt{(\frac{\beta_i}{\lambda_i} - 1)^2 + \frac{4v_i}{\lambda_i^2 s_i^2 T}}\ ) \qquad (5\text{-}12)$$

There are three major approaches to the problems of optimization under uncertainty: stochastic optimization, robust optimization, and simulation-based optimization (Rockafellar, 2001). To account for demand uncertainty to some extent, the stochastic programming approach (i.e., the percentile delay) is employed by assuming that the traffic demand follows a certain stochastic distribution (e.g., a Poisson distribution). Similar to Synchro, traffic flow is modelled under five percentile scenarios, the 90th, 70th, 50th, 30th, and 10th percentile scenarios. The simplified formula to determine the adjusted volumes is:

$$V_P = V + [Z * \sqrt{V * C / 3600}] * \frac{3600}{C} \qquad (5\text{-}13)$$

where V_P is traffic volume for percentile P; C is cycle length (s); Z is the number of standard deviations needed to reach a percentile from the mean. Z equals to -1.28, -0.52, 0, 0.52 and 1.28 for percentile 10, 30, 50, 70 and 90, respectively. The average percentile delay is the weighted sum of the total delay across all demand percentiles.

(2) Stops Calculation at Signalized Intersections

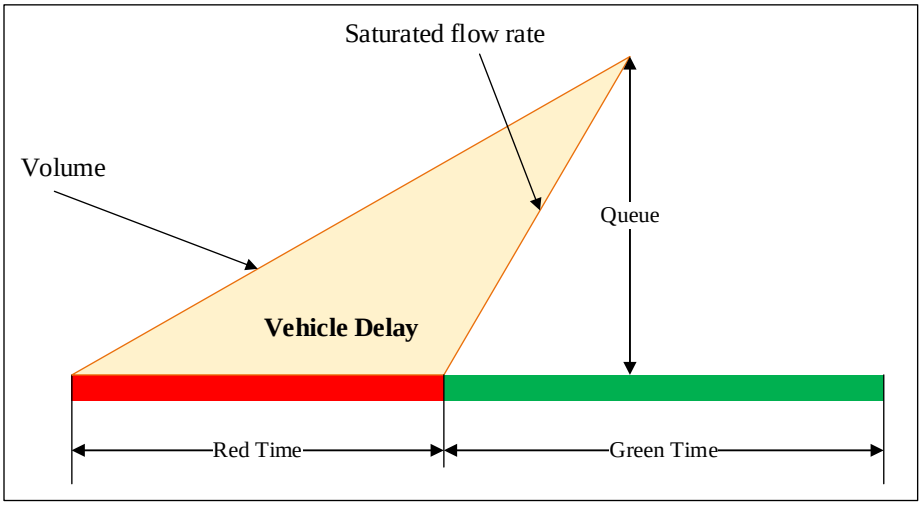


Figure 5.2 Arrival Departure Graph

Stops are calculated similarly to the calculation of delays. Considering the arrival departure graph in Figure 5.2, the total number of vehicles being delayed is equal to the number of vehicles queued (the number of vehicles that leave the stop line) designated as Queue in the arrival-departure diagram. However, vehicles being delayed for less than 10 seconds do not make a full stop. Thus, the numbers of stopped vehicles are calculated by accounting the number of delayed vehicles for each delay time and adjusting these vehicles as shown in Table 5.3, which is taken from the TRANSYT 7-F User's Manual. The same adjustment is made for partial stops used by TRANSYT and SYNCHRO.

Table 5.3 Stop Adjustment

Vehicle Delay(s)	0	1	2	3	4	5	6	7	8	9
Percent of Stop	0%	20%	58%	67%	77%	84%	91%	94%	97%	99%

These stops are calculated for each percentile scenario and averaged for cycle failures and over capacity vehicles. The stop calculations model 100 cycles similar to the delay calculations, to calculate stops for congestion. (If traffic is observed for 100 cycles, the 90^{th} percentile would have 90 cycles with less volume (10 with the same or more), the 10^{th} percentile would have 10 cycles with less volume (90 with the same or more), and the 50^{th} percentile would represent average traffic conditions.

(3) Emission Equation at Signalized Intersections

The emission equation (representing total emission) is the function with respect to total control delay and total stops based on the relationship study in chapter 4, as shown in the following equation:

$$\begin{cases} E^{CO_2} = \beta_{01} + \beta_{11}(TD) + \beta_{21}(TD)^2 + \beta_{31}(TS) + \beta_{41}(TS)^2 + \varepsilon_1 \\ E^{CO} = \beta_{02} + \beta_{12}(TD) + \beta_{22}(TD)^2 + \beta_{32}(TS) + \beta_{42}(TS)^2 + \varepsilon_2 \\ E^{NO_x} = \beta_{03} + \beta_{13}(TD) + \beta_{23}(TD)^2 + \beta_{33}(TS) + \beta_{43}(TS)^2 + \varepsilon_3 \\ E^{PM} = \beta_{04} + \beta_{14}(TD) + \beta_{24}(TD)^2 + \beta_{34}(TS) + \beta_{44}(TS)^2 + \varepsilon_4 \\ E^{SO_2} = \beta_{05} + \beta_{15}(TD) + \beta_{25}(TD)^2 + \beta_{35}(TS) + \beta_{45}(TS)^2 + \varepsilon_5 \end{cases} \quad (5\text{-}14)$$

where E^{CO_2}, E^{CO}, E^{NO_x}, E^{PM} and E^{SO_2} represent the total emissions of five pollutants at the intersection, namely carbon dioxide (CO_2), carbon monoxide (CO), nitrogen oxides (NO_x), particulate matter (PM) and sulfur dioxide (SO_2), respectively; TD is the Total delay at the intersection; TS is the Total number of stops at the intersection.

(4) The Economic Weighting Parameters

To consider the delay, fuel, and emissions together in a single objective function (i.e., in terms of dollar value), the economic weighting parameters (i.e., the value) for time, fuel and different types of emissions are used. The value of time/delay is adopted from the Texas A&M Transportation Institute (TTI) mobility report (Schrank et al., 2012). In the 2012 TTI Urban Mobility Report, the value of travel time delay was estimated at $16.79 per hour of person travel and $88.81 per hour of truck time, while excess fuel consumption was estimated using state average cost per gallon for gasoline and diesel (Schrank et al., 2012). Similarly, the state average cost per gallon for fuel was adopted in this dissertation study. The emissions were monetized using the marginal damage costs (MDCs) based on Yu's study (Yu et al., 2013), where an extensive literature review was performed to harvest a large sample for a more reliable MDC estimation. MDC is the cost of emitting an additional unit of air pollutant that the general public needs to pay to offset the effects on environment (Guo et al., 2014c). The value of time and MDCs for environmental factors used in this study as economic weighting parameters are summarized in Table 5.4. In the future, when more MDCs data are readily available for each county in the U. S. for criteria

pollutants, given the location of each arterial street, more detailed estimation can be performed (Guo et al., 2014c).

Table 5.4 Economic Weighting Parameters for Time, Fuel and Different Pollutants

	The economic weighting parameters						
Type	**CO_2**	**CO**	**NO_x**	**PM**	**SO_2**	**Time**	**Fuel**
Unit	$/kg	$/kg	$/kg	$/kg	$/kg	$/hr	$/gallon
Value	0.05	0.354	5.511	7.851	9.695	16.79	3.2

5.3 Global Optimization—Genetic Algorithm

The above objective function is a constrained non-linear optimization problem that is difficult to work out with a closed-form function by applying conventional algorithms/solvers such as the sequential quadratic programming method. Initially, we tried to solve this problem with the MATLAB routine, *fmincon* function (local optimization solver), for constrained nonlinear problems, but failed to find the global solution. As suggested by previous studies (Goldberg, 1989; Kesur, 2009; Zhang et al., 2013; Ma et al., 2014), such signal optimization problems can be solved via meta-heuristics, using a mostly genetic algorithm (GA), which is an appealing global optimization method rooted in the mechanisms of natural selection and evolutionary theory (Goldberg, 1989). The GA encodes a potential solution for a specific problem into simple chromosome-like data structures and applies recombination operators to the structures so as to preserve critical information. Due to the complexity of the objective function in this study, GA is adopted to search for better solutions (global solutions) by manipulating a population of potential solutions with the implementation of a “survival of the fittest” concept. Thus, to solve our multi-objective nonlinear traffic signal optimization problem, global optimization algorithm— GA is used in MATLAB.

(1) Objective function

The objective or evaluation function of a signal timing problem at the intersection level is the total marginal damage cost of the study scope (e.g., intersection level). The total costs include the costs

for delay, fuel and different types of emissions as illustrated in section 5.2. In a GA, a population of candidate solutions (i.e., individuals) for signal timing is evolved toward better solutions. For each generation, the objective/evaluation function is applied to each solution/individual so as to determine its priority to breed the next generation (i.e., the successive population). Each candidate solution or individual has a set of decision variables (i.e., green time for each group movement and cycle length) and each decision variable has its own search domain (i.e., constraints) as shown in section 5.2.

(2) Genetic Operators

There are four genetic operators in GA: (a) selection; (b) reproduction; (c) crossover; and (d) mutation. The selection operator specifies how the GA choose parents for the next generation (e.g., stochastic uniform selection, roulette selection and tournament selection) (MathWorks, 2014). The reproduction operator specifies how the GA creates children for the next generation without any alterations (e.g., Elite count specifies the number of individuals that are guaranteed to survive to the next generation and a Crossover fraction specifies the fraction of the next generation, other than elite children, that are produced by Crossover). The crossover operator creates children (new individuals) by combining information from the selected parents for the next generation by using functions such as scattered, single point, two-point, arithmetic etc. The mutation operator is used to introduce new information into the population and avoid the premature convergence of a GA (by searching a broader space), where small random changes can be made in the individuals to create mutation children.

(3) Procedure/Flowchart of GA

The GA is essentially an iterative process, which is repeated until a termination condition has been reached. The terminating conditions (stopping criteria) include: (a) Maximum generation: Reach the max generation; (b) Convergence criteria: Reach a plateau where successive iterations no longer produce better results; (c) Time limit: Reach the maximum time the GA runs before stopping; and (d) Stall generations: The average relative changes in the best value over stall generations is less than or equal to function tolerance.

As shown in Figure 5.3, GA uses the following steps to find the optimal solution: (a) randomly create an initial population of *M* individuals that represent potential solutions to the objective function for signal timings; (b) evaluate the fitness of each individual in the current population; (c) select the parent(s) that will be used to produce offspring/children; (d) produce offspring by reproduction, crossover or mutation until the predetermined population size *M* has been reached; (e) replace the *M* old individuals by new generated *M* individuals; (f) repeat steps b-e until the terminating condition (stopping criteria) has been reached; (g) designate the parameters/chromosomes with the best objective value based on the results of the optimization problem.

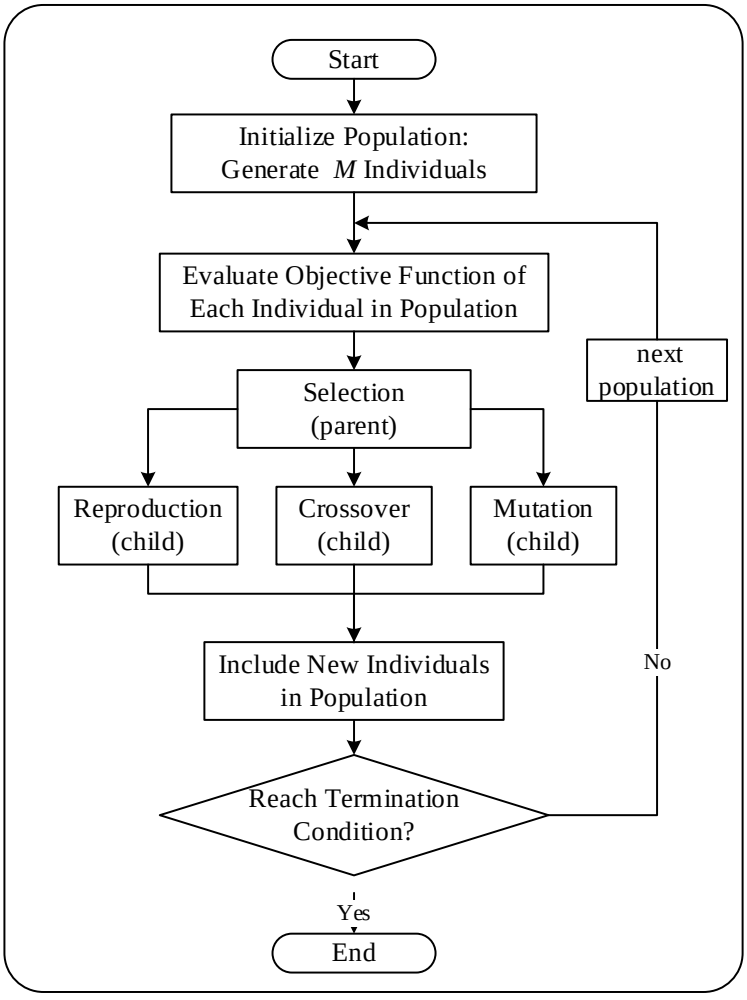


Figure 5.3 Flowchart of Genetic Algorithm

(4) Other Settings for Global Optimal

Ideally, the goal of our optimization is to find the global minimum—a point where the objective value is smaller at any other point in the search space. However, optimization algorithms sometimes return a local minimum—a point where the objective value is smaller than at nearby points, but possibly greater than at a distant point in the search space. The GA can sometimes overcome this deficiency with the right settings. One way to make the GA explore a wider range of points, that is, to increase the diversity of the populations, is to increase the initial range. As demonstrated by Srinivas and Patnaik (1994), values of crossover probability and mutation probability play significant roles on search space in terms of global searching. Usually, the higher the mutation probability is, the bigger the area covered by the search space. Moreover, an effective way to improve the values of the objective function is to include a hybrid function such as *fmincon*, which runs after the GA terminates by using the final point from the GA as its initial point.

5.4 Illustrative Example and Results

In this subsection, a case study is conducted to demonstrate the application of the proposed method. The arterial in our case study, the Bloomingdale Avenue corridor, consists of 14 traffic signals over a length of 5.8 miles. It is a four-lane, divided roadway located in Hillsborough County, Florida. The Average Daily Traffic (ADT) volumes for weekday travel ranged from 29,100 vehicles per day (vpd) (east end) to 42,600 vpd (west end). The illustrative intersections in traffic simulation models are developed based on one type of intersection (2*1) along the studied corridor. The same procedures can be conducted for other intersections.

5.4.1 Macroscopic Relationships between Emissions and Mobility

Chapter 4 explores the macroscopic relationships between emissions and mobility via micro-simulation. First, to assess the impact of various levels of traffic demand, 30 scenarios for each type of intersection were designed for traffic simulation and emission estimation with consideration of exclusive/shared left/right lanes and different percentages of turning movements (Table 4.1). Second, the

traffic signal optimization tool (e.g., SYNCHRO or TRANSYT-7F) was used to develop mobility-based signal timings for different levels of traffic volume. Third, with the signal timing and basic inputs (geometry and traffic), traffic micro-simulation software (e.g., VISSIM) was applied to generate the detailed information needed for MOVES (e.g., vehicle speed, acceleration, and location, within the network on a second by second basis). Fourthly, based on the detailed vehicle trajectory information and some default data in the MOVES model, the project level emissions are were quantified for signalized intersections. Finally, given the mobility and emission measurements, econometrics tools (e.g., MMLR analysis) were used to unveil the relationship between environmental externalities and mobility measurements.

Table 5.5 Results of MMLR with Coefficients and t-values (Original Data)

Mobility vs. Environmental Factors	Y1 (CO_2) (ton)	Y2 (CO) (kg)	Y3 (NO_x) (kg)	Y4 (PM_{10}) (kg)	Y5 ($PM_{2.5}$) (kg)	Y6 (SO_2) (kg)	Y7 (Fuel) (Gigajoule)
Adj. R^2	0.901	0.909	0.988	0.977	0.978	0.725	0.900
Constant	-3.422	-29.300	-5.854	-0.339	-0.348	-0.0530	-47.403
X2 (*Total delay*) (10^2h)	0.516	3.788	3.420	0.076	0.0722	0.00517	7.115
X2*X2	-0.0368	-0.284	-0.039	-0.00374	-0.00326	-0.000487	-0.511
X3 (*Stops per vehicle*)	12.605	107.050	20.836	1.217	1.222	0.190	174.615
X3*X3	-9.525	-77.478	-16.997	-0.896	-0.891	-0.142	-131.941
Type (*Intersection type*)	-0.180	-1.721	-0.044	-0.0123	-0.0122	-0.00307	-2.504
							N-60

Table 5.5 shows the regression results of different types of total emissions as a function of total control delay and total stops at the intersection level for the case study. Similar to the results in chapter 4, the regression models are polynomial in the quadratic models of the form. The difference is that the scaled original data were used in this chapter while the standardized data were used in chapter 4. The magnitude of the regression coefficients depends upon the scales of measurement used for the dependent variables and the explanatory variables. For purpose of meaningful comparisons of regression coefficients, the units of measurements and variances of the explanatory variables should be scaled or standardized.

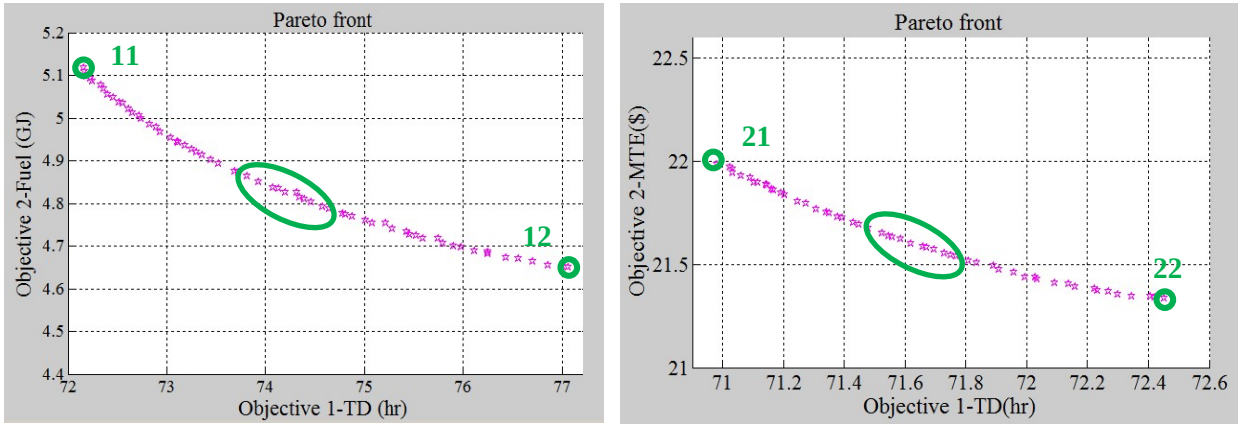
An important challenge in the implementation of this step is the computational requirements since multi-runs of microscopic traffic simulation (e.g., VISSIM) and instantaneous emission estimation (e.g., MOVES) are both computationally expensive. Multi-runs of microscopic simulation with different random seeds (e.g., 10 runs for each scenario in our study) are used to make statistically reliable evaluation of all scenarios. To achieve a compromise between computational cost and statistical requirement, the integrated method proposed in this study accelerates the simulation process by directly calling VISSIM simulator interfaces for multi-runs and introducing the parallel computing so that multiple simulation runs can be carried out simultaneously. Similarly, codes are developed to automatically call MOVES for emission estimation with automatic modifications of user-defined inputs (e.g., vehicle trajectories), which greatly reduce the repeating interactions between human and computers.

5.4.2 Pareto Frontier for Multi-Objective Optimization Problem

Traffic signal timing design is generally known as an optimization problem with several objectives (e.g., delay, stops and progression), which are traded in some way. The relative importance of these objectives is not generally known until the system's best capabilities are determined and tradeoffs between the objectives are fully understood. Technically, a general goal in multi-objective optimization is to construct the Pareto frontier, also known Pareto optima or noninferior solution (MathWorks, 2014).

As the number of objectives increase, tradeoffs tend to become more complex and less easily quantified. In this subsection, only three pairs of objectives (total delay vs. total stops, total delay vs. fuel consumption and total delay vs. marginal costs of emissions) are examined to illustrate the key components of the problem. To solve the bi-objective optimization model, the *gamultiobj* solver in MATLAB was applied to create a Pareto frontier for three pairs of objectives. The *gamultiobj* solver uses the genetic algorithm for finding the local Pareto frontier. For example, the resulting Pareto frontiers for TD vs. Fuel and TD vs. MTE are shown in Figure 5.4, where one point represents a particular signal timing plan. For example, point 11 (corresponding to signal timing plan 11) minimizes the total fuel consumption and point 12 (corresponding to signal timing plan 12) minimizes the total vehicle delay at

intersection level. Figure 5.4 (a) shows that the total fuel consumption resulting from these signal timing plans (points) varies from 5.12 to 4.65 Giga-gallon. Contrastively, the total vehicle delay changes from 72.1 to 77.1 vehicle-hours. Figure 5.4 (b) shows that the marginal cost of total emissions (i.e., MTE) resulting from these signal timing plans (points) varies from $22 to $21.4 and the total vehicle delay changes from 70.9 to 72.48 vehicle-hours. The frontier presents the tradeoff between mobility/congestion and environment (fuel consumption and emissions), allowing decision makers to understand the problem before committing to a final decision on a preferred signal timing plan.



(a) TD vs. Fuel (b) TD vs. MTE

Figure 5.4 Pareto Frontier from the GA -based Algorithm

5.4.3 Optimizing Different Performance Measures at Intersection Level

As mentioned in section 5.3, appropriate GA settings (e.g., initial points and settings in selection, crossover and mutation) could lead to improved optimization performance. In our case study, different combinations/sets of commonly used GA operators were evaluated for best convergence performance during the experiments. The final operator settings, using tournament selection, two point crossover, and adaptive feasible mutation, showed the most efficient combination. In the settings of stopping criteria, 300 generations, 100 stall generations and 1.000e-08 function tolerance were used since they showed the best results. In summary, the GA setting options in Table 5.6 (e.g., operators and corresponding parameters) were used for global optimization. Note that there are slightly different settings for different objectives in the optimization process (e.g. generations and stall generations).

Table 5.6 Parameter Setting Options for GA

Options		Setting	Options		Setting
Population	Population type	Double Vector	**Selection**	Selection Function	Tournament
	Population size	200		Tournament pool size	4
Stopping criteria	Generations	200~400	**Reproduction**	Elite Count	10
	Time limit	Inf		Crossover Fraction	0.8
	Fitness limit	-Inf	**Crossover**	Crossover Function	Two point
	Stall generations	100	**Mutation**	Mutation Function	Adaptive feasible
	Stall time limit	Inf	**Hybrid**	Hybrid Function	*fincon*
	Stall test	average change	**Fitness scaling**	Scaling function	Rank
	Function tolerance	1.000e-08	**Migration**	Direction	Forward/Both
	Constraint tolerance	1.000e-06	**Algorithm settings**	Penalty	Default

Experiments were carried out to find the optimal signal timing parameters (green ratio and cycle length) in terms of different objectives (e.g., delays, stops and emissions) by using GA. The abbreviations of the performance metrics are explained in Table 5.7. Since the speed limits are 45 mph for major roads and 30 mph for minor streets, the yellow change intervals correspond to 4.8s and 4.0s for major and minor roads, respectively (Table 5.1). All red clearance intervals are 2.0 s for all lane groups. Considering the used yellow extension (around half) for effective green time, the lost time (i.e., the unused portion of the yellow change interval and red clearance interval) for each ring is set as 16s. Similar to SYNCHRO, the delay and stops in this example adopt the percentile delay and percentile stops.

Table 5.7 Abbreviations of the Performance Metrics

Abbr.	**TD**	**TS**	**Fuel**	**CO2**	**CO**	**NOx**	**PM_{10}**	**$PM_{2.5}$**	**SO_2**	**MTE**	**TC**
Full Name	Total Delay	Total Stops	Total Fuel	Total CO_2	Total CO	Total NO_x	Total PM_{10}	Total $PM_{2.5}$	Total SO_2	Marginal Cost of Total Emissions	Total Costs
Unit	(hr)	(#)	(Giga joule)	(ton)	(kg)	(kg)	(kg)	(kg)	(kg)	($)	($)

When total delay was set as the objective or policy goal, the cycle length of 150s indicated the best performance (i.e., least total delay), as shown in Table 5.8. For the purpose of comparison, the optimal parameters were also applied to evaluate other measurements of effectiveness (MOEs) such as stops and emissions. The results clearly show that the least total delay does not mean the least emissions or stops. In contrast, the cycle length of 180s demonstrated the best results in terms of total number of stops. The cycle length of 120s showed the best results for fuel consumption, different types of emissions as well as marginal cost of total emissions (i.e., MTE). Nevertheless, for the total cost of Equation (5-4), it showed the consistent result with total delay as the economic weighting parameter for excessive travel time (i.e., delay) is larger than the parameters for fuel or emissions.

Table 5.8 Results of Minimizing Total Delay (TD)

Cycle length (s)		110	120	130	140	150	160	170	180
Obj.	TD(hr)	77.21	71.50	68.83	67.64	**67.39**	67.79	68.61	69.71
MOEs	TS(#)	3839	3831	3673	3671	3668	3665	3661	**3658**
	Fuel(GJ)	4.5893	4.3571	6.4990	6.4516	6.4694	6.5304	6.6436	6.7586
	CO_2(ton)	0.3335	0.3165	0.4711	0.4676	0.4690	0.4735	0.4816	0.4900
	CO(kg)	4.8185	4.6936	5.7914	5.7649	5.7745	5.8065	5.8645	5.9251
	NOx(kg)	1.5539	1.3819	1.6526	1.6168	1.6142	1.6332	1.6703	1.7146
	PM_{10}(kg)	0.0685	0.0653	0.0780	0.0773	0.0774	0.0779	0.0788	0.0799
	$PM_{2.5}$(kg)	0.0658	0.0627	0.0749	0.0743	0.0743	0.0748	0.0757	0.0767
	SO_2(kg)	0.0026	0.0025	0.0048	0.0047	0.0048	0.0048	0.0049	0.0050
	MTE($)	28.02	26.13	35.96	35.57	35.62	35.97	36.62	37.32
	TC($)	1401.51	1300.71	1320.66	1299.67	1296.19	1304.44	1321.33	1342.83

Figure 5.5 illustrates the GA results for each generation in TD optimization with a cycle length of 150s, where the blue dot shows the mean function value of TD among all individuals at corresponding generation and black dot represents the function value of the best-fitted individual. After 120 generations, the best effective green times for each phase (22.2s, 79.4s, 8.6s, 23.8s, 11.7s, 89.9s, 14.6s and 17.8s) were obtained with the least total delay of 67.39 hours at the intersection level.

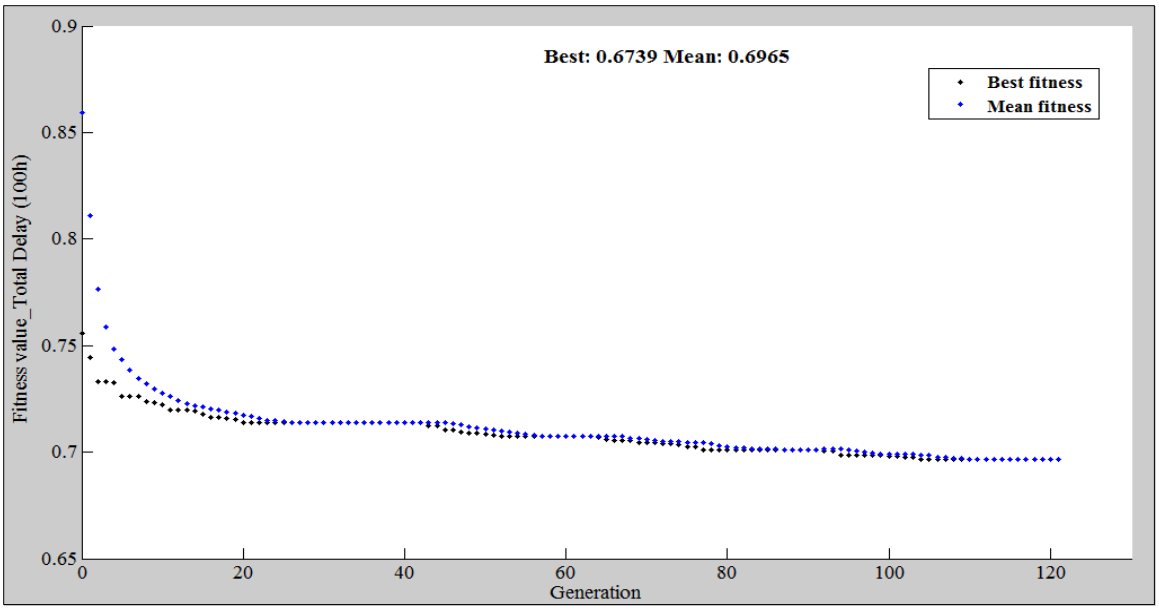


Figure 5.5 GA Results for Each Generation in TD Optimization (Cycle length=150s)

When total number of stops was set as the objective or policy goal, the cycle length of 180s indicated the smallest value of total number of stops, as shown in Table 5.9. For the purpose of comparison, the optimal parameters were also applied to evaluate other MOEs such as delay and emissions. The results clearly show that the least total number of stops does not lead to the least emissions or delays, that is, minimizing total delay and total stops show different results. For our case study, the cycle length of 110s~130s showed the better results in terms of different types of emissions as well as MTE. In terms of total delay and total cost, the cycle lengths of 130s and 150s demonstrated the better results. Previous studies have shown that solutions by minimizing total number of stops may result in more traffic congestions (Sun eta l., 2003; Ma et al., 2014). Actually, when there is more congestion in traffic, number of stops may be reported less in a time interval since vehicle drives less and hence stops less frequently. Since the minimization of total stop number may lead to deterioration in travel delay measure, there is a tradeoff between minimizing delays and stops. Thus, total number of stops might not be an effective objective concerning the ability to improve traffic conditions.

Table 5.9 Results of Minimizing Total Number of Stops (TS)

Cycle length (s)		110	120	130	140	150	160	170	**180**
Obj.	TS(#)	3807	3790	3740	3773	3684	3713	3594	**3551**
MOEs	TD(hr)	84.06	78.82	73.51	77.08	73.92	75.64	79.76	82.80
	Fuel (GJ)	5.5648	6.1045	6.0445	6.6086	5.4554	6.0628	6.2230	6.4467
	CO_2(ton)	0.4017	0.3967	0.4253	0.4064	0.4842	0.4625	0.5947	0.6456
	CO(kg)	5.3123	5.2732	5.4729	5.3411	5.8899	5.7388	6.6696	7.0256
	NOx(kg)	1.8628	1.7272	1.6631	1.7068	1.8009	1.7941	2.1817	2.3670
	PM_{10}(kg)	0.0766	0.0746	0.0754	0.0749	0.0807	0.0793	0.0920	0.0973
	$PM_{2.5}$(kg)	0.0735	0.0716	0.0724	0.0719	0.0775	0.0762	0.0883	0.0934
	SO_2(kg)	0.00343	0.00347	0.00400	0.00365	0.00485	0.00450	0.00617	0.00697
	MTE($)	33.44	32.40	33.57	32.80	37.51	36.31	45.60	49.38
	TC($)	1403.61	1317.10	1231.81	1289.20	1242.44	1269.24	1345.60	1399.07

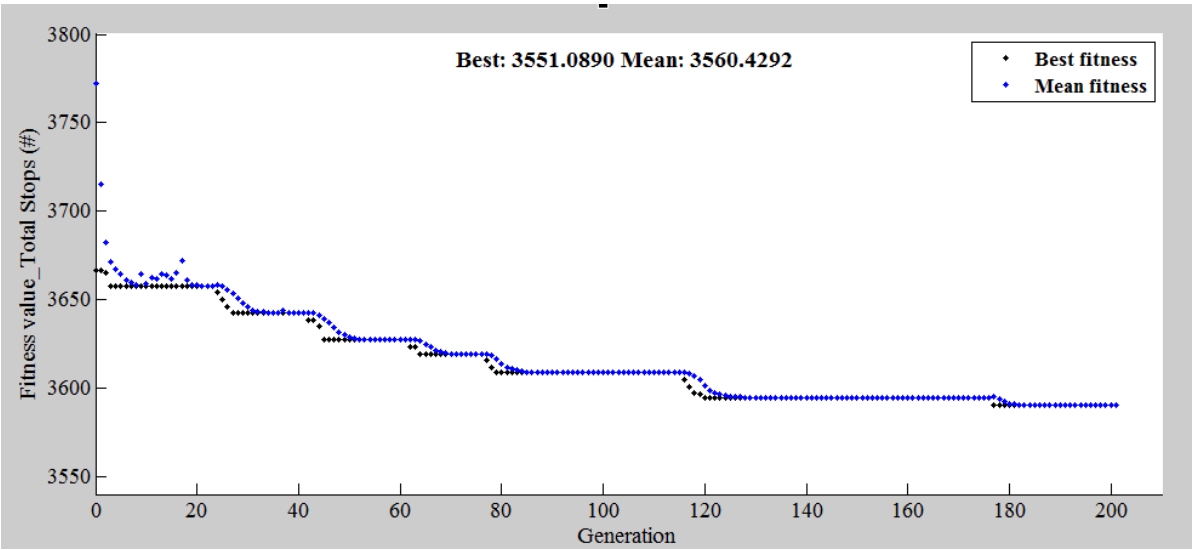


Figure 5.6 GA Results for Each Generation in TS Optimization (Cycle length=180s)

Figure 5.6 illustrates the GA results for each generation in TS optimization with a cycle length of 180s, where the blue dot shows the mean function value of TS among all individuals at corresponding generation and black dot represents the function value of the best-fitted individual. After 200 generations, the best effective green times for each phase (19.4s, 108.1s, 9.4s, 27.1s, 13.3s, 114.2s, 14.1s and 22.4s) were obtained with the least total stops of 3551 at the intersection level.

When total fuel consumption was considered as the objective function, a very similar trend and result can be found by minimizing total CO_2 or CO emissions. It can be explained by the fact that the total fuel consumption and total CO_2 emissions are highly related, as illustrated in chapter 4. To avoid the repeated findings, the results for minimizing fuel consumption are not shown here.

The environmental-oriented criteria were adopted by minimizing total emission costs (weighted values for different types of emissions). When marginal cost of total emissions (i.e., MTE) was set as the objective or policy goal, the cycle length of 150s indicated the smallest value, as shown in Table 5.10. For the purpose of comparison, the optimal parameters were also applied to evaluate other MOEs such as delay and stops. The results show that the least MTE leads to the best results in terms of delay, fuel consumption and different types of emissions in our case study (except the total number of stops). In terms of total number of stops, the best result does not show significant difference when comparing to others.

Table 5.10 Results of Minimizing Marginal Cost of Total Emissions (MTE)

Cycle length (s)		110	120	130	140	150	160	170	180
Obj.	MTE($)	24.96	22.78	21.77	21.15	**21.13**	21.93	21.84	22.44
MOEs	TD(hr)	82.51	77.85	75.92	75.56	76.17	78.27	79.11	81.31
	TS(#)	3908	3910	3912	3918	3921	3923	3928	3933
	Fuel (GJ)	3.7913	3.4661	3.3105	3.1894	3.1679	3.2755	3.2329	3.2936
	CO_2(ton)	0.2759	0.2523	0.2410	0.2323	0.2307	0.2386	0.2355	0.2400
	CO(kg)	4.4043	4.2323	4.1501	4.0865	4.0754	4.1325	4.1104	4.1429
	NOx(kg)	1.5589	1.3975	1.3276	1.3005	1.3118	1.3785	1.3922	1.4543
	PM_{10}(kg)	0.06508	0.06162	0.06005	0.05917	0.05922	0.06053	0.06051	0.06156
	$PM_{2.5}$(kg)	0.06237	0.05905	0.05755	0.05670	0.05674	0.05800	0.05797	0.05896
	SO_2(kg)	0.00164	0.00141	0.00128	0.00117	0.00113	0.00120	0.00113	0.00115
	TC($)	1464.90	1378.54	1342.23	1332.66	1342.02	1379.73	1392.27	1430.24

Figure 5.7 illustrates the GA results for each generation in MTE optimization with a cycle length of 150s, where the blue dot shows the mean function value of MTE among all individuals at

corresponding generation and black dot represents the function value of the best-fitted individual. After 200 generations, the best effective green times for each phase (47.2s, 53.8s, 7.8s, 25.1s, 12.4s, 88.6s, 14.9s and 18.0s) were obtained with the least total emission cost of $21.13 at the intersection level.

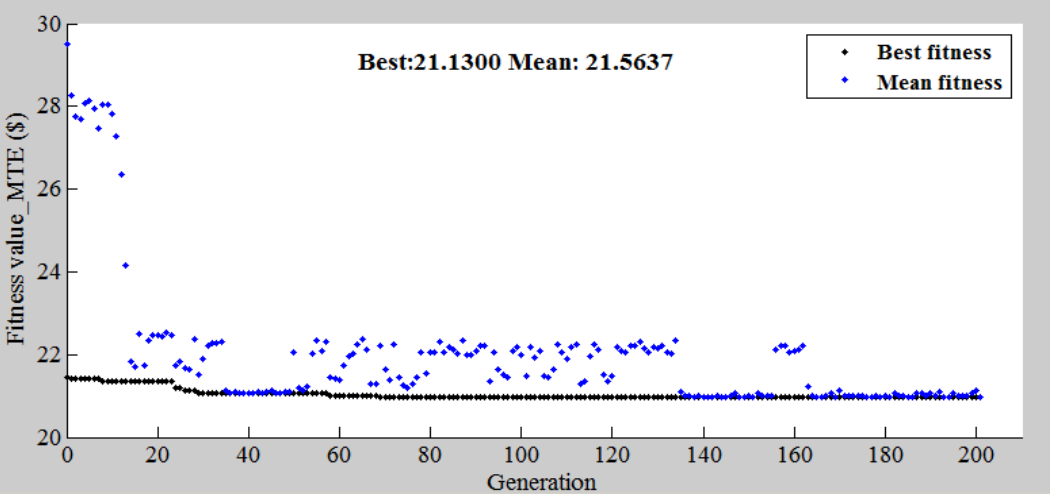


Figure 5.7 GA Results for Each Generation in MTE Optimization (Cycle length=150s)

Table 5.11 summarizes and compares all performance measures obtained from calculation when five objectives (TD, TS, Fuel, MTE and TC) were optimized, where minimizing TD (column 2) was the baseline scenario. When TD was minimized (baseline), the TS, fuel consumption and MTE were 3.53%, 51.5% and 40.7% higher than the optimal values, respectively. When TS was set as the goal, total delay was 22.9% higher than the baseline scenario. When fuel consumption was set as the goal, total delay was 17.2% higher than the baseline scenario. When MTE was set as the goal, total delay was 13.0% higher than the baseline scenario. The results show that there is an obvious trade-off between travel delay and environmental factors (fuel consumption and emissions) in the signal optimization problem. When comparing results, corresponding to minimum total cost (i.e., TC) (column 6) with baseline scenario, TC was just 5% higher than the baseline scenario and total delay was just 0.93% higher than the optimal TC. This can be explained by the magnitudes of economic weighting parameters in Table 5.4, where the weight for delay is much higher than the weights for others. As a single objective function considering delay, fuel consumption and emissions together, minimizing TC showed the most relatively reliable results for all the aspects.

Table 5.11 Comparison of Performance Measures for Different Objectives

Obj.	***Min*** **TD (baseline)**	***Min*** **TS**	***Min*** **Fuel**	***Min*** **MTE**	***Min*** **TC**
Cycle length (s)	150	180	150	150	140
TD (hr)	**67.39**	82.80	78.96	76.17	68.02
TS (#)	3668	**3551**	3933	3921	3585
Fuel (GJ)	6.4694	6.4467	**3.1352**	3.1679	4.0505
MTE ($)	35.62	49.38	21.36	**21.13**	24.20
TC ($)	1296	1399	1308	1342	**1234**

Table 5.12 summarizes all performance measures for signal timing parameters obtained when different types of emissions were optimized (column 3-8) and minimizing total delay (column 2) was the baseline scenario. As shown in Table 5.12 , the results from minimizing CO_2 and minimizing CO were very close, meaning these two objectives can substitute for each other. Similarly, minimizing PM_{10} and $PM_{2.5}$ indicated very similar results, meaning these two objectives can substitute for each other as well. The mobility-based optimization did not seem good enough to reduce CO_2, CO, NO_x, PM_{10} and $PM_{2.5}$ emissions, especially SO_2 emission. When CO_2 or CO was set as the goal, total delay was 17% higher than baseline scenario. When NO_x emission is set as the goal, total delay is 4.7% higher. When PM_{10} or $PM_{2.5}$ was set as the goal, total delay was 11% higher. When SO_2 was set as the goal, total delay was 34% higher. For emission-related or environment-oriented optimization, the results seem to be unreliable from the aspect of congestion.

It is worth pointing out that poor traffic conditions might not be recognized when total fuel consumption or emissions are considered as the objective function. This can be explained from the following perspective: When traffic is congested and vehicles stop more, often being idling, fuel consumption and emissions are, therefore, less than the situation when vehicles keep running at a certain speed. As a result, if total fuel consumption and emissions are minimized, traffic congestion can to be perceived as a favorable outcome.

Table 5.12 Comparison of Performance Measures for Minimizing Different Emissions

Obj.	***Min* TD (baseline)**	***Min* CO_2**	***Min* CO**	***Min* NO_x**	***Min* PM_{10}**	***Min* $PM_{2.5}$**	***Min* SO_2**
Cycle length (s)	150	150	150	150	140	140	170
TD (hr)	**67.39**	79.05	78.76	70.59	74.70	74.99	90.61
CO2 (ton)	0.3189	**0.2285**	**0.2285**	0.2620	0.2344	0.2336	0.2356
CO (kg)	5.7741	**4.0594**	**4.0590**	4.3006	4.1016	4.0963	4.1116
NOx (kg)	1.6141	1.3762	1.3691	**1.2445**	1.2843	1.2897	1.6690
PM_{10} (kg)	0.0774	0.0599	0.0598	0.0603	**0.0591**	**0.0591**	0.0639
$PM_{2.5}$ (kg)	0.0743	0.0574	0.0573	0.0578	**0.0567**	**0.0566**	0.0612
SO_2 (kg)	0.0048	0.0010	0.0010	0.0017	0.0012	0.0012	**0.0009**

Table 5.13 Results of Signal Timing Parameters for Different Objectives

Objective (MOEs)	**Cycle length (s)**	**Effective green time for each phase (phase 1-8) (s)**							
		g1	**g2**	**g3**	**g4**	**g5**	**g6**	**g7**	**g8**
Total Delay(TD)	150	22.2	79.4	8.6	23.8	11.7	89.9	14.6	17.8
Total Stops(TS)	180	19.4	108.1	9.4	27.1	13.3	114.2	14.1	22.4
Total Fuel Consumed	150	48.6	52.0	7.8	25.6	12.6	87.9	15.1	18.4
Total CO_2	150	48.7	52.0	7.8	25.5	12.8	87.9	15.3	18.3
Total CO	150	48.6	52.1	7.8	25.5	12.6	88.0	15.2	18.2
Total NOx	150	35.8	65.8	7.8	24.6	12.1	89.5	14.6	17.8
Total PM_{10}	140	42.8	51.0	7.3	23.0	11.2	82.5	13.6	16.7
Total $PM_{2.5}$	140	42.9	50.9	7.3	22.9	11.4	82.4	13.6	16.6
Total SO_2	170	55.6	57.1	11.7	29.6	15.0	97.7	18.9	22.4
Marginal Costs of Emission(MTE)	150	47.2	53.8	7.8	25.1	12.4	88.6	14.9	18.0
Total Cost(TC)	140	22.7	71	8	22.2	10.3	83.4	13.6	16.7

Table 5.13 shows the final signal timing parameters for all the different objectives. It indicates that minimizing total cost (TC) can yield results similar to minimizing total delay (TD) by sacrificing total delay a little bit (0.93% reduction) while reducing the negative environmental impacts to a certain extent (20% ~55% reduction) as shown in Figure 5.8. When comparing the MOEs differences between

optimal values and those from minimizing TC, the differences were in the range of 0.6% to 30%, except for SO_2 emission (144%). More research should be conducted to study the SO_2 emission.

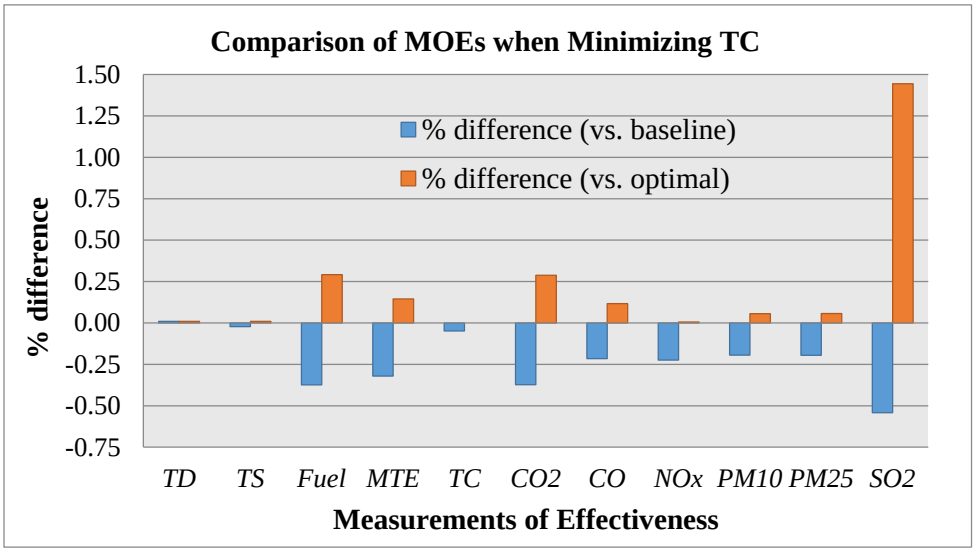


Figure 5.8 Comparison of MOEs Differences when Minimizing TC

The objective of minimizing TC, including costs for excessive travel time (i.e., delay), fuel consumption and different types of emissions, can be viewed and explained in another aspect. As mentioned in chapter 2, an index of a linear combination of the measures (e.g., delay and stops) is currently used as one of the objectives in the macroscopic traffic signal optimization tools such as a performance index (PI) in SYNCHRO and a disutility index (DI) in TRANSYT-7F (the definition of PI in TRANSYT 7F is different from that in SYNCHRO). The PI and DI are calculated as follows:

SYNCHRO: $PI= [D*1+St*10]/3600$ (5-15)

TRANSYT-7F: $DI=delay+\text{“}K\text{”}*stops$ (5-16)

where D refers to total delay in second; St refers to total vehicle stops; delay refers to total delay in veh-hr; stops refers to total stops in veh-hr. DI=[Delay (veh-hr) on a link*a link _specific delay weighting factor]+[a system-wide “stop penalty”*stops (veh-hr)*a link_specific stops weighting factor].

From equations (5-15) and (5-16), we find the “K” factor which is a weighting factor used to consider the total delay and stops together in the objective function. Currently, there’s no consensus about the reasonable value of this “K” factor. In our study, when minimizing total costs in a single objective

optimization, delay was converted to dollar value and fuel consumption as well as different types of emissions, which are the functions of delay and stops, which were all converted to dollar values. In other words, our single objective optimization considers delay and stops simultaneously using the economic weighting factors from the new perspective of total costs. It seems to be a relatively reliable objective function to minimize delay, stops, fuel consumption and emissions. When compared with delay-oriented optimization, the total delay increased slightly (0.93%), while fuel consumption and most emissions reduced by 20% ~55% (except SO_2 emission), as shown in Figure 5.8.

5.5 Summary

This chapter optimizes cycle lengths and green splits for individual intersections by adopting the delay calculation method in the Highway Capacity Manual (2010) that considers terms of both uniform delay and incremental delay. At the intersection level, the multi-criterial signal timing optimization problem was formulated with the objective function considering the delay, fuel and emissions simultaneously (i.e., in terms of money value). The genetic algorithm method was adopted to find the optimal cycle length and effective green ratio for each approach group. The performance metric of different objectives were compared and evaluated.

This chapter highlights the following findings: (1) Minimizing delay and minimizing stops show different results; (2) There are obvious tradeoffs between delay and marginal costs of total emissions; (3) For emission-related or environment-oriented optimization, the results seem to be unreliable from the aspect of mobility; (4) Our study considered total costs (including delay, fuel and emissions) as a single objective function, which showed relatively reliable results for all aspects; (5) Compared to direct optimization, the surrogate model-based optimization in this chapter saved much time by relieving computational loads.

CHAPTER 6: ARTERIAL OFFSETS OPTIMIZATION FOR PROGRESSION

The appropriate arterial offsets are critical for establishing quality of vehicle progression in a corridor with multiple signalized intersections. In this chapter, the second-stage optimization problem is the arterial offsets optimization under the condition of fixed green time and cycle time, developed in chapter 5. At the corridor level, vehicles departing from a queue at a traffic signal typically travel in a platoon that disperses as vehicles travel further downstream. To assess the coordination effects on an arterial road, mobility-offset relationships are developed through TRANSYT-7F by considering the platoon dispersion for each link in the platoon dispersion model. Moreover, the mobility-environment relationships are extended to the entire intersection spacing (i.e., link between two adjacent intersections) in the coordinated direction. Based on the mobility-offset relation as well as the mobility-environment relation, the optimization problem is formulized with intersection offsets as decision variables. Then a dynamic programming procedure is adopted to minimize the total link costs of delay, fuel and emissions in an arterial signal optimization. The optimal common cycle length in the corridor is also investigated in a small loop (in an enumerative way), with a reasonable range determined at the intersection level.

6.1 Quality of Progression

On arterials, traffic delays are especially significant at intersections where higher traffic density, longer vehicle idling time, and excessive stop-and-go driving cycles occur. The start-and-stop operation of signals tends to create platoons of vehicles that travel along a link. Usually, coordinated signals at multiple intersections operate as a system to give priority to progressive traffic flow along the arterial.

The offset is the time relationship, which is expressed in seconds or percent of cycle length. It is determined by the difference between each offset reference point and a system reference point (master clock or sync pulse) (FHWA, 2008; MnDOT, 2013). The offset reference point is defined as that point within a cycle in which the local controller's offset is measured relative to the master clock. Each

signalized intersection will therefore have an offset point referenced to the master clock and thus each will have a relative offset to each other. It is through this association that the coordinated phase is aligned between intersections to create a relationship for synchronized movement. Proper determination and application of intersection offsets have a substantial impact on arterial platoon travel times. Offsets are generally determined so that, to the extent possible, traffic can flow through a number of signals without stopping. Traditionally, offset optimization for coordinated traffic signals is based on average travel times between intersections and average traffic volumes at each intersection without consideration of the stochastic nature of field traffic. Note that all the intersections along the corridor share the same cycle length in a coordinated control system.

(1) Progression Factor

In HCM (2010), to account for coordination, the progression factor (PF_i) is used to adjust the uniform delay for quality of progression, as clearly shown in Equation (5-8) of Chapter 5. Terms in control delay follows: (1) d_{i1}, uniform delay for lane group i, gives an estimate of control delay assuming perfectly uniform arrivals and a stable flow. It is based on the first term of Webster's delay formulation; (2) d_{i2}, incremental delay for lane group i, is due to no uniform arrivals and individual cycle failures (i.e., random delay) as well as delay caused by temporary periods of oversaturation (i.e., oversaturation delay); (3) d_{i3}, initial queue for lane group i, is the delay experienced by newly arrived vehicles when a queue from the previous period at the start of the analysis (usually not considered); and (4) PF_i, progression factor for lane group i, takes into account the effect of coordination (Gartner & Deshpande, 2009).

Quality of progression is an indication of the degree to which through traffic movements are platooned and the time of the platoon's arrival at the downstream signal relative to the start of the signal phase. A favorable coordination scheme will have a PF_i value of less than 1, reducing overall delay. Therefore, the PF_i has a strong bearing on the calculation of control delay and the determination of the

overall Level-of-service (LOS) on the arterial. The HCM 2010 propounds that the PF_i be computed using the following Equation (6-1):

$$PF_i = \frac{(1 - P_i)f_p}{1 - g_i/C} \tag{6-1}$$

where P_i is the proportion of all vehicles in lane group i arriving during the green phase, which is computed as the count of vehicles that arrive during the green indication divided by the count of vehicles that arrive during the entire signal cycle; f_p is the supplemental adjustment factor to take account for the cases when the platoon arrives during the green time; and g_i/C is effective green ratio for lane group i.

Table 6.1 Relationship between Arrival Type and Progression Quality*

Platoon Ratio (R_{pi})	Arrival Type	Progression Quality and Description
0.33	1	Very poor (Dense platoon): more than 80% of the lane group volume arrives at the start of the **red** phase.
0.67	2	Unfavorable (Moderately dense platoon): forty percent to 80% of the lane group volume arrives throughout the **red** phase.
1.00	3	Random arrivals: main platoon contains less than 40% of the large group volume
1.33	4	Favorable (Moderately dense platoon): forty percent to 80% of the lane group volume arrives at the start of the **green** phase
1.67	5	Highly favorable(Dese to moderately dense platoon): more than 80% of the lane group volume arrives at the start of the **green** phase
2.00	6	Exceptionally favorable (Reserved for exceptional progression quality on routes with near-ideal characteristics): it represents dense platoons progressing over several closely spaced intersections with minimal or negligible side street entries.

*Note: * HCM2010_Chapter 18 (Exhibit 18-8)*

As shown in Equation (6-1), the PF_i is determined by the g_i/C ratio (i.e., effective green ratio) and the proportion of vehicles arriving on green (P_i), which is related to the arrival type. The HCM 2010 suggests that arrival type can be determined by approximating a time-space diagram or by using field observations, where the proportion of all vehicles arriving during the green indication at the intersection

can be measured. With this proportion (P_i) and the g_i/C ratio, a platoon ratio (R_{pi}) is calculated as Equation (6-2). There are six different arrival types in HCM 2010, depending on the traffic conditions, as shown in Table 6.1.

$$R_{pi} = \frac{P_i}{(g_i/C)} \tag{6-2}$$

where P_i is the proportion of all vehicles in lane group i arriving during the green phase; g_i/C is effective green ratio for lane group i . and R_{pi} is a platoon ratio.

Table 6.2 shows an example of determining the progression adjustment factor PF_i, given the arrival type and green ratio. For the uncoordinated lane group, arrival type 3 (random arrivals) is used. And for the coordinated lane group, arrival type 4 is selected.

Table 6.2 Progression Adjustment Factor as a Function of Green Ratio*

Arrival Type	Progression Adjustment Factor PF as a Function of Green Ratio (g_i/C)					
	0.2	0.3	0.4	0.5	0.6	0.7
Uncoordinated (Type 3)	1.00	1.00	1.00	1.00	1.00	1.00
Coordinated [a] (Type 4)	0.92	0.86	0.78	0.67	0.50	0.22

*Note: * Exhibit 31-46 from HCM2010_Chapter 31; a: PF= (1-[1.33 g/C])/ (1-g/C)*

(2) Platoon Dispersion Model

Quality of progression assessment is an important component in the evaluation process of urban street performance. Various studies have shown limitations of the PF_i to adequately take into account the effect of coordination (Washburn et al., 2003; Deshpande, 2009). An alternative way to determine the arrival type (relatively more accurately) is to model and incorporate platoon dispersion along the corridor through software such as the TRANSYT-7F (Gartner & Deshpande, 2009 &2013).

Vehicles departing from a queue at a traffic signal typically travel in a platoon that disperses as vehicles travel further downstream. To derive the mobility-offset relation of a link, it is necessary to have a method to predict the traffic flow profile at the downstream end of the link. To present the real situation

with computational efficient models or mathematical models, a simplified representation of reality with sufficient accuracy is widely used. Lighthill and Witham (1955) used a kinematic wave theory approach to describe the platoon traffic behavior as it travels along a link based on fluid flow theory. Pacey (1956) then presented a purely kinematic theory to model the diffusion of a platoon of vehicles moving along a roadway, the first model for predicting the downstream arrival flow rate considering the dispersion of traffic platoons. Robertson (1969) used a recurrent relationship to describe the platoon dispersion phenomena. Because of the simplicity of applying this model, Robertson's platoon dispersion model became a virtual universal standard platoon dispersion model and has been implemented in various traffic simulation tools (e.g., TRANSYT, SCOOT). A platoon dispersion model (PDM) can transform the flow profile at the upstream end of any link into the arrival flow profile at the downstream end of the link (i.e., the stop line). Alternatively, the cell transmission model (CTM) (Shen et al., 2007; Han et al., 2012) and finite capacity queuing theory (FCQT) have been used to describe real-world traffic flow under different conditions. These mathematical models (e.g., PDM, CTM and FCQT) possess their own pros and cons (e.g., one subtle issue associated with CTM is the phenomenon known as traffic holding, which stems from the linear relaxation of the nonlinear dynamic). However, they are all mathematically concise and computationally efficient, which is especially useful for larger scale traffic network problems.

Platoons originated at traffic signals disperse over time and space. Platoon dispersion creates non-uniform vehicle arrivals at the downstream signal, and non-uniform vehicle arrivals affect the calculation of vehicle delays at signalized intersections. Note that the effectiveness of signal timing and progression diminishes when platoons are fully dispersed (e.g., due to long signal spacing).

For each time interval (step), t, the downstream arrival flow is determined by the following recurrence equation:

$$Q_{(t+\beta T)} = F \times q_t + [(1-F) \times Q_{(t+\beta T-1)}] \tag{6-3}$$

$$F = \frac{1}{1+\alpha \times \beta T} \tag{6-4}$$

where $Q_{(t+\beta T)}$ is the predicted flow rate in time interval $(t+\beta T)$ of the predicted platoon; q_t is the flow rate of the initial platoon during step t; β is an empirical factor, generally 0.8 (which can be calibrated on the Edit>Optional>Global>Model Coefficients screen); T is the cruise travel time on the link (free-flow travel time) in steps; F is a smoothing factor; and α is an empirically derived constant, called the platoon dispersion factor, usually 0.50 for heavy traffic, 0.35 for moderate traffic and 0.25 for light traffic.

6.2 Mobility-Offset Relationships for Links with Coordinated Signals

The impact of platoon dispersion on traffic network performance is significant, which is one of the reasons that TRANSYT-7F is more effective than SYNCHRO for arterial progression analysis. The degree of platoon dispersion has an intimate effect on the percentage of vehicles arriving on green (PVG), which in turn directly affects uniform vehicle delay, stops, queuing, and other measures of effectiveness. TRANSYT-7F simulates the flow profile very carefully, so it can compute the PVG (the number of arrivals on green over the total volume) from a cyclic flow profile as shown in Figure 6.1.

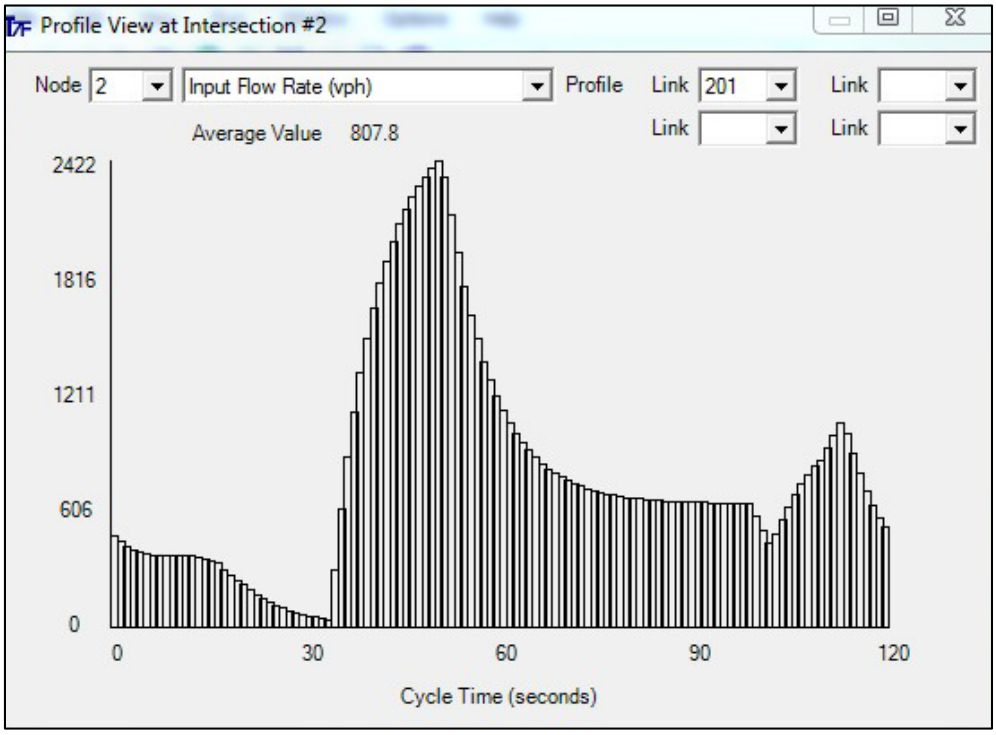


Figure 6.1 Cyclic Flow Profile View

A cyclic flow profile is designated for each coordinated signal approach and represents arrival conditions for an average cycle during a given analysis period. The number of arrivals on green is simply the portion of the vehicle profile captured by the green band. Alternatively, the flow profile can be obtained from the simulations in VISSISM modeling as well as the detector data in the field.

The most recent HCM (2010) still uses arrival types and a progression factor to incorporate the effects of coordination in the calculation of delay and the determination of level of service on signalized links, which can substantially differ from the delay estimated by TRANSYT-7F with a platoon dispersion algorithm (Gartner and Rahul, 2013). Given the more realistic simulation of flow profile by TRANSYT-7F, the concept and practice of platoon dispersion to take into account signal coordination for delay calculation may be added in the upcoming version of HCM scheduled for release in 2016. For example, as proposed by Gartner and Rahul (2009), a new factor, the coordination adjustment factor (CAF), can then be used in place of the existing PF_i in the calculation of delay, that is,

$$d_i = d_{i1}(CAF_i) + d_{i2} + d_{i3} \tag{6-5}$$

instead of $d_i = d_{i1}(PF_i) + d_{i2} + d_{i3}$

where CAF is the coordination adjustment factor derived by the cyclic coordination function (CCF). The CAF is defined as the ratio of the values of CCF at a particular point (i.e., at a given offset) with the underlying average delay (i.e., the uncoordinated delay). Details can be found in the original reference.

Basically, CCF measures mobility performance (e.g., delay, travel time and stops) as a function of offsets along a signalized link. If the signals at the ends of the link are coordinated and synchronized (i.e., have the same cycle time), the function is continuous and periodic with the common cycle time. Figure 6.2 illustrates a simple example of mobility offset relation, including delay-offset and stop-offset relationships derived from TRANSY-7F. Note that the CCF depends on a variety of factors, including traffic flow characteristics (e.g., volume, density, speed, dispersion and turning movements), link/roadway physical characteristics (e.g., length, width and capacity), and traffic signal controls (e.g.,

cycle length, green ratio and offsets). Thus, the approximated relationships are suitable for a given set of factors such as the determined link distance, speed, traffic volume, cycle length and green ratios.

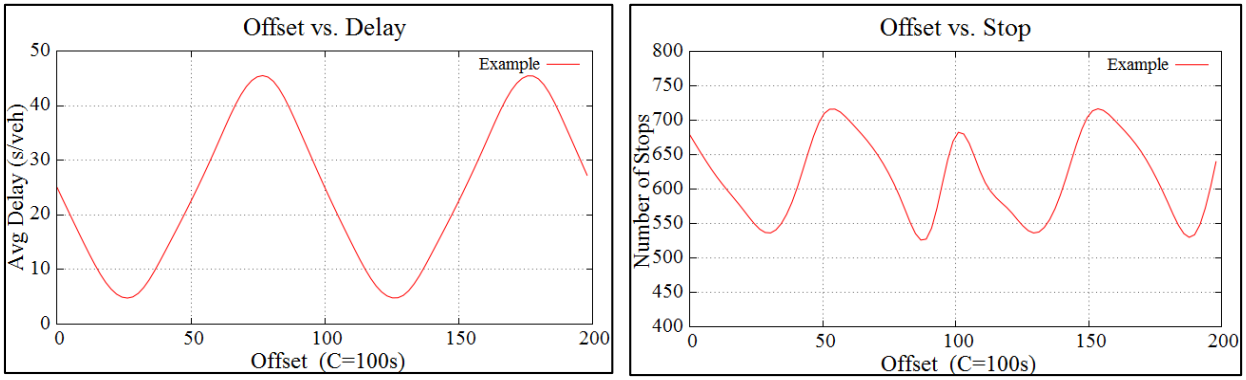


Figure 6.2 Example of Mobility-Offset Relationships

Since CCF is periodic with the common cycle length, it can be modelled as a Fourier series, which is an expansion of a periodic function in terms of a sum of sines and cosines (Gartner and Rahul, 2013). Given link distance, travel speed, traffic volume, percentage of turning movements, cycle length and green ratio, the Fourier series CCF (for two harmonics) can be written in terms of the cycle time C(seconds) and offset x(seconds) as shown in the following equation:

$$f(x) = \frac{A_0}{2} + a_1 \cos(\frac{2\pi x}{C}) + b_1 \sin(\frac{2\pi x}{C}) + a_2 \cos(\frac{4\pi x}{C}) + b_2 \sin(\frac{4\pi x}{C}) \quad (6\text{-}6)$$

where *f(x)* represents the mobility measures (e.g., average delay per vehicle in seconds or number of stops). The value of the parameters of the harmonics can be determined by the following relationships:

$$\begin{aligned} A_0 &= 2 * mean\ value\ of\ f(x) \\ a_1 &= 2 * mean\ value\ of\ f(x)\cos(\frac{2\pi x}{C}) \\ b_1 &= 2 * mean\ value\ of\ f(x)\sin(\frac{2\pi x}{C}) \\ a_2 &= 2 * mean\ value\ of\ f(x)\cos(\frac{4\pi x}{C}) \\ b_2 &= 2 * mean\ value\ of\ f(x)\sin(\frac{4\pi x}{C}) \end{aligned} \quad (6\text{-}7)$$

where A_0, a_1, a_2, b_1 and b_2 are calculated from the values of delay $f(x)$ and offset (x); a_n and b_n are the amplitudes of the cosine and sine components of the n^{th} harmonic, respectively. This is called harmonic

analysis, and the individual components are called harmonics. A limited number of harmonics (e.g., two harmonics give a very close match in most cases) can provide good approximations to the original functions for a given set of factors. The details can be found in the original references by Gartner and Deshpande (2009 & 2013).

To measure the accuracy of the predicted values (e.g., delay and stops), the discrepancy in the mean squared error (DMSE) is used, which is akin to R^2 in traditional regression analysis. DMSE is calculated by Equation (6-8):

$$\%DMSE = 100 * \left(\frac{\sum_{i=1}^{n} f(x_i)^2 - \sum_{i=1}^{n} error_i^2}{\sum_{i=1}^{n} f(x_i)^2} \right) \quad (6\text{-}8)$$

where $f(x_i)$ represents actual value at offset i; $(error)_i$ is actual value minus predicted value at offset i; and $i = 1, \cdots, n$ means the *n* possible values of offset.

6.3 Dynamic Programming Procedure for Offsets Optimization

Dynamic programming (DP) is a method/procedure for solving a complex problem by breaking it down into a collection of simpler sub-problems. It is applicable to problems exhibiting the properties of overlapping sub-problems and optimal substructure. There are two major advantages of DP: (a) it takes far less time than the naïve methods (e.g., enumerative method) that don't take advantage of the sub-problem overlap (like depth-first search) and (b) it can find the optimal solution thereby outperforming some alternative methods such as greedy algorithm, which picks the locally optimal choice at each branch/stage and does not guarantee an optimal solution. Recent research studies have demonstrated the effectiveness of using the DP models, an offshoot of the combination method, for signal offsets optimization by using link performance functions (Day and Bullock, 2011; Gartner and Rahul, 2009 & 2013; Meng Li et al., 2014).

The DP procedure for offsets optimization is described given an example of an arterial road with four coordinated intersections, where the coordinated signalized intersections are denoted as nodes 1, 2, 3 and 4 as shown in Figure 6.3. Correspondingly, the arterial links between these nodes are defined as

link=2, 3 and 4. Links 1 and 5 are inbound and outbound flows for node 1 and node 4, respectively. For simplicity, the branches (i.e., minor streets) are not shown in Figure 6.3, which are taken into account for simulation. The set of offsets for different nodes is defined as $\boldsymbol{\Phi} = [\Phi_1, \Phi_2, \Phi_3, \ldots]$. The coordinated intersections can be extended to more than four nodes, on a case-by-case basis.

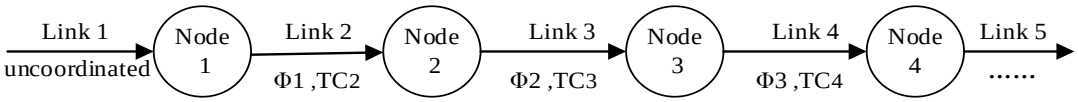


Figure 6.3 An Illustration of Offsets and Coordinated Intersections at Arterial

For four nodes problem with three coordinated links in Figure 6.4, the computation load for the enumerative method (C1= K1*K2*K3*3) (e.g., if K1=K2=K3=10, then C1=3000) is much higher than the computation load for dynamic programming (C2=K1+K1*K2+K2*K3) (e.g., if K1=K2=K3=10, then C2=210). With the increases of coordinated nodes and increases in possible values of offsets (i.e., the increases of K1, K2 and K3), DP would show more noticeable savings in computation load, which is especially superior for the large scale optimization problem.

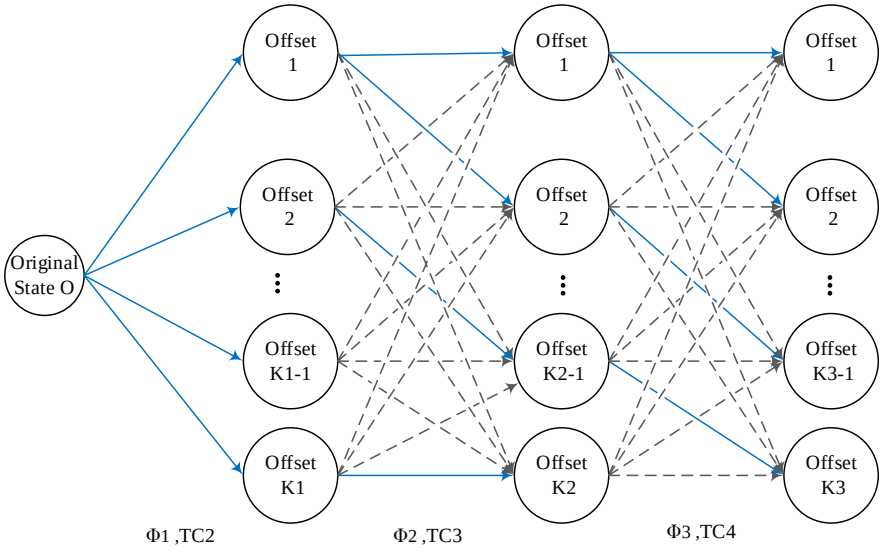


Figure 6.4 An Illustration of Dynamic Programming of Offsets

Table 6.3 Pseudo Code of the DP Coordination as an Example

```
% Dynamic Programming for offset optimization
% Example-corridor with four coordinated intersections
% Only the lane groups in coordinated phase are considered in total cost function TC
% TC means cumulative total costs of delay, fuel& emissions on each link

Initialize: possible values of offsets
for m=1:K3;
for n=1:K2;
for j=1:K1;
Compute delay2 (j), stops2 (j), emissions2 (j), TC2 (j);  %link2
f2 (j) =TC2 (j);  %link2

Compute delay3 (n, j), stops3 (n, j), emissions3 (n, j), TC3 (n, j); %link3
f3_temp (n, j) =TC3 (n, j) +f2 (j);  %link2&3

f3 (n) = min (f3_temp (n, j));

Compute delay4 (m, n), stops4 (m, n), emissions4 (m, n), TC4 (m, n); %link4
f4_temp (m, n) =TC4 (m, n) +f3 (n);  %link2&3&4

f4 (m) = min (f4_temp (m, n));

Objective=min (f4 (m));  %objective

Return optimal offset3; Return optimal offset2; Return optimal offset1; ….
end
end
end
```

Table 6.3 shows the Pseudo code of the DP coordination as an example. Before conducting DP for offset optimization, the DP model needs original input parameters including cycle length (C), mobility-offset relationships and environment-mobility relations for calculations. Then**,** a process of DP is illustrated in the following steps: (a) by setting offset intervals δ_1, δ_2, δ_3, …, there are K1, K2 and K3 offsets for node 2, 3 and 4, respectively (e.g., $K1 = C / \delta_1$); (b) every connection in Figure 6.4 means the total costs on link *i* (*i*=2, 3 and 4), where offset Φ_i between nodes *i* and *i-1* will be associated with former offset sequence; (c) the total costs on link *i* (denoted as TC_i) can be computed by developed mobility-offset equations and the environment-mobility equations; (d) by comparing the total costs, we could obtain the offset Φ_i and get a temporary optimized offset sequence from Φ_1 to Φ_i; (e) by repeating the

above three steps for each link, the optimal offset sequence $\mathbf{\Phi}_{opt}^{C,g}$ can be finally determined under the given cycle time and green time; (f) a sum of total costs for the set of links in the arterial is a significant parameter for evaluating the arterial signal control effectiveness. Corresponding to the optimal offset sequence $\mathbf{\Phi}_{opt}^{C,g}$, the minimum total costs for all links can be obtained by the DP procedure.

6.4 Illustrative Example and Results

In this subsection, a case study is conducted to demonstrate the application of the proposed method for offsets optimization at the arterial level. For the example arterial shown in Figure 6.5, DP optimization is used to determine the optimum offset sequence in the coordinated direction (i.e., East bound direction). In our case study, three links (link 205, 305 and 405) with four signalized intersections are considered to develop environment-mobility relation as well as mobility (delays and stops) versus offsets curves.

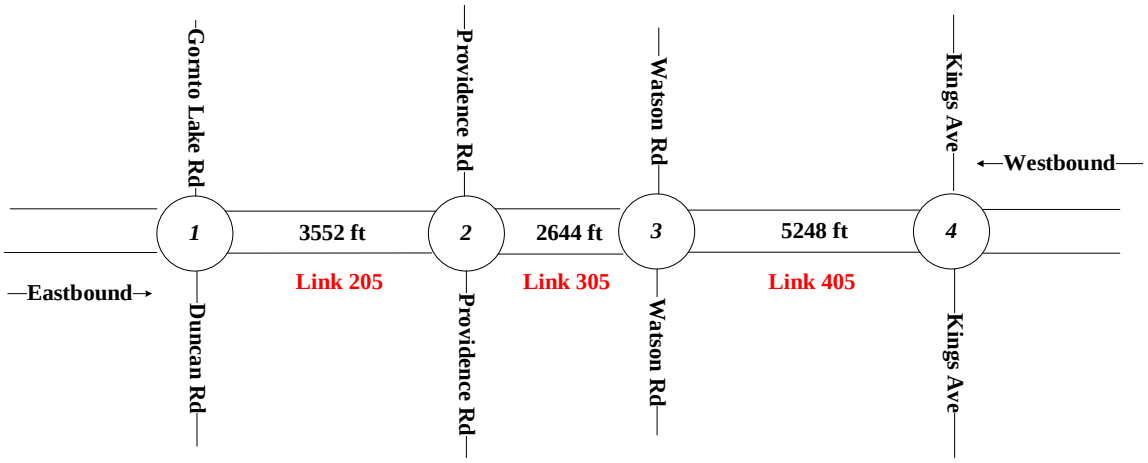


Figure 6.5 Sample Arterial—Bloomingdale Ave (Coordination Direction: EB)

6.4.1 Environment Factors vs. Mobility Measures for Coordinated Links

Emission equation (emissions in coordinated lane groups) would be the function with respect to total delay and total stops based on the modified relationship study.

Figure 6.6 shows an example of a VISSIM model for mobility-environment relationships in a coordinated direction. In the microscopic simulation, all the vehicles at the coordinated intersections are

simulated. While in MOVES, instead of estimating all the vehicles from simulation, only the through vehicles in the coordinated link between two intersections are used for fuel and emissions calculation.

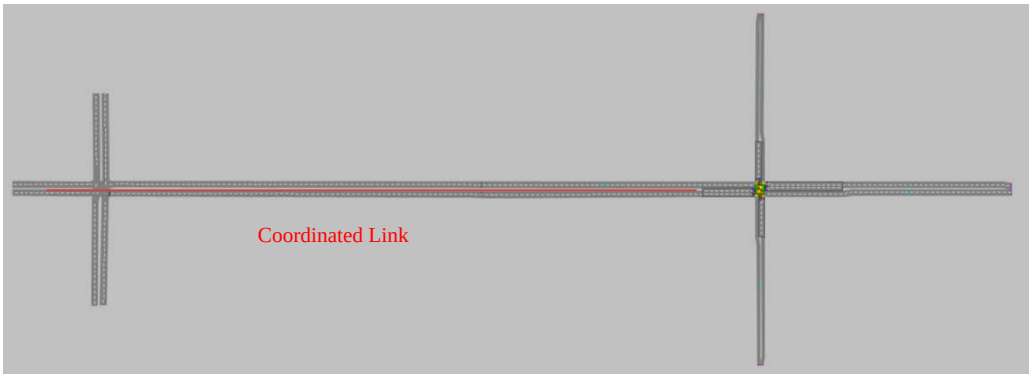


Figure 6.6 VISSIM Model for Mobility-Environment Relation in Coordinated Direction

Table 6.4 Results of MMLR with Coefficients in Coordinated Direction

Mobility vs. Environmental Factors		Y1 (CO_2) (kg)	Y2 (CO) (g)	Y3 (NO_x) (g)	Y4 (PM_{10}) (g)	Y5 ($PM_{2.5}$) (g)	Y6 (SO_2) (g)	Y7 (Fuel) (Mega joule)
Constant	Link205	-85.68	-72.03	-52.29	-2.57	-3.42	-1.62	-1184.64
	Link305	-69.77	-1001.83	-26.24	-5.96	-6.11	-1.23	-962.67
	Link405	-126.58	-106.43	-77.25	-3.80	-5.05	-2.40	-1750.28
X2 (*Total delay*) (10h)	Link205	140.43	2945.16	278.97	22.40	20.42	2.33	1936.47
	Link305	148.15	2480.65	287.02	20.53	18.75	2.67	2044.52
	Link405	207.49	4351.41	412.17	33.10	30.18	3.45	2861.09
X2*X2	Link205	-5.50	-294.11	-13.74	-1.77	-1.60	-0.039	-75.46
	Link305	-5.34	-116.88	-10.98	-0.84	-0.76	-0.098	-73.69
	Link405	-8.13	-436.02	-20.31	-2.61	-2.37	-0.057	-111.50
X4 (*Total Stops*) (10^2)	Link205	88.57	804.00	135.03	8.43	7.94	1.53	1223.90
	Link305	83.53	1238.12	132.20	10.38	9.60	1.35	1153.34
	Link405	130.86	1187.90	199.51	12.46	11.73	2.27	1808.28
X4*X4	Link205	-4.97	-50.50	-8.04	-0.50	-0.47	-0.095	-68.61
	Link305	-4.90	-87.34	-8.52	-0.69	-0.64	-0.085	-67.66
	Link405	-7.34	-74.61	-11.88	-0.74	-0.69	-0.14	-101.36

Similar to the methodological procedure in Chapter 4, the regression results for the modified relationship study are shown in Table 6.4. Note that the units for dependent and independent variables in

Table 6.4 differ from those in previous tables. The magnitude of the regression coefficients depends upon the scales of measurement used for the dependent variables and the explanatory variables. For purpose of meaningful comparisons of regression coefficients, the units of measurements and variances of the explanatory variables should be scaled or standardized.

6.4.2 Mobility vs. Offset in Coordinated Direction

In this study, the approach for assessment of coordination effects in the control delay equation is based on the platoon dispersion model. This approach supplants the progression factor (PF_i) in the HCM (2010) method with the values (e.g., capacity and PVG) obtained from the macroscopic simulation from TRANSTY-7F, which allows the delay/stop model to recognize more complex traffic operations.

In our case study, three links (link 205, 305 and 405) with four signalized intersections were considered to develop mobility (delay and stops) versus offset curves given determined distance, speed, the turning movement counts, common cycle length and effective green ratios. Specifically, the common cycle lengths and corresponding effective green ratios for each lane group were determined from optimizing total costs at the intersection level in Chapter 5. Since different intersections show different optimal cycle lengths (i.e., from 110s to 130s), three common cycle lengths (110s, 120s and 130s) were tested and the one with best arterial performance (e.g., least arterial total cost) was selected for the optimization at the arterial level.

Figure 6.7 shows the mobility (delay and stop) vs. offset relationships in coordinated links (205, 305 and 405) for the cycle length of 110s. It can be seen that two harmonics give a very close match (all DMSE values larger than 99%). For link 205, the offset of 90 and 30 illustrates the best performance in terms of delay and number of stops, respectively. For link 305, the offset of 40 and 20 illustrates the best performance for delay and number of stops, respectively. For link 405, the offset of 80 and 10 illustrates the least delay and number of stops, respectively.

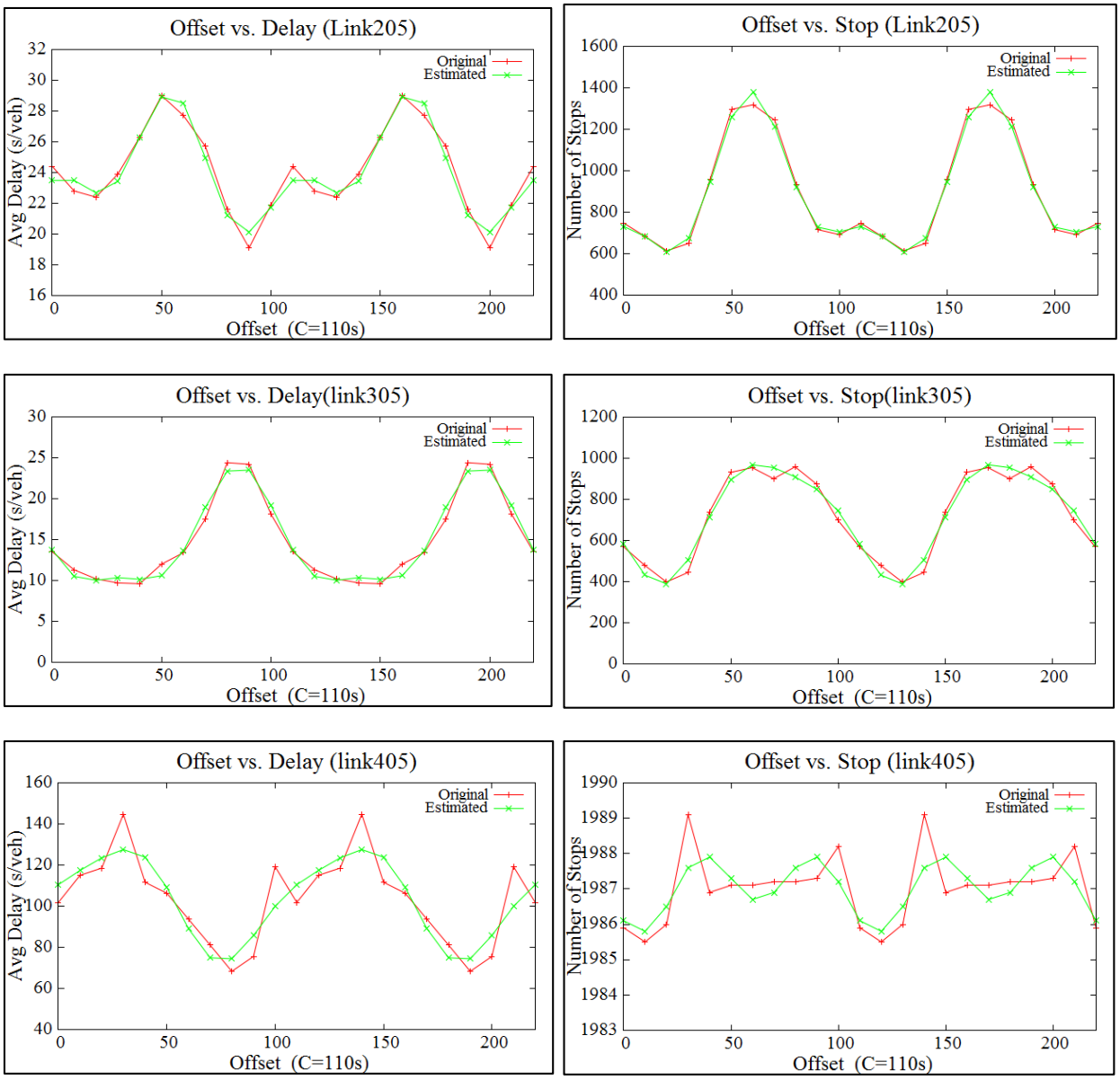


Figure 6.7 Mobility and Offset Relations in Coordinated Direction (C=110s)

Figure 6.8 shows the mobility (delay and stop) vs. offset relationships in coordinated links (205, 305 and 405) for the cycle length of 120s. Two harmonics give a very close match (all DMSE values larger than 99%). The stop-offset curve for link 405 is not smooth, which can be explained by the relatively small changes in number of stops during congested condition. For link 205, the offset of 80 and 90 illustrates the best performance in terms of delay and number of stops, respectively. For link 305, the

offset of 60 and 0 illustrates the best performance for delay and number of stops, respectively. For link 405, the offset of 80 and 100 illustrates the least delay and number of stops, respectively.

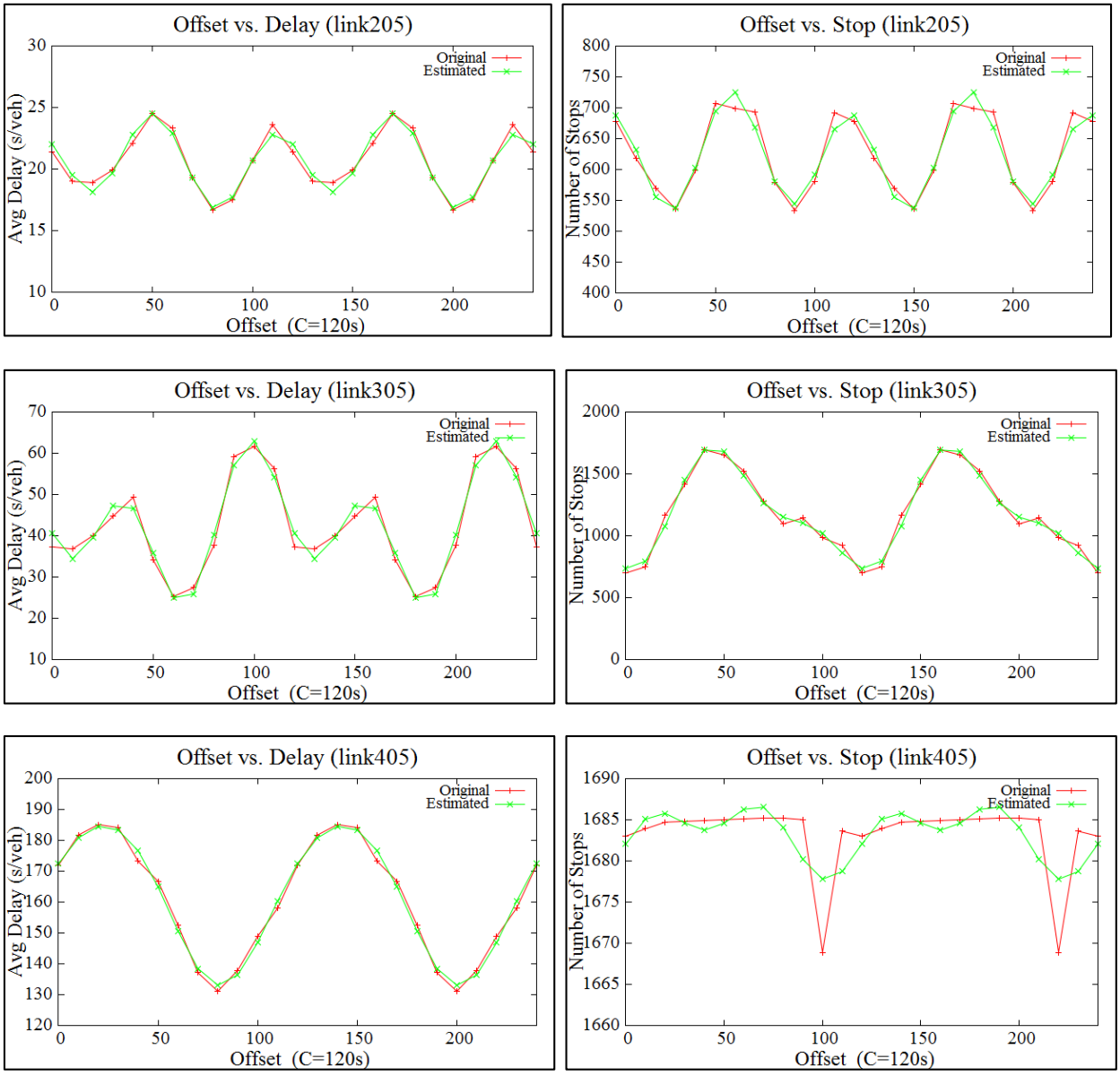


Figure 6.8 Mobility and Offset Relations in Coordinated Direction(C=120s)

Figure 6.9 show the mobility (delay and stop) vs. offset relationships in coordinated links (205, 305 and 405) for the cycle length of 130s. The Fourier series curves form a very close match with two harmonics (all DMSE values larger than 99%). For link 205, the offset of 80 and 0 illustrates the best performance in terms of delay and number of stops, respectively. For link 305, the offset of 60 and 60

illustrates the best performance for delay and number of stops, respectively. For link 405, the offset of 70 and 110 illustrates the least delay and number of stops, respectively.

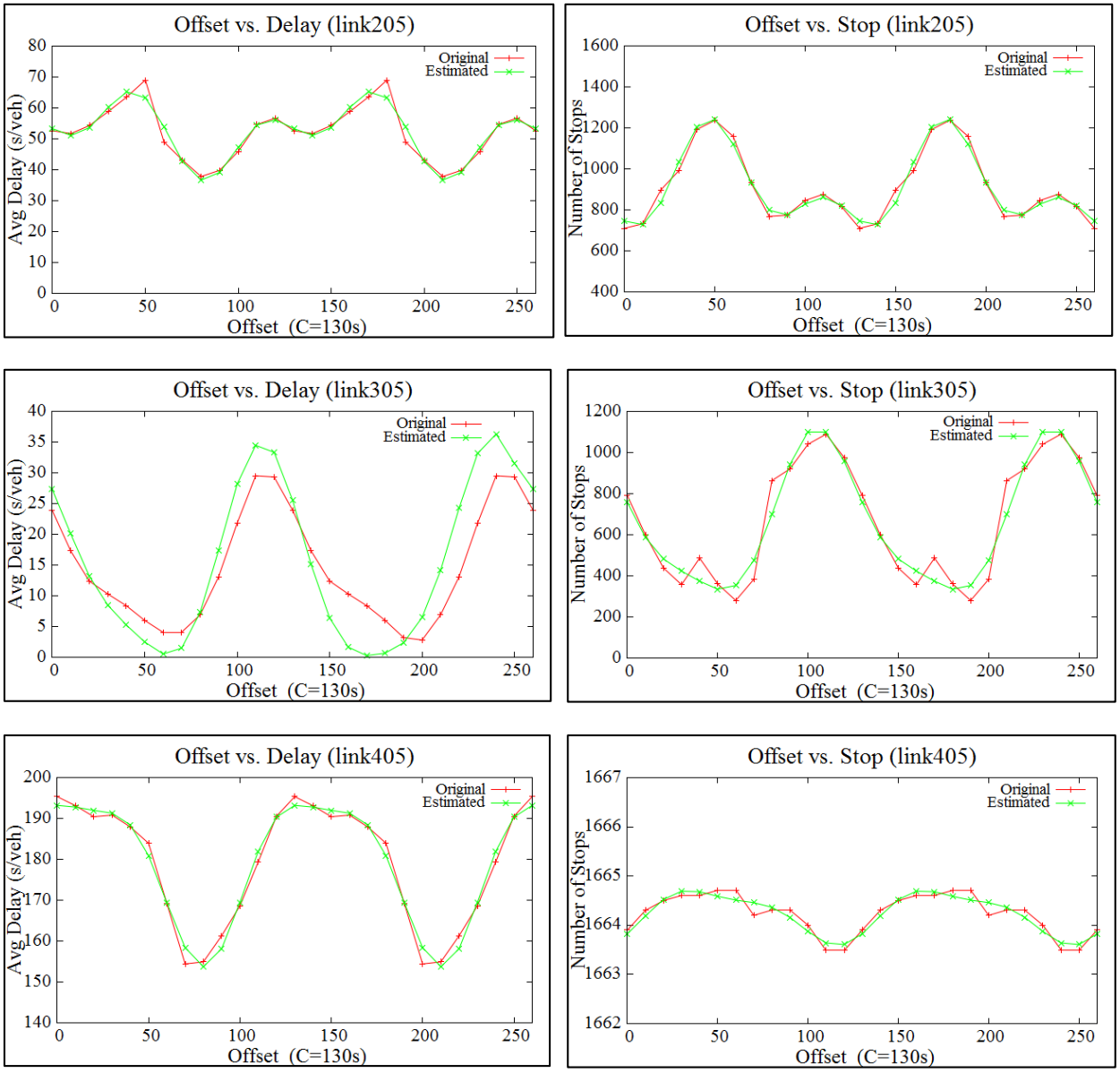


Figure 6.9 Mobility and Offset Relations in Coordinated Direction(C=130s)

6.4.3 Dynamic Programming for Offset Optimization

With the environment-mobility relations and mobility-offset curves, the arterial offsets optimization problem was formulated with the objective to minimize the total link costs, including the costs of delay, fuel and emissions along the corridor. For the purpose of comparison, the alternative

objectives (minimizing delay, number of stops and marginal cost of total emissions) were also used, and the corresponding measurements of effectiveness (MOEs) were calculated. By following the DP procedure in section 6.3, the arterial level optimization problem was solved with the offsets as the decision variables.

Table 6.5 Comparison of Offset Optimization Results for Different Cycle Lengths

Obj.	Cycle length (s)	Offsets (s)	TD (h)	TS (#)	MTE ($)	TC ($)
***Min* TD**	110	[88,17,75]	**32.248**	2945	59.68	5623.80
	120	[82,64,81]	53.520	3634	84.14	9253.60
	130	[82,67,80]	58.450	2875	97.11	10132.55
***Min* TS**	110	[22,18,8]	47.204	2796	73.24	8145.51
	120	[27,3,102]	63.671	2939	103.37	11020.67
	130	[7,53,116]	74.004	**2717**	105.63	12724.62
***Min* MTE**	110	[60,18,75]	34.420	3571	**54.16**	5944.73
	120	[87,47,80]	58.788	3941	73.18	10048.31
	130	[83,57,80]	59.044	2782	95.08	10216.08
***Min* TC**	110	[89,17,75]	32.251	2932	59.58	**5623.46**
	120	[83,64,81]	53.520	3634	84.14	9253.60
	130	[82,66,80]	58.462	2861	96.75	10132.22

As shown in Table 6.6, the optimal offset sequences [88, 17, 75], [22, 18, 8], [60, 18, 75] and [89, 17, 75] were obtained for minimizing TD, TS, MTE and TC, respectively, with the common cycle length of 110s. For the common cycle length of 120s, the optimal offset sequences [82, 64, 81], [27, 3, 102], [87, 47, 80] and [83, 64, 81] were obtained for minimizing TD, TS, MTE and TC, respectively. For the common cycle length of 130s, the optimal offset sequences [82, 67, 80], [7, 53, 116], [83, 57, 80] and [82, 66, 80] were obtained for minimizing TD, TS, MTE and TC, respectively. Since minimizing fuel shows the same results as minimizing MTE, fuel was not included in Table 6.6. The minimized total cost for three links along the corridor was $5623.46 for the common cycle length of 110s, which is smaller than

the cases with cycle lengths of 120s and 130s. Thus, the common cycle length of 110s showed the best performance in terms of total link cost. Likewise, the common cycle length of 110s showed the best performance in terms of total delay (i.e., TD) and marginal cost of total emissions (i.e., MTE). For total number of stops (i.e., TS), the common cycle length of 130s yielded the best result and the result for 110s cycle length was just 2.9% higher than the best result. Therefore, the cycle length of 110s was selected as the common cycle length in our example.

As detailed in Table 6.6 for the common cycle length of 110s, it is obvious that minimizing Fuel shows the same results as minimizing MTE. Minimizing TD and minimizing TC show similar results in this case, because the economic weighting parameter for delay is much higher than the parameters for other measures such as emissions (chapter 5). The minimized total cost for the three links along the corridor was $5623.46, with improvements of 30.96% and 5.4% when compared to the TC values of minimizing TS and MTE ($8145.51 and $5944.73). When TC is minimized, TS and MTE in the coordinated links are 2932 stops and $59.58, compared with the optimal values of 2796 stops and $54.16, which are 4.86% and 10% higher, respectively. Yet, when MTE is minimized, an improvement of 9.25% and 26.05% are made in terms of MTE, compared to the MTE values from minimizing TD and TS, respectively. For link 305 (intersection 2: Providence Rd @ Bloomingdale Ave), the traffic demand for the minor street (i.e., Providence Rd) is medium and minimizing MTE/Fuel shows different results from those of minimizing the mobility measures (TD and TS). For link 305 (intersection 3: Watson Rd @ Bloomingdale Ave), the traffic demand for the minor street (i.e., Watson Rd) is low and all the MOEs show similar results for different objectives. For link 405 (intersection 4: Kings Ave @ Bloomingdale Ave), the traffic demand for the minor street (i.e., Kings Ave) is almost as high as that for the major road and TS values are the same for all the objectives. Thus, different conclusions can be made for different levels of traffic demand. Better quality of progression can be achieved if traffic flow in the minor street is small. When considering the three links as a whole, results of minimizing environmental factors (MTE or

Fuel) are different from those of minimizing the mobility measures (TD and TS) along the corridor. Especially, minimizing TS and minimizing MTE/Fuel showed obvious differences.

Table 6.6 Optimization Results for Offsets (C=110s)

Link (EB)	**C=110s**		Measurements of Effectiveness (MOEs)				
	Offset	Obj.	TD (h)	TS (#)	Fuel (GJ)	MTE ($)	TC ($)
205	88	*Min* TD	5.164	753	5.12	24.43	994.37
305	17		3.078	385	3.10	15.29	594.69
405	75		24.006	1807	4.06	19.96	4034.74
Sum	**[88,17,75]**		**32.248**	**2945**	**12.28**	**59.68**	**5623.80**
205	22	*Min* TS	5.825	605	4.81	23.18	1093.14
305	18		3.079	385	3.10	15.29	594.83
405	8		38.300	1805	7.18	34.77	6457.54
Sum	**[22,18,8]**		**47.204**	**2796**	**15.09**	**73.24**	**8145.51**
205	60	*Min* Fuel	7.334	1379	4.02	18.91	1315.17
305	19		3.079	385	3.10	15.29	594.83
405	**75**		24.006	1807	4.06	19.96	4034.74
Sum	**[60,18,75]**		**34.420**	**3571**	**11.19**	**54.16**	**5944.73**
205	60	*Min* MTE	7.334	1379	4.02	18.91	1315.17
305	18		3.079	385	3.10	15.29	594.83
405	75		24.006	1807	4.06	19.96	4034.74
Sum	**[60,18,75]**		**34.420**	**3571**	**11.19**	**54.16**	**5944.73**
205	89	*Min* TC	5.166	740	5.10	24.32	994.03
305	17		3.078	385	3.10	15.29	594.69
405	75		24.006	1807	4.06	19.96	4034.74
Sum	**[89,17,75]**		**32.251**	**2932**	**12.26**	**59.58**	**5623.46**

An optimization for offset was also performed for the same arterial using the TRANSYT-7F model for the purpose of comparison. The optimum offsets from TRANSTY-7F and DP were used to calculate TD, TS, MTE and TC along the corridor. As Table 6.7 shows, the TD and TS in the coordinated direction (EB) using offsets determined by DP procedure are 32.25 hours and 2932 stops, compared with 33.73 hours and 3024 stops for TRANSYT-7F optimized offsets, which showed improvements of 4.4% and 3%, respectively. The results indicate that DP has a more rigorous optimization procedure than TRANSYT-7F, which is based on heuristic hill climbing. Moreover, the improvements in MTE and TC

(6.9% and 4.6%, respectively） are obvious, which indicates the effectiveness of using total link cost as an objective at the corridor level.

Table 6.7 Comparison between TRANSYT-7F and DP Optimization in Coordinated Direction

Link (EB)	TRANSYT-7F （C=110s）					Dynamic Programming (C=110s)				
	Offset (s)	TD (h)	TS (#)	MTE ($)	TC ($)	Offset (s)	TD (h)	TS (#)	MTE ($)	TC ($)
205	93	5.22	712	24.11	1001.18	89	5.17	740	24.32	994.03
305	31	3.19	505	18.45	633.48	17	3.08	385	15.29	594.69
405	69	25.31	1806	21.47	4257.33	75	24.01	1807	19.96	4034.74
Sum	/	33.73	3024	64.02	5891.98	/	32.25	2932	59.58	5623.46

As pointed out by Garner and Deshpande (2013), the delay on any link may also be dependent on offsets on previous links due to its effect on the flow pattern at an arterial road, especially at a low v/c ratio. They found that as the v/c ratio increases, the effect from previous link(s) vanishes. For illustrative purpose, our study only considered link delay and stops as dependent only on the offsets on that link since the v/c ratios were relatively high in our case study, and the effects from previous links were not obvious. In the future, the DP optimization can be expanded to consider one (or more) previous link(s), as well as coordination of two directions. More importantly, the procedure can be extended to grid networks in a similar way to show how the original combination method was applied (Day and Bullock, 2011).

6.5 Summary

Offset optimization can be described as a mathematical optimization problem in which decision variables (i.e., the adjustable parameters) are the offsets, and the objective is to minimize or maximize a performance measurement that is a complex function of those parameters. In our study, the objective is to minimize the total link costs, including the costs of delay, fuel and emissions along the corridor. To associate the total link costs (i.e., objective) with the offset (i.e., decision variable), the mobility-offset relationships were developed first based on a cyclic flow profile. Then the dynamic programming

procedure, which takes far less time than the naïve method (e.g., enumerative method), was adopted to minimize the total link costs of delay, fuel and emissions in an arterial signal optimization.

This chapter highlights the following findings: (1) Different conclusions can be made for different levels of traffic demand and better quality of progression can be achieved if the traffic flow in the minor street is small; (2) When considering the three links as a whole, results of minimizing environmental factors (MTE or Fuel) are different from those of minimizing the mobility measures (TD and TS) along the corridor; (3) Especially, minimizing TS and minimizing MTE/Fuel show obvious differences; (4) The comparison results indicate that DP has a more rigorous optimization procedure than TRANSYT-7F; (5) The improvements in MTE and TC by DP procedure are obvious, which indicates the effectiveness of using total link cost as an objective at the corridor level.

CHAPTER 7: CONCLUSIONS AND FUTURE WORK

The surface transportation system has significant impacts on the quality of individual lives as well as the economic and social health of the nation. Among the many components of the surface transportation system, the traffic signal control system is one of the most critical components as it regulates the flow patterns of vehicular demands in congested and high-carbon urban areas. The overall goal of this research was to investigate a more balanced and sustainable traffic signal control system at arterials. The developed framework was established to achieve signal timing plans (e.g., day plan schedule, cycle lengths, splits and offsets) that are suitable for real traffic conditions with the consideration of multi-criterial performance in the surface transportation system (e.g., vehicular delay, fuel consumption and various emissions). The outcomes of this study can be easily implemented by traffic operators as part of their daily signal timing routine thereby helping to reduce delay, fuel consumption and emissions. Implementation of this research can contribute to a livable, sustainable, and healthy community.

As reviewed in chapter 2, the current practices of the urban traffic signal control system operations are mostly devoted to implementing an optimal traffic signal timing plan that minimizes vehicular delay and stops or similar measures. Existing emission estimation methods in the current traffic signal optimization and micro simulation tools are grossly inaccurate. They assume a drive cycle consisting of constant fractions of free flow and congestion travel rather than actual traffic characteristics. Some of the environmental externalities can be reasonably assessed while others are mostly speculative. Recent emission estimators (e.g., MOVES) have emerged with comprehensive vehicle emission databases, which are established by conducting extensive studies on vehicle emission testing and modeling using advanced equipment. These estimators require detailed traffic information, such as second-by-second speed and acceleration rate of individual vehicles, which can be obtained from a traffic microscopic

simulation model. One of the benefits of using microscopic models is the flexibility of utilizing various intersection types, vehicle types, and other characteristics such as drivers' behaviors on accelerations or decelerations.

All these present both opportunities and challenges to develop a framework that will systematically enable the use of these integrated data and models for a multi-criteria traffic signal timing design. Such a design would utilize the large quantities of traffic condition data collected by system detectors or non-intrusive data collection platforms as well as the powerful tools for microscopic traffic modeling and instantaneous emission estimation. The challenge is how to effectively deal with this big data either from field collection or detailed simulation, and provide useful information for decision makers in practice. Methodologically, there's a tradeoff between the accuracy of objective function values (i.e., the opportunity) and the computational efficiency of simulation and optimization (i.e., the challenge). To address this need, in this dissertation, traffic signal timing design for surface traffic operations was investigated and analyzed in four steps: 1) TOD breakpoints identification for day plan schedule using cluster analysis (unsupervised learning), 2) relationship between mobility and environmental factors for signalized intersections by regression analysis, 3) multi-criterial optimization of cycle length and splits using heuristic algorithm, and 4) dynamic programming-based arterial offsets optimization for sustainable traffic signal control. Conclusions, practical implementations, limitations and future research directions are drawn based on these four steps in the following sections.

7.1 Traffic Pattern Identification for Day Plan Schedule

In this sub-study, a cluster analysis-based procedure was developed to identify TOD breakpoints for coordinated semi-actuated traffic signal systems using continuous traffic data obtained through innovative, non-intrusive collection techniques. A novel modification, which proposes that time of traffic occurring be taken into account as a dimension, addresses the shortcomings of previous clustering approaches. The signal timing plans for the recommended TOD intervals were developed and evaluated

in the simulation analysis. The results of a case study for a corridor located in Tampa, Florida, demonstrated that the proposed method significantly improved the performance of the corridor.

In current practice of traffic signal control, the experience of traffic engineers and an imprecise analysis of traffic volume data usually determine the day plan schedules of signal timing. This study provides a mathematical way to identify TOD breakpoints through a data-driven method, where the results and visualizations can be easily implemented in practice. Regarding practical implementation, a tool or app (e.g., web-based, MS Office Excel-based tool or mobile app) can be developed to help practitioners automatically determine appropriate TOD breakpoints for day plan schedule. Instead of going through the detains in algorithms, the practitioners only need to enter the inputs of traffic volume data (e.g., 24 hours volume data in 15 minutes interval) and obtain the results as well as visualized figures by simply running the tool or app, which possesses the function of our advanced cluster analysis for multi-dimensional data. Ideally, the tool or app can be incorporated into existing signal timing optimization software.

In the future, a further step could be to develop several timing plans for the recommended TOD intervals, while considering the operational tradeoff between directional traffic flows. Another interesting direction is semi-supervised learning such as constrained clustering, where constraints of must-link and cannot-link are considered in cluster analysis. Furthermore, efforts are needed to demonstrate the best way to estimate the necessary number of clusters while simultaneously considering both traffic flow directions. A sensitivity analysis should be performed for a variety of cluster numbers for this purpose. Also, for corridors with a large number of intersections, the dimension of the dataset used for cluster analysis will be considerably higher. Due to the inherent difficulties encountered when working with high-dimensional data, innovative methods that can be used to convert multi-dimensional variables into one scalar are worth exploring. In future research, dynamic traffic flow on urban arterial networks can be analyzed not only on a macroscopic level (i.e., time-of-day breakpoints study) but also on microscopic level. For example, several key traffic phenomena of dynamic traffic patterns that accompany significant

vehicle deceleration/acceleration at signalized intersections can be addressed from the underlying traffic flow model (car-following, lane-changing, gap acceptance, etc.). The important role of driver behaviors (aggressive, timid), vehicle type (age, weight), and traffic composition (e.g., trucks, pedestrian, and bicyclists) can be investigated in details.

7.2 Relationship between Mobility and Environmental Factors

Characterizing the relationship between environmental impacts from transport with mobility is critical for sustainable development. In this sub-study, a mathematical framework was developed to determine how environmental externalities are related to mobility measurements during the same time period at signalized intersections. A metamodeling-based framework, involving experimental design, microscopic simulation (i.e., a traffic signal optimization tool, a microscopic simulation model, and an instantaneous emission estimator), and multivariate regression analysis were developed to explore the environment-mobility relationship at signalized intersections. Given the microscopic simulation databases, MMLR analysis was conducted to approximate the environmental responses to the mobility measurements. The results showed good fits for multiple-responses. However, t-values, which indicate if the coefficients of independent variables are statistically significant, showed varied conclusions for different response variables (i.e., energy and emissions). The regression outcomes showed that, to reduce SO_2, mobility-based optimization is not good enough. The relationships for certain pollutants (e.g., NOx, PM_{10}, and $PM_{2.5}$) are not simply linear. Furthermore, the relationships between these emissions and mobility measurements considered in this study are different for various types of intersections, which requires the consideration of trade-offs between different intersections in a coordinated arterial while pursuing eco-friendly traffic control. The results of quantitative assessment from the microscopic emission estimator were compared with the estimation from the current signal optimization tool SYNCHRO. The comparison results recommended the improvement of the current emissions module in the tool for more accurate analyses (e.g., benefit-cost analysis) in practical signal retiming projects.

In this study, the proposed framework and methodology are the focus. VISSIM is used only for the illustration of our method. In the metamodeling technique, simulation software was used to get the measurements of performance when some inputs (e.g., traffic volume levels, turning movements and geometry) were changed while keeping others (e.g., maximum acceleration rate) the same. The research priority is given to the scenario-based method and the powerful simulation tools (e.g., VISSIM), which provide the flexibility of using various intersection types, traffic volume levels, vehicle types, and other characteristics such as driver behavior. As a result, the aggregated/macroscopic outcomes from micro-simulation are used to characterize the relationship between environmental externalities and mobility measurements, which is critical for sustainable traffic control (e.g., metamodel-based optimization). Moreover, the results from MOVES and those from SYNCHRO were compared in this research, which provides new insights to readers as well.

In future research, other types of regression models such as radial basis functions, multivariate adaptive regression spines, Kriging, quantile regression and support vector machine (SVM) can be used and compared with MMLR used in this study (Guo et al., 2015). It should be noted that traffic simulation models may not accurately represent vehicle dynamics and the speed and acceleration distributions can be different from field data depending on how the parameters for human behavior in VISSIM are calibrated (Song et al., 2013). If the readers intend to apply our proposed framework, they are encouraged to carefully calibrate the simulation model and obtain the specific correlation between mobility and emissions for their study regions. We also recommend incorporating NGSIM vehicle trajectory datasets and field travel time data using advanced technologies (i.e., BlueTOAD^{TM} technology, a Bluetooth-based travel time measuring platform developed by TrafficCast) to validate the simulation model. Validation is a confirmation process to justify whether the calibrated simulation network reliably replicates real traffic conditions with a new set of field data that are not used in the calibration process. Another extension of this study could be metamodeling-based optimization for a sustainable traffic signal control system that can simultaneously improve mobility and reduce emissions.

7.3 Multi-criterial Signal Timing at Intersection Level

Based on the developed mobility-environment relationship, the multi-criterial signal timing optimization problem was formulated with the objective function considering delays and emissions simultaneously (i.e., in terms of money value). For comparison purposes, different objective functions, including total delay, total stops, fuel consumption, emissions, total emission costs and total costs, were explored as well. To solve this multi-objective nonlinear traffic signal optimization problem, the global solution algorithms, GA and multi-objective GA, were used to find the optimal cycle length and effective green ratio for each approach group with careful selection of option settings. The tradeoffs between different objectives were discussed and optimal signal plans with respect not only to traffic mobility performance but also other important measures for sustainability were compared and evaluated. Based on the mobility-environment relationship, the surrogate model-based optimization presented in this chapter saves much time by relieving computational loads when compared to direct optimization.

In the future, the impacts of heavy vehicles are recommended to be investigated and incorporated into the coordinated traffic signal control for arterial roads, especially for those with significant traffic of heavy vehicles (more than 10% of total traffic) such as US 301. Incorporating dynamic traffic features will support more reliable traffic controls to mitigate traffic congestion and smooth traffic flow on arterial roads. Conventional traffic controls count the impact of heavy vehicles with passenger car equivalency (PCE) value, i.e. one truck is equivalent to X passenger cars in traffic control computation of performance measures such as delay (HCM, 2010). Although recent work improved the value to better capture the impact of heavy vehicles, the conventional method does not consider the different lane-changing and car following features of heavy vehicles specifically. Studies show that heavy vehicles affect traffic flow and platoon dispersion through their generally inferior acceleration rate, splitting a platoon if positioned in the middle, or concentrating it if positioned at the front (Ramsay and Bunker, 2004). Heavy vehicles are also major contributors to increased headways particularly with turning movements (Cuddon and Ogden, 1992).

Another recommended extension of this study is to improve the algorithm in multi-objective optimization. In section 5.4.2, it converted a simple genetic algorithm to a multi-objective genetic algorithm by adding some new operators. Nevertheless, these methods may suffer from disadvantages such as their high computational complexity, non-elitist approach, and their needs for setting an arbitrary sharing parameter. In addition, only fixed control was investigated in this study. Future efforts should be addressed to two well-known problems with vehicle-actuated signal coordination: the early return to green problem and the uncertain intersection queue length problem.

7.4 Arterial Offset Optimization for Progression

At the corridor level with multiple signalized intersections, mobility-environment relationships were extended to the entire intersection spacing (i.e., link between two adjacent intersections) in a coordinated direction. Then, based on the mobility-offset relationship considering the platoon dispersion for each link, the optimization problem was formulized with the intersection offsets as decision variables, given the effective green ratios determined at the intersection level. The dynamic programming procedure was adopted to minimize the total costs of delay and emissions in an arterial signal optimization. The optimal common cycle length in the corridor was investigated in an enumerative way with a reasonable range determined at the intersection level.

The development of online data collection in traffic signal controller firmware has provided more opportunities in offsets optimization of signal timing design. In the future, it is recommended to optimize arterial offsets with high resolution controller data (e.g., recording number of vehicles arriving on green in the delay estimation). In other words, the modeled cyclic flow profiles in TRANSYT-7F can be replaced with the measured flow profiles from the field data. Alternatively, these sensor data can be obtained from the installed detectors in microscopic simulation (e.g., VISSIM) to measure vehicle arrival times, which can be used to calculate the ratio of the flow rate during the green time to the flow rate during a cycle (i.e., the platoon ratio). It should be noticed that calibration issues accompany the use of any microscopic traffic simulation models. Similarly, advanced technologies can be used to measure real travel times along

the corridor. Moreover, field operations tend to directly optimize the timings of actuated signals in ways similar to fixed-time signals, with slight modifications made subsequently to account for specific field conditions (Skabardonis, 1996; Henry, 2005; Zhang and Lou, 2013). In the future, specific efforts can be made in offset optimization for actuated and adaptive controls for field implementation.

The proposed framework and methodology in this dissertation could be generalized by using portable activity measurement systems (PAMS) device or portable emission measurement systems (PEMS). For example, the second-by-second vehicle trajectory profiles (generated in VISSIM in our study) can be obtained from PAMS device (e.g., GPS recorder). The emission measurements can also be collected by PEMS, which is designed to measure emissions during the actual use of an internal-combustion engine vehicle/equipment in its regular daily operation. A PEMS unit usually consists of a set of gas analyses with heated sample lines directly connected to the tailpipe, plus an engine diagnostics scanner designed to connect with the on-board diagnostics link of the vehicle and an on-board computer that provides data regarding emissions, fuel consumption, vehicle speed, engine speed and temperature, throttle position and other parameters (Franco et al., 2013). In some cases, other instruments may be used, such as accelerometers to record instantaneous acceleration (Opresnik et al., 2012), altimeters or video/photographic equipment to document traffic conditions during test runs. However, special attention should be paid to the well-known accuracy and repeatability issues and large variability problems of these on-board measurements devices.

This proposed study advocates a sustainable traffic control system by considering travel time, fuel consumption, and emissions. The outcomes of this study can be easily implemented by traffic operators in their daily life of retiming signal timing, and can help reduce delay, fuel consumption, and emissions. It can contribute to a livable, sustainable, and healthy community. Furthermore, the proposed approach could be extended to incorporate health impact analyses with air pollution dispersion models. The dispersion models allow estimating exposure of both users (i.e., drivers) and non-users (i.e., pedestrian and cyclists) to vehicle emissions. This study will help to formulate reasonable air pollution abatement

strategies for minimizing adverse health effects of vehicle emissions. The outputs and findings of this study can also provide additional references to urban transportation planners and policy makers about land-use planning when they consider negative environmental and health impacts on vulnerable objects such as hospitals, schools and office buildings in the vicinity of intersections.

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APPENDICES

Appendix A: Different Types of Emissions

Transportation is one of the major contributors to man-made Greenhouse Gas (GHG) emissions and polluting emissions. GHG emissions are closely related to climate change. A substance in the air that can be harmful to humans and the environment is known as an air pollutant. Pollutants can be in the form of solid particles, liquid droplets, or gases. The United States Environmental Protection Agency (EPA) is mainly concerned with emissions which are or could be harmful to public health. EPA calls this set of principal air pollutants, criteria pollutants. The criteria pollutants are carbon monoxide (CO), Nitrogen oxides (NO_X, nitrogen dioxide NO_2), lead (Pb), ozone (O_3), particulate matter (PM), and sulfur dioxide (SO_2). There are also a large number of compounds which have been determined to be hazardous which are called air toxics. GHG emissions and air pollutants are two major concerns related to climate change and human health impacts in a sustainable transportation system. The following subsection lists the GHG emissions and some criteria pollutants that are considered in this research study.

(1) Greenhouse Gas (GHG) Emissions

A greenhouse gas, abbreviated as GHG, is a gas in an atmosphere that absorbs and emits radiation within the thermal infrared range. This process is the fundamental cause of the greenhouse effect. The primary greenhouse gases produced by the transportation sector are carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and hydro-fluorocarbons (HFC). Greenhouse gases greatly affect the temperature of the Earth; without them, Earth's surface would average about 33°C colder than the present average of 14 °C (57 °F).

Since the beginning of the Industrial Revolution, the burning of fossil fuels has contributed to a 40% increase in the concentration of carbon dioxide in the atmosphere from 280 ppm to 397 ppm. Anthropogenic carbon dioxide (CO_2) emission, coming from combustion of carbon based fuels, principally wood, coal, oil and natural gas, accounts for 95 percent of transportation GHG emissions in the United States. It is a colorless, odorless, non-toxic greenhouse gas also associated with ocean acidification, emitted from sources such as combustion, cement production, and respiration. It is

otherwise recycled in the atmosphere in the carbon cycle. CO_2 is an extremely efficient greenhouse gas which contributes to enhance global warming.

Transportation GHG emissions account for 29 percent of total U.S. GHG emissions, and over 5 percent of global GHG emissions (EPA 2011). Transportation GHG emissions have been growing steadily in recent decades. From 1990 to 2006 alone, transportation GHG emissions increased 27 percent, accounting for almost on-half of the increase in total U.S. GHG emissions for the period. For some cities, Tampa as an example, that rely primarily on automobile travels, this percentage may be higher. As reported by Population figures from 2010 Census, Tampa, ranked in the third place in greenhouse gas emissions among U.S. cities, emits more carbon than some cities twice its size in population, both by the community as a whole and by emissions produced solely by government operations. Statistics show that the surface transportation is the major source for GHG emissions with the light-duty vehicles accounting for 63% and the heavy-duty vehicles accounting for 21% GHG emissions. Transportation is the primary sector using petroleum and the second largest contributor to carbon dioxide emissions.

(2) Particulate Matter (PM)

Particulates, alternatively referred to as particulate matter (PM), atmospheric particulate matter, or particle pollution, are tiny particles of solid or liquid suspended in a gas. PM_{10} is particulate matter 10 micrometers or less in diameter and $PM_{2.5}$ is particulate matter 2.5 micrometers or less in diameter (generally described as fine particles). Sources of particulates can be man-made or natural. Some particulates occur naturally, originating from volcanoes, dust storms, forest and grassland fires, living vegetation, and sea spray. Human activities, such as the burning of fossil fuels in vehicles, power plants and various industrial processes also generate significant amounts of aerosols. Increased levels of particulate matter in the air are linked to health hazards such as heart disease, altered lung function and lung cancer. Particulates are the deadliest form of air pollution due to their ability to penetrate deep into the lung and blood streams unfiltered. In 2013, a study involving 312,944 people in nine European countries revealed that there was no safe level of particulates and that for every increase of 10 μg/m3 in

PM_{10}, the lung cancer rate rose 22%. The smaller $PM_{2.5}$ were particularly deadly, with a 36% increase in lung cancer per 10 μg/m3 as it can penetrate deeper into the lungs (Ole et al., 2013).

(3) Nitrogen oxides (NOx)

Nitrogen oxides (NO_x) refer to Nitric oxide (NO) and nitrogen dioxide (NO_2). They are emitted from high temperature combustion, and are also produced naturally during thunderstorms by electric discharge. These two chemicals are important trace species in Earth's atmosphere. In the troposphere, during daylight, NO reacts with partly oxidized organic species (or the peroxy radical) to form NO_2, which is then photolyzed by sunlight to reform NO. NO_x can be seen as the brown haze dome above or plume downwind of cities. Statistics show that the most significant sources of NO_x emissions are the road transportation sector, with the increase from 39.3% in 2008 to 40.5% in 2010. NOx leads to the formation of ozone and contributes to the formation of smog and acid rain. It also causes irritation to human mucus membranes, reduces lung function and increases risk of respiratory problems. The subsequent impacts of acid deposition can be significant, including adverse effects on aquatic ecosystems in rivers and lakes and damage to forests, crops and other vegetation. Eutrophication can lead to severe reductions in water quality with subsequent impacts including decreased biodiversity, changes in species composition and dominance, and toxicity effects. It is NO_2 that is associated with adverse effects on human health, as at high concentrations it can cause inflammation of the airways. NO_2, the reddish-brown toxic gas, has a characteristic sharp, biting odor. It also contributes to the formation of secondary particulate aerosols and tropospheric ozone in the atmosphere - both are important air pollutants due to their adverse impacts on human health.

(4) Other Toxic Air Pollutants: SO_2, CO, HC

Toxic air pollutants have negative impacts on human health. Sulfur oxides (SO_x), especially sulfur dioxide, are a chemical compound with the formula SO_2. SO_2 is produced by volcanoes and in various industrial processes. Since coal and petroleum often contain sulfur compounds, their combustion generates SO_2. Further oxidation of SO_2, usually in the presence of a catalyst such as NO_2, forms H2SO4,

and thus acid rain. This is one of the causes for concern over the environmental impact of the use of these fuels as power sources. Carbon monoxide (CO) is a colorless, odorless, non-irritating but very poisonous gas. It is a product by incomplete combustion of fuel such as natural gas, coal or wood. Vehicular exhaust is a major source of carbon monoxide. CO reduces the flow of oxygen in the bloodstream and is harmful to every living organism. In some urban areas, the motor vehicle contribution to carbon monoxide emissions can exceed 90 percent. Hydrocarbon (HC) emissions result from fuel that does not burn completely in the engine. It reacts with nitrogen oxides and sunlight to form ozone, which is a major component of smog. Ozone is one of the EPA's defined pollutants known to cause irritations of the eyes, damage the lung tissue and affect the well-being of the human respiratory system. Furthermore, hydrocarbons emitted by vehicle exhaust systems are also toxic and are known to cause cancer in the long term.

In summary, the transportation sector is becoming increasingly linked to environmental problems. The most important impacts of surface transportation systems on the environment relate to climate change and air quality. The activities of the transport industry release several million tons of gases each year into the atmosphere and have a significant impact on climate change, notably the global warming. Transportation is also the major source of pollution in the form of gas and particulate matters emissions that affects air quality causing damage to human health. Toxic air pollutants are associated with cancer, cardiovascular, respiratory and neurological diseases. Carbon monoxide when inhale affects bloodstream, reduces the availability of oxygen and can be extremely harmful to public health. An emission of nitrogen dioxide from transportation sources reduces lung function, affects the respiratory immune defense system and increases the risk of respiratory problems. The emissions of sulfur dioxide and nitrogen oxides in the atmosphere form various acidic compounds that when mixed in cloud water creates acid rain. Acid precipitation has detrimental effects on the built environment, reduces agricultural crop yields and causes forest decline. The reduction of natural visibility by smog has a number of adverse impacts on the quality of life and the attractiveness of tourist sites. Particulate emissions in the form of dust emanating from

vehicle exhaust as well as from non-exhaust sources such as vehicle and road abrasion have an impact on air quality. The physical and chemical properties of particulates are associated with health risks such as respiratory problems, skin irritations, eyes inflammations, blood clotting and various types of allergies.

Appendix B: Concepts of Traffic Signal Operation

(1) Three Modes of Traffic Signal Operation

a. Fixed-Time Control

Fixed-time control is the simplest, less expensive and easier to maintain. The signals assign right-of-way at intersections according to predetermined schedules, i.e., timing plans. The phase sequence, phases splits, cycle length and (or) offset for each signal are fixed, and determined based on historical traffic pattern. Because it does not account for any traffic demand variations, fixed-time signal control may cause additional delay (FHWA, 2008).

b. Actuated Control

Signal timing in actuated control, in contrast, consists of intervals that are called and extended in response to vehicle activations. The traffic controller attempts to adjust green time continuously and in some cases, the sequence of phasing. These adjustments occur in accordance with real-time measures of traffic demand from vehicle detectors placed at the intersection approaches. Depending on the settings of the controller, the adjustments are constrained by necessary controller parameters. Actuated control usually reduces delay, increases capacity and can be safer than the fixed-time control, though they are more expensive to implement and also require advanced training of practitioners to operate properly (FHWA, 2008).

Traffic-actuated control can be of two types, semi-actuated and fully actuated control, depending on the traffic approaches to be detected.

In semi-actuated control, the monitored phases include any protected left-turn phases and phases of the side streets. The major movements are called “sync” phase, served unless there is a conflicting call on a minor movement phase. Minor movement phases receive green only after the sync-phase yield point and are terminated on or before their respective force-off points. These points occur at the same point during the background signal cycle and ensure that the major road phase will be coordinated with the adjacent signals. If there are no calls present at the yield point, the non-coordinated phases will be skipped

for an entire cycle length. The major disadvantage of semi-actuated control is that continuous demand on the minor phases can cause excessive delay to the major movements if the maximum green and passage time parameters are not set appropriately (FHWA, 2008).

In fully-actuated control, vehicle detectors are installed on all traffic approaches. For each phase, there is a set of minimum and maximum green time. If there are no opposing vehicles that waiting for the right-of-way, the moving traffic will receive additional green time. Fully actuated signals are mostly found at intersections that exhibit large fluctuations of traffic volumes from all of the approaches during the day.

Much of the benefit of traffic-actuated control is derived from the ability of the controller's proactively responding to the fluctuations in traffic volume, which provides greater efficiency compared to fixed-time control by servicing cross-street traffic only when required. The primary disadvantage of fixed-time control is avoided as the main street traffic is not interrupted unnecessarily. This is particularly beneficial during off-peak conditions, resulting in fewer stops and smaller delays to the traffic on the major arterial, which ultimately leads to a decrease in fuel consumption and pollutant emissions. However, actuated traffic signal can only respond to the traffic flow fluctuation to a certain degree. A retiming is needed after a period of time to ensure its efficiency.

c. Traffic Responsive Control and Adaptive Control

The term "adaptive traffic control" has been used for decades. The first functional deployments were seen in the early 1980s. These kinds of systems rely on advanced detection and information technologies and increasing computation speed to adjust the lengths of signal phases based on solving certain optimization problems in every few seconds (Zhang, 2010). With such a mechanism, adaptive signal systems are obviously more capable of optimizing signal timings against fluctuating traffic conditions, and generally can save up to 10% in total travel time (Boillot, 1992). On the other hand, these systems are expensive, beyond the budget of many agencies. The distinction between these systems may be clarified by reclassify adaptive systems into two categories: responsive adaptive and real-time adaptive.

The main differences between traffic responsive control and adaptive control are the response lag time and location of the processing algorithm. A responsive system collects data over several minutes or cycles, transmits the data to an offsite location where software on a central computer system compares the field data to a menu of predetermined options based on preset parameters, and implements the selected option by uploading new timing plans to the field controllers. There is inherent response time lag in this methodology that is reflected in the amount of time that it takes for adjustments to be made. On the other hand, a real-time adaptive control generally performs the same task using more complex algorithms, but with fewer constraints and no lag time. While data is collected similar to the responsive control, the intelligence or processing algorithms are located in the field. Some literature shows that adaptive control is cycle free, while responsive control is not. Adaptive control is more expensive than the responsive control as well.

(2) Configuration of Intersections

a. Isolated Intersection

Isolated traffic signals can be timed without considering other adjacent signals, allowing the flexibility of setting timings that optimize different objectives for individual intersections.

b. Arterial

For intersections located along a major arterial, isolated operations can be improved by considering coordination of the major movements along the arterial. Common cycle lengths are often employed to facilitate this coordination.

c. Grid Network

Intersections to be considered are often located in grid networks with either crossing arterials or a series of intersecting streets with comparable function and traffic volumes. In these situations, the entire network is often timed together. Those grid networks with short block spacing, particularly in downtown environments, are frequently timed using fixed settings and no detection (FHWA, 2008).

Appendix C: Macroscopic Tools, Micro-Simulation and Emission Estimators

(1) Macroscopic Traffic Signal Optimization Tools

In order to optimize signal control settings, a variety of macroscopic optimization tools have been developed and widely used all over the world, including SYNCHRO (Trafficware, 2006), TRANSYT-7F (Hale, 2008), PASSER (Venglar et al., 1998) and SIDRA INTERSECTION (Akcelik, 1984). In these programs, the mathematical models are developed to represent the complex interactions between traffic state evolution and key control parameters so that signal timings can be optimized based on the performance indices generated from the underlying traffic flow model (Liu and Chang, 2011). These macroscopic models are computationally fast and simple in input requirements. Delay and its derivatives are commonly used as objective functions in most optimization software. For example, Synchro (Trafficware, 2006) optimizes signal settings using a percentile delay, which considers cycle-by-cycle traffic variations, and TRANSYT-7F (Hale 2008) optimizes signal settings using disutility index, which is based on a combination of delay and stops. To summarize the features and limitations of existing signal optimization tools, two most widely-used signal timing optimization programs in the United States, TRANSYT-7F and Synchro, are briefly introduced in the following.

a. TRANSYT-7F

TRANSYT-7F is a macroscopic traffic simulation and signal timing optimization program for signal timing design. The original TRANSYT model (TRAffic Network StudY Tool) was developed by the Transport Research Laboratory (formerly Transport and Road Research Laboratory) in the United Kingdom at the end of the 1960s (Hale 2008, Robertson 1968 and 1969). TRANSYT, version 7 was "Americanized" for the Federal Highway Administration (FHWA); thus the "7F." TRANSYT-7F Release 11 introduced in January 2008 included the ability to optimize cycle length, phase sequence, green splits and offsets using a genetic algorithm (GA) and a traditional hill-climb technique (MacTrans 2008). The traffic simulation model in TRANSYT-7F is among the most realistic of those available in the family of computerized macroscopic traffic models. A macroscopic model is one that considers platoons of vehicles

rather than individual vehicles. TRANSYT simulates traffic flow macroscopically, but in a step-wise manner. The cycle length is divided into small, equal time increments, called steps. A step is typically from one to three seconds, although the relationship between seconds and steps need not be an integer conversion.

TRANSYT uses the Highway Capacity Manual delay model, but further uses macroscopic simulation results to allow this delay model to recognize complex traffic operations. Several delay model values (e.g., capacity, PVG, Xu) are obtained from simulation, instead of user input. The model estimates average "control" delay, which includes initial deceleration delay, queue move-up time, stopped delay, and final acceleration delay. The delay equation contains three terms as in HCM.

TRANSYT-7F develops a signal timing plan that produces an optimal value of the user-selected performance index (PI). PI, also known as the objective function, allows the user to define their preferences regarding performance of the traffic network. One of the most important parts of the objective function is the disutility index (DI). DI is a measure of disadvantageous operation; that is, stops, delay, fuel consumption, etc. Unless the DI has specifically been defined as excess fuel consumption, its value has no intrinsic meaning, since it is simply a linear combination of delay and stops, whose units differ. An excess maximum back of queue penalty can optionally be included within the disutility index.

b. SYNCHRO

SYNCHRO, developed by Trafficware Inc., is a delay-based program for modeling and optimizing traffic signal timings for arterials and networks. Its objective function also minimizes stops and queues by applying penalties for these MOEs. SYNCHRO's traffic model is similar to the link-based model in TRANSYT 7F. It optimizes the signal timing parameters by evaluating a series of cycle lengths, applying a heuristic method for green splits, conducting an exhaustive search for left-turn phase position and a quasi-exhaustive search for offsets (Yun and Park 2005). To optimize timings for an arterial, the program requires the user to apply several manual steps in a specific order: (1) optimize cycle lengths and green splits for individual intersection; (2) optimize a background cycle length for network; and (3)

optimize offsets and left-turn phase position for network. SYNCHRO optimizes cycle length by analyzing all cycles in the defined range. It optimizes offsets using a multi-stage process and it uses a different step-size depending on the optimization level selected by the user at each stage. For instance, if the user requests extensive offset optimization, SYNCHRO first simulates all offsets in 4-second increments, followed by a search using 2-second increments. Finally, it performs another search using 1-second increments near the best offset from the second stage.

Unlike TRANSYT-7F, SYNCHRO does not consider platoon dispersion. It calculates a coordinatability factor using link distance, travel time, and traffic volumes as input. The factor recommends when to coordinate two adjacent signals. Offsets in SYNCHRO are optimized through what the manual describes as a five-step search process. In steps 1, 3, and 5, local offsets are adjusted by considering all acceptable values of the offset. In steps 2 and 4, the offsets of "clusters" of signals are optimized together. Clusters appear to be identified according to the coordinatability factor.

SYNCHRO uses a percentile delay as the optimization criterion. The basic premise of the percentile delay method is that traffic arrivals follow a Poisson distribution. The percentile delay method calculates vehicle delays for five different scenarios (i.e., 10^{th}, 30^{th}, 50^{th}, 70^{th} and 90^{th} percentiles) and takes a volume weighted average of delays predicted for each scenario (Husch and Albeck, 2006). The percentile delay computation uses only the first and third delay terms of the HCM. The incremental delay and the progression factor for the uniform delay in the HCM method are dropped. The incremental delay term of the HCM is modified for X>1 to use the saturation flow rate. The fourth term, queue delay, is added to cover delays due to queue blockages resulting in unused green time.

SYNCHRO has an excellent user interface that provides features to easily fine-tune a timing plan. Furthermore, it provides for data conversion to other popular software. Due to this, SYNCHRO popularity has grown at a phenomenal rate since its initial availability during the mid-1990s. Because of its ease of use, many engineers use it as an input processor for TRANSYT and CORSIM.

(2) Microscopic Traffic Simulation Models

Besides macroscopic optimization tools, signal timing optimization models have been developed by using some microscopic traffic models, such as TSIS-CORSIM, VISSIM and Transportation analysis and simulation system (TRANSIMS), to evaluate and improve the quality of signal timings (Hale 2008, Stevanovic 2007 &2009). Traffic micro simulation models are becoming widely used as valuable tools in modeling existing and planning future transportation networks in various traffic conditions. These models can help transportation professionals make important decisions on such topics as new roadway alignments and configurations, new interchange configurations and locations, the addition of freeway auxiliary lanes, work zone management strategies and plans, operational and intelligent transportation system strategies and plans, coordination and timing of traffic signals, and the addition of high-occupancy toll lanes. Although many of the micro simulation models used today are robust and provide a wide range of analysis options, some gaps and limitations still exist that can affect the accuracy of their results. To summarize the features and limitations of existing micro simulation tools, two most widely-used programs in the United States, TSIS-CORSIM and VISSIM, will be briefly introduced in the following.

a. TSIS-CORSIM

The CORridor-microscopic SIMulation program (CORSIM), a stochastic microscopic simulation model, was first developed by FHWA during the 1970s. CORSIM is a core component of the traffic software integrated system (TSIS) package, which is one of the most widely used microscopic simulation models in the United States. CORSIM consists of an integrated set of two microscopic simulation models that represent the entire traffic environment. NETSIM represents traffic on urban streets and FRESIM represents traffic on freeways. Microscopic simulation models represent movements of individual vehicles, which include the influences of deriver behavior (FHWA, 2007). The key characteristics of TSIS-CORSIM (car-following, lane-changing and gap acceptance, emission estimation) are summarized as follows.

The car following model in CORSIM sets a desired amount of headway for individual drivers (there are ten user-definable driver types) corresponding to a specific amount of headway. Within the constraints of traffic control devices and other system elements, vehicles seek to maintain a minimum car-following distance while not exceeding their maximum speed. CORSIM uses an interval-based simulation approach, moving every vehicle (represented as a distinct object) and updating each traffic signal every second. When a vehicle is moved, its position (both lateral and longitudinal) on the link and its relationship to other vehicles nearby are recalculated based on its speed, acceleration, and status.

Lane changing might occur if there is a need for turning movement, speed change or on freeways to avoid exiting vehicles. Gap acceptance is an important element in most lane-changing models. The ten driver types in CORSIM are assigned variable gap acceptance parameters for permissive left-turns, right turn on red, and other gap acceptance situations. Each gap acceptance decision is independently made by an individual driver considering the current available gap and a personal gap acceptance value.

NETSIM and FRESIM now use the same tables for fuel consumption and emissions. Detailed vehicle characteristics for fuel consumption and pollutant emissions can be specified. Record Type 173 is used to specify the maximum acceleration tables used to define vehicle performance for both NETSIM and FRESIM. Record Type 172 is used to specify the data tables for both NETSIM and FRESIM. The fuel consumption rates can be specified for autos, trucks, and buses. Only one rate of HC emissions, CO emissions, and NOx emissions can be set for all types of vehicles. The environment table file is an optional input. In this version of TRAFED (Version 6.0) the individual values cannot be edited. However, the user can specify a TRF file containing Record 172 or containing Record 172 records customized by the user. Use the Browse button to select the correct file.

b. VISSIM

VISSIM (Verkehr In Staedten SIMulation) was developed at the University of Karlsruhe, Germany, during the 1970s. VISSIM is a microscopic, behavior-based simulation model that uses a psychophysical driver behavior model developed by Wiedemann, which employs stochastic car-following

models and dynamic speeds (PTV, 2008). It consists of two different programs, a traffic simulator and signal state generator. The traffic simulator includes car-following and lane-changing logic, and it is capable of simulating up to one-tenth of a second. The key characteristics of VISSIM (car-following, lane-changing and gap acceptance, emission estimation) are summarized as follows.

The car following model in VISSIM is the psycho-physical driver behavior model developed by Wiedemann in 1974. The basic concept of this model is that the driver of a faster moving vehicle starts to decelerate as he reaches his individual perception threshold to a slower moving vehicle. Since he cannot exactly determine the speed of that vehicle, his speed will fall below that vehicle's speed until he starts to slightly accelerate again after reaching another perception threshold. This results in an iterative process of acceleration and deceleration. VISSIM, like CORSIM, uses an interval-based simulation approach. VISSIM simulates traffic flow by moving "driver-vehicle units" through a network. Stochastic distributions are used to replicate individual driver-vehicle unit behavior and dynamic headway. Every driver with his specific behavior characteristics is assigned to a specific vehicle.

Gap acceptances in VISSIM is user-definable and location specific. Therefore, gap acceptance can vary from on point to another with a particular network based on the type of operations being simulated (e.g., permitted left turns, right turns on red, U-turns, and all-way stop control). Gap acceptance can also be varied by vehicle types. VISSIM provides an unlimited number of user-definable vehicle types.

VISSIM uses the same formula to estimate fuel consumption as SYNCHRO and TRANSYT-7F. The emissions statistics are based on the simple emission estimation according to U.S. guidelines. There's an optional VISSIM Emissions module with full VISSIM licenses. The emission calculation settings will only be effective if an emission model (optional VISSIM module) is activated.

In contrast to less complex models that use constant speeds and deterministic car-following logic, VISSIM uses the psychophysical driver behavior model developed by Wiedemann (1974). This model can model the process while drivers modify vehicles' gap in terms of the current traffic conditions. In

VISSIM, vehicles' activities are determined by the acceptable vehicles' gap and the desired speed of drivers. If not hindered by other vehicles, a driver will travel at his desired speed. If the current speed is less than the desired speed, a driver will accelerate at a specific acceleration to reach the desired speed. And if the vehicles' gap is small, a driver will decelerate to correspond with the vehicle at its front. The lane change logic also replicates individual driver behavior characteristics. To a certain extent, VISSIM model can capture the real operations of vehicles' following and lane changing behaviors.

(3) Emission Estimation Models

Emission estimation models have been used to estimate the effect of proposed transportation alternatives and to compare competitive alternatives from an air quality perspective. In previous decades, several emission estimation models have been developed. Among these, a few models are based on second-by-second vehicle speed and acceleration emissions. These include Comprehensive Modal Emission Model (CMEM; Barth et al. 2001), the VT-Micro model (Ahn et al, 2002) and Motor Vehicle Emission Simulator (MOVES) (EPA, 2009). These microscopic models estimate vehicle pollutants at a second-by-second level of resolution using either vehicle engine or vehicle speed/acceleration data.

a. Comprehensive Modal Emission Model (CMEM)

The CMEM, which is one of the newest power demand-based emission models, was developed at the University of California, Riverside (Barth et al., 2001). The model estimates LDV and LDT emissions by utilizing analytical formula and various parameters that represent characteristics of vehicle operating modes. The term 'comprehensive' is utilized to reflect the ability of the model to predict emissions and fuel use for a wide variety of LDVs and LDTs in various operating states (i.e., properly functioning, deteriorated, and malfunctioning).

The development of the CMEM model involved extensive data collection for both engine-out and tailpipe emissions of over 300 vehicles, including more than 30 high emitters. These data were measured at a second-by-second level of resolution on three driving cycles, namely: the federal test procedure (FTP), US06, and the modal emission cycle (MEC). The MEC was developed by the UC Riverside researchers in

order to determine the load at which a specific vehicle enters into fuel enrichment mode. CMEM predicts second-by-second tailpipe emissions and fuel consumption rates for a wide range of vehicle/technology categories. The model is based on a simple parameterized physical approach that decomposes the entire emission process into components corresponding to the physical phenomena associated with vehicle operation and emission production. The model consists of six modules that predict engine power, engine speed, air-to-fuel ratio, fuel use, engine-out emissions, and catalyst pass fraction. Vehicle and operation variables (such as speed, acceleration, and road grade) and model calibrated parameters (such as cold start coefficients, engine friction factor) are utilized as input data to the model.

Vehicles were categorized in the CMEM model based on a vehicle's total emission contribution. Twenty-eight vehicle categories were constructed based on a number of vehicle variables. These vehicle variables included the vehicle's fuel and emission control technology (e.g., catalyst and fuel injection), accumulated mileage, power-to-weight ratio, emission certification level (tier0 and tier1), and emitter level category (high and normal emitter). In total, 24 normal vehicles and 4 high emitter categories were considered (Barth et al., 2001).

b. The Virginia Tech Microscopic Energy and Emission Model (VT-Mirco Model)

The VT-Micro model was developed from experimentation with numerous polynomial combinations of speed and acceleration levels. Specifically, linear, quadratic, cubic, and quartic terms of speed and acceleration were tested using chassis dynamometer data collected at the Oak Ridge National Laboratory (ORNL). The final regression model included a combination of linear, quadratic, and cubic speed and acceleration terms because it provided the least number of terms with a relatively good fit to the original data. The ORNL data consisted of nine normal emitting vehicles including six light duty automobiles and three light duty trucks. These vehicles were selected in order to produce an average vehicle that was consistent with average vehicle sales in terms of engine displacement, vehicle curb weight, and vehicle type. The data collected at ORNL contained between 1300 and 1600 individual measurements for each vehicle and Measures of Effectiveness (MOEs) combination depending on the

envelope of operation of the vehicle, which has a significant advantage against emission data collected from few driving cycles since it is impossible to cover the entire vehicle operational regime with only a few driving cycles. In VT-Mirco model, second-by-second vehicle emission and fuel consumption rates are obtained by establishing polynomial regression equations consisting of speed, acceleration, and coefficients given for each measure of effectiveness (MOE). The VT-Micro model coefficients are available for fuel consumption and emissions including CO, HC, NO_x, and CO_2 (Rakha et al, 2004).

c. Motor Vehicle Emission Simulator (MOVES)

Since the late 1970s, EPA's MOBILE models, previous version of MOVES, have been used to conduct regional air quality analysis from transportation sources. In 2010, the U.S. EPA's Office of Transportation and Air Quality (OTAQ) released the initial full version of the Motor Vehicle Emission Simulator (MOVES) (EPA 2009). This new emission modeling system is probably the most sophisticated emissions model to date and is being applied at a number of different modeling scales: all the way from the micro-scale (project-level, e.g., parking lot) to the macro-scale, where national-scale inventories are being generated for precursor, criteria, and greenhouse pollutants from on-road mobile sources.

MOVES, the latest emission model released by EPA, classifies the operating mode into 23 categories to estimate emissions based on second-by-second speed profiles of individual vehicles at the microscopic level (EPA, 2009). This microscopic modeling of emissions conceivably produces different emission estimates from those that were expressed as linear combinations of macroscopic performance measures such as delay, stops, and queue length for the entire intersection. MOVES can be implemented based on microscopic simulation output to evaluate emission performance. MOVES estimates emissions for highway vehicles for CO_2, CO, NO_x, hydrocarbons, and others based on second-by-second measurements of vehicle emissions divided into operating mode bins.

One of the most important parameters in MOVES is Vehicle Specific Power (VSP), the primary metric to determine operating modes and to estimate emissions. VSP is an estimation of engine load based on the vehicle type, the vehicle's speed and acceleration, and the road grade. Except for braking

and idling, the operating mode bins are stratified by speed ranges (<25mph, 25 to 50 mph, and >50mph) and by VSP. The operating mode bins are weighted by time spent in each bin to represent any driving cycle. For project scale analysis, a user can enter link-based average speeds or second-by-second "driving schedules" that include vehicle speed and road grade. The operating mode bin emission rates for each vehicle technology in the MOVES default database represent a base scenario of conditions for temperature, humidity, air conditioning load, fuel properties, and other factors. MOVES adjusts the default emission rates to represent user specific values of these factors.

MOVES is designed to model fleet emissions, but the project scale in MOVES allows us to model a single vehicle on a link (road segment). The project scale requires the user to import detailed data, including vehicle population. By importing a vehicle population of one and importing a drive schedule with speeds (velocity) at each second of travel, we can define the entire vehicle behavior (acceleration, deceleration, cruise, and idle) and get emissions output for that vehicle. MOVES reports the results as an aggregate over an hour of operation. We can also get activity (number of vehicles, number of hours, number of miles, etc.), so a rate (mass per vehicle, mass per mile, etc.) can be determined manually.

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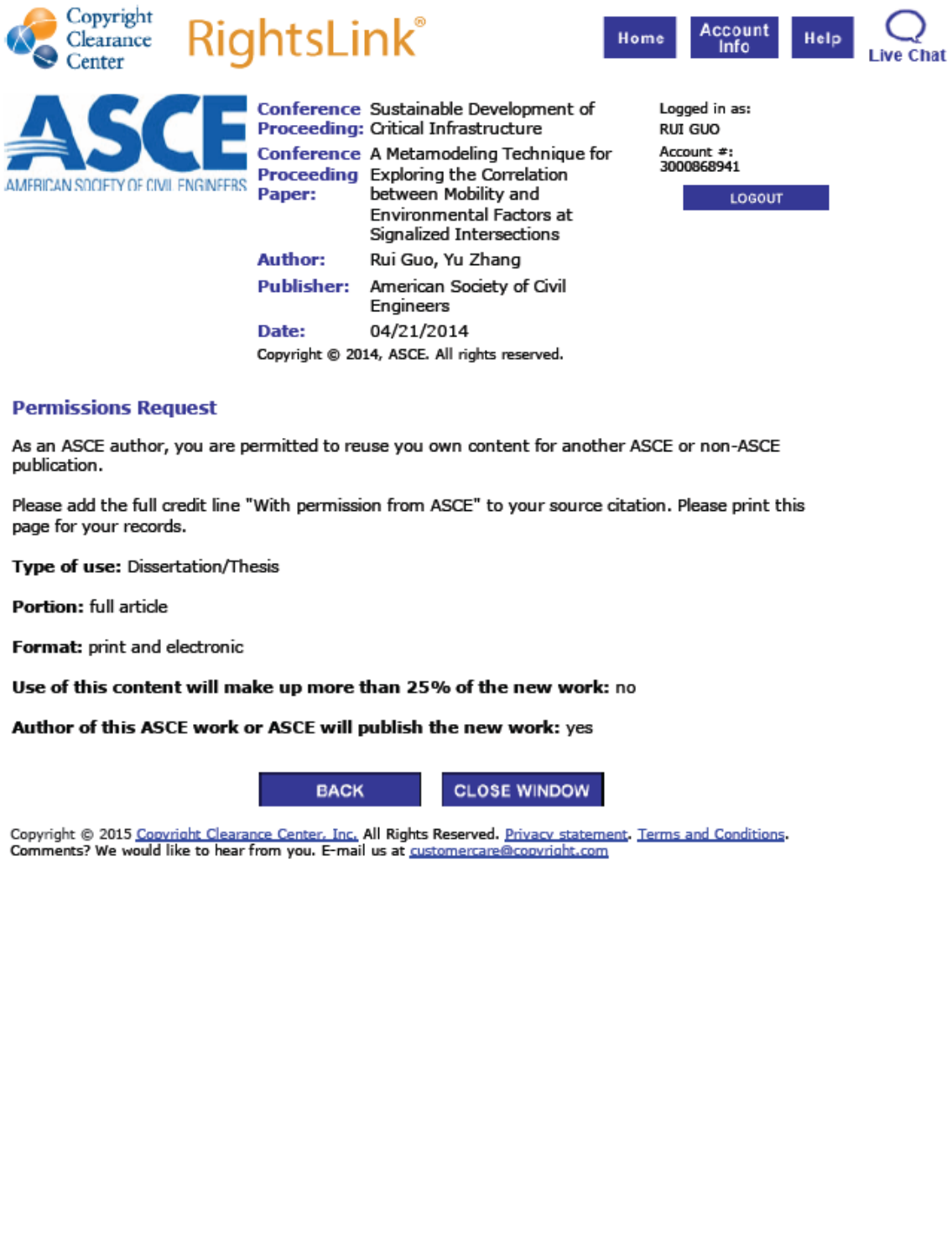

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Publisher:	American Society of Civil Engineers
Date:	04/21/2014

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