Traffic Simulation Model for Urban Networks: CTM-URBAN

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ABSTRACT

TRAFFIC SIMULATION MODEL FOR URBAN NETWORKS: CTM-URBAN

Kuo Cheng Huang

Congestion on urban transportation networks around the world is frequently encountered and its economic and environmental footprint cannot be ignored. One of the solutions used to alleviate this problem is deployment of Intelligent Transportation Systems (ITS). The effectiveness of ITS solutions to manage traffic demand more efficiently relies heavily on accurate travel time prediction, which is a difficult task to achieve using currently available simulation methods. This study proposes an urban network simulation model named CTM-URBAN, a modified version of the Cell Transmission Method (CTM) which was originally developed to simulate highway traffic. CTM-URBAN is a simple and versatile simulation framework designed to simulate more realistically traffic flows in an urban network with various traffic control devices. CTM-URBAN allows building, calibrating, and maintaining a large simulation network with a minimum of effort. A case study is presented to demonstrate that CTM-URBAN is able to predict travel time through signal-controlled intersections more accurately than the original CTM based on comparison with results from a microscopic simulator.

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LIST OF ABREVIATED UNITS

Unit	Description
ft	Feet
km/hr	Kilometers per hour
m	Meters
mph	Miles per hour
plpc	Per lane per cell
veh/hr	Vehicles per hour
vphpl	Vehicles per hour per lane

CHAPTER 1 INTRODUCTION

1.1 Research Motivation

Congestion on urban transportation networks around the world is frequently encountered and the impact of its economic and environmental footprint cannot be ignored. Over the past few decades traffic congestion in urban area rise rapidly and the problem is likely to escalate, if it is not effectively managed, as densely populated cities sprout in emerging countries. One common challenge traffic management agencies face in managing road congestion is the lack of accurate tools to assess the effectiveness of network-wide control strategies.

One of the solutions used to alleviate this problem is deployment of Intelligent Transportation Systems (ITS), but the effectiveness of ITS solutions to manage traffic demand more efficiently relies heavily on accurate travel time prediction, which is a difficult task to achieve by currently available travel time prediction methods. The degree of complexity of urban network, randomness of the traffic demand, and lack of validation data has made reliable prediction of travel time on urban networks a subject that still requires significant development.

This thesis intends to contribute to the development of urban travel time prediction technology. The belief is that advancements in urban travel time prediction can ultimately contribute to reduce the time spent by many urban dwellers on commuting and traveling on roads.

1.2 Problem Statement

Recurring urban congestion drives a need for better road operations and management strategies. Research has shown that implementation of Intelligent Transportation Systems (ITS) can achieve reduction of congestion (Van Zuylen 2003) but the effectiveness of the technology relies on accurate travel time prediction. More specifically, a reliable **real-time data-driven short-term travel time prediction tool for large scale urban network** is required. Each feature of such tool represents additional research challenges. Until recently, no candidate among the existing methods emerges to be capable of incorporating these features in one method.

Among the available travel time prediction methods, traffic simulation methods are among the few methods that have demonstrated limited success in predicting urban traffic travel time at the network level. Traffic simulation methods are commonly classified based on the level of simulation detail under three categories: macroscopic, mesoscopic, and microscopic simulators. Among them, traditional macroscopic simulation methods do not provide travel time prediction reflecting real time road condition and traffic progression. Microscopic can keep track of travel time for each vehicle and can simulate car following behaviors, however, in order to achieve stochastic and statistic relevance, many simulation runs are often required. This is one drawback that can limit the method's possibility as a real-time simulation tool. It is also suggested that the level of expertise and effort required in maintaining microscopic models may prove to be impractical when the scope is at a network wide level (Liu 2008).

The thesis identifies one macroscopic simulation method, Cell Transmission Method (CTM), capable of being implemented in such a way that mimics the capability of microscopic simulators therefore having the potential of fulfilling the desired role (*i.e.* a real-time data-driven short-term travel time prediction tool for large scale urban network.) Being macroscopic in nature, the model is simple, robust, and is suitable for distributed computing environment. This makes it a good candidate for **real-time application at large network scale.** The model is **data-driven** and has the potential to capture accurately propagation of traffic flows and queue formation, information essential to provide **short-term travel time prediction**. The area that requires more development is to expand CTM's capability in capturing the characteristics of traffic flows on **urban** roadways in simulation.

The characteristics of urban traffic can be defined by frequent interruptions in flow due to a variety of traffic control devices, queue spillback effect due to traffic demand in excess of capacity, geometrically non-homogenous road sections, frequent occurrences of congestion, and the high variability in traffic demand over time (e.g. daily, seasonally, etc.).

CTM was intended and designed as simulation tool for highway networks. The model may lack features that can adequately address traffic dynamics and effect of control facilities that are unique in an urban network. First, although the model has been adopted in some studies to simulate traffic flows in urban network, no study is known to have validated CTM is able to accurately capture the additional complexity in urban traffic flow dynamics (e.g. effects of complex traffic control devices, queue spillbacks, non-homogeneous network conditions.) Second, a generic framework that accommodates practical applications of CTM on large scale urban networks is not available. Finally, a simple procedure to calibrate CTM for urban traffic simulation cannot be found.

1.3 Objectives

The objective of this study is to develop a CTM-based simulator that accommodates these various network features specific to urban roadways. Consequently, a generic algorithm will be developed and implemented in a traffic simulator to account for vehicle movements around the most complex surface transportation facilities (i.e. signalized intersections). The formulation shall remain simple to allow real-time implementation and easy maintenance of the simulated network. The ultimate goal is to advance the development in CTM towards an algorithm that is capable of performing real-time short-term traffic forecasting for large scale urban network. The following tasks are identified to achieve the objective proposed in this study.

1.4 Research Task

1. A generic model/framework for applications of CTM in an urban network will be proposed. The framework should have the capability to accommodate the dynamic nature of urban traffic flows and road conditions.
2. A new algorithm for simulating traffic flows through signal controlled intersections will be proposed. The proposed algorithm should reflect and address common urban traffic phenomenon more accurately compared to the existing CTM models. (e.g. modeling of queue spillback effects, lane overflow, stoppage and delay induced by signal controls, flow capacity reduction due to flow conflicts.)
3. The proposed algorithm should conform to the new proposed framework and should ensure compliance/compatibility with the original CTM formulation. This is needed to allow for transparent integration of isolated intersection into a larger roadway network (i.e. freeways and other transportation facilities). Also, future developments of CTM in general should be easily applied to the proposed framework, and the advantages of CTM such as real-time simulation potential should be retained.
4. Calibration and validation of the proposed model against the results obtained from a microscopic simulator will be performed.

1.5 Research Significance

The availability of such simulation tool will allow transportation researchers and practitioners to investigate the potential of various real-time applications in providing online and on-route information about the road network performance and prevailing traffic conditions, respectively. This information could be used by transportation management agencies to improve the operations, to manage emergency situations, and to evaluate and adjust the system performance as needed.

1.6 Organization of the Thesis

This thesis is organized as follows: Chapter 1 introduces the topic of this study, formulates the problem statement and lists the objectives for the study. Chapter 2 presents a literature review of those subjects relevant in the development of CTM as an urban traffic network simulator. Chapter 3 contains background information on CTM. The first part presents the details about the topological conventions of CTM. The second part comments on the applicability of CTM to urban networks and identifies areas where modifications can be made to improve the applicability. Chapter 4 introduced the proposed model. The first part provides the definition and notations used in the model framework and the model formulation. The second part describes in detail the formulation and the usage of model components. The third part summarizes the capacities and limitation of the proposed model. Chapter 5 describes the experiments conducted to validate the calibration procedures and the accuracy of the proposed simulation model by comparison against results obtained from a microscopic simulator. Chapter 6 presents concluding statements, identifies the limitation of the proposed model, and suggests directions for future research work.

CHAPTER 2 LITERATURE REVIEW

The objective of this research study is to improve the basic version of the Cell Transmission Model (CTM) to make it more suitable for travel time prediction in urban roadways context. To provide a better understanding of this context a review of the topics regarding urban travel time prediction is provided in this chapter. This chapter provides the need, the methods, and the state of the art in travel time prediction of urban roadways. Also, this chapter identifies the challenges associated with modeling traffic flows on urban roadways. Several travel time prediction methods are described and, among them, CTM is identified as a candidate to have good potential to provide reliable information in travel time prediction applications. Reviews of recent developments that extend CTM to the context of urban network are also presented.

2.1 Short-Term Travel Time Prediction of Urban Network

Despite various traffic-control measures aimed to reduce urban network congestions (Papageorgiou *et al.* 2003), the level of network congestions and the cost associated with the problem have been steadily climbing in the past decades. One common challenge traffic management agencies face in managing congestions is the lack of accurate tools to assess the effectiveness of network-wide control strategies. One of the solutions used to alleviate this problem is deployment of Intelligent Transportation Systems (ITS).

ITS technologies provide transportation practitioners with new and more efficient methods to process information about traffic conditions and various tools to manage traffic dynamically. Van Zuylen (2003) estimated implementations of ITS based management measures can contribute to reduce 10-20% of delays on urban roads.

While ITS technology generated many applications suitable to uninterrupted facilities, there is significant potential for ITS applications to help alleviate congestion on interrupted facilities in urban networks. One of the main challenges to demonstrate the effectiveness of ITS in an urban setup is the availability of real-time information about the network traffic conditions and the ability to accurately estimate short-term travel times for the entire network (Viti, 2006). Both are difficult to collect or to generate. Upon reviewing the forecasting algorithms to date, (Vlahogianni and Karlaftis, 2004) it was observed that despite the significant amount of research studies, a clear description of the scope and requirements involved to achieve a feasible short-term traffic forecasting solution is not available. The authors presented a new structured methodology to outline the various requirements involved in short-term traffic forecasting modeling.

Viti (2006) presented a thorough study on the dynamic behavior of vehicle flows through signal controlled urban intersections and the uncertainties that arise in predicting queues and delays due to heavy interaction between the traffic and the various types of signal controls . The study proposes and validates several probabilistic models which quantify various aspects of queues and delays at signal controlled urban intersections.

Van Hinsbergen *et al.* (2007) provided an extensive structured overview of available short-term traffic prediction methods. In this study, the reviewed methods are classified into three primary categories: Naïve, Parametric, and Non-Parametric models, and subsequently a number of sub-categories. Along with a review on each method, the paper concludes that the vast majority of the models focused on traffic prediction on a single location or fixed routes on freeways. Among the 186 reviewed models, Traffic Simulation Models stand out to be the only models that exhibit capability to forecast travel time in an urban setup and at the network level, albeit small networks. The authors state that for any of the studied prediction method to be practical, capability to predict traffic on a much larger scale is required. A review of state-of-the-art of travel time prediction model conducted in Liu (2008) confirmed similar conclusions. The author stated that few methods aim at short-term travel time prediction for urban routes and very few of the methods have been validated with empirical data Among the reviewed methods, Liu concluded the only models capable of performing real-time predictions are the K-nearest neighbor models and the simulation models.

While the simulation models emerge as the method that satisfies the most review criteria, some studies identify several shortcomings. For example Liu (2008) noted that field validation data are not generally available, especially for large networks. Van Hinsbergen *et al.* (2007) pointed out that few comparisons are made between the simulation models and other models, which makes the accuracy of the model difficult to assess. Liu (2008) suggested the high degree of expertise required for design and maintenance and the intensive model/parameter calibration required may still prevent the use of simulations methods in real-life applications. Finally, Van Lint (2004) found simulation models still have to be improved by addressing the problem of online parameter calibration and OD estimation.

Despite the shortcomings identified by some authors, simulation methods remain a promising candidate and continue to be actively developed. Van Hinsbergen *et al.* (2008) suggested that simulations models may be the most suitable model to represent the dynamics and the complexity of urban traffic. Based on the level of detail, simulation models relevant to this study can be found under three categories: macroscopic, microscopic and mesoscopic simulators. Chevallier and Leclercq (2007) proposed a dynamic macroscopic model to estimate the delay of unsignalized intersections. Alecsandru and Ishak(2008) presented a mesoscopic cell based model that can potentially be used as an operational analysis tool for large-scale road networks. Miska (2007) developed an online microscopic simulator that is aimed for real-time traffic management of urban networks. More extensive reviews of the simulation models can be found in literature (Hoogendoorn and Bovy, 2001; Alecsandru 2006; Donieca *et al.*, 2008).

Although macroscopic simulation models are fast and require relatively less effort to calibrate, they are generally incapable of representing urban traffic dynamics such as queue spillback due to traffic demand in excess of capacity on urban networks, and effects of stochastic departure times on traffic flow (Van Hinsbergen 2007). It is also questionable if macroscopic simulations are suitable for traffic operation purpose as the outputs are average values and do not describe the dynamic evolution of traffic conditions over short periods of time. On the other hand, microscopic simulation models capture interactions between individual vehicles and between vehicles and traffic control facilities. However, microscopic simulation requires additional computer resources and significant calibration effort when applied to large-scale networks, therefore some challenges have to be addressed to use these models in real-time applications.

With the advancement of computing power, and continuous research effort exploring the subject, it seems that many limitations that set these models apart have been overcome. Recently, Liu (2008) presents the first neural network method that can predict travel time at the network level. Avram and Boel (2005) implemented an online Java based distributed simulator which utilizes both macroscopic and microscopic algorithms to simulate different components of a large network in real-time. Miska (2007) demonstrated that the use of real-time microscopic simulation for urban network is possible. Similarly, it is possible to implement CTM, a macroscopic simulation model, in such a way that mimics the capability of microscopic simulators in order to model more complex elements of urban networks while retaining the macroscopic advantage of simplicity (Alecsandru, 2006).

2.2 Characteristics of Urban Traffic Flows

The high level of complexity associated with urban networks characteristics and traffic flow dynamics limit the applicability of most travel time prediction models to relatively small sections of an urban network. There are many research studies that focused on analyzing and providing a better interpretation of these characteristics. This section provides a review of several recent approaches that attempted to understand and quantify the characteristics of traffic flows on urban networks. The sample of studies selected serve to introduce the research topics considered in developing the proposed model, and is not intended as a comprehensive review on the subject.

The most notable characteristic of urban traffic that differs from highway traffic is the frequent occurrences of flow interruptions, either by conflicting flows or by traffic control devices. Chen *et al.* (2008) identified four general types of conflicts: zero conflict, merging conflict, diverging conflict, and crossing conflict. The study proposes a kinematic wave traffic flow model to take into account the effect of all four conflicts. Viti (2006) defined similar flow interaction/interruption in terms of same direction flow, controlled facility, and intercepting flow. He further observed that travel delay in urban networks is primarily due to interruptions by control devices rather than same direction flows.

The delay or effect of various types of traffic control devices and schemes are under scrutiny of many studies. Traditionally, the delay at signal controlled intersection is estimated by analytical methods. Akcelik (1981) described the methods that estimate various types of delays generally occur at signal controlled intersections. Akcelik (1993) further explored the effect of variable demand on the delays and presented a new delay model. Dion *et al.* (2004) found that delay estimations according to various design manuals may differ when the flow becomes saturated. The study concludes while the delay estimation results are generally consistent between the capacity guide methods and a microscopic simulator based on a one-lane study, efforts should be made to confirm this consistency for more complex situations. A recent study (Akgüngör 2008) introduces the analysis period as a new parameter to improve the accuracy in estimating signalized delays compared to conventional methods.

Flow interruptions at intersections cause the formation of vehicle queues and stop delays. Accurate estimation of queue lengths at signal controlled intersections is another subject of studies focusing on urban traffic flows (Tarko, 2000; Akcelik, 2001; Liu *et al.* 2011). Additional delays can occur when the demand exceeds the designed intersection capacity and queue spillback/overflow develops. (Viti and Van Zuylen , 2004; Geroliminis, 2009).

Discharge flow rate is another important parameter in estimating the capacities of signalized intersections. It is traditionally estimated based on the assumption of constant saturation flow. However, Lin and Tseng (2004) demonstrated the existence of discrepancies between field data and saturation flow models. Akcelik and Kellly (2002) presented a more accurate method to estimate the capacities of signal controlled intersections by incorporating an exponential queue discharge flow and speed relationships. The findings of the study can be used to improve the accuracy of microscopic simulation models and signal time optimization models.

In addition to signal controlled intersections, non-signal controlled intersections are common elements in urban networks. Traffic parameters such as delay and queue dynamics observed at various types of non-signal controlled intersections have been investigated by previous studies (Troutbeck, 1986; Troutbeck and Kako, 1999; Troutbeck, 2002; Chevalier and Leclercq 2007). The findings are valuable to the development of urban traffic flow simulators.

Finally, different transportation modes (e.g. transit vs. private/freight vehicles, motorized vs. non-motorized traffic, etc.) interact at various levels on urban networks. The effect of these interactions between different modes of transportation including public transit was investigated by Jayakrishnan *et al.* (2003) and it was shown that it can influence the simulation outcome. Lebacque (1998) introduced impact of multimodal flows (e.g. bus) on macroscopic simulations. Tuerprasert(2010) recently introduced multi-class input for macroscopic implementation. Intersection delays caused by other modes of transportation such as pedestrian (Milazzo *et al.*, 1998), bicycles and heavy vehicles (Troutbeck, 2010) are also subject of recent studies.

Integration of modeling components capturing all thes urban traffic flow characteristics should help in representing traffic flows on urban roadways more realistically. Nevertheless, due to space limitations they are not included among the objectives of this study. The modular approach of the proposed framework permits easy integration of additional features at a later time and they shall be considered in expanding the capacity of the proposed model.

2.3 Development of Cell Transmission Model

The Cell Transmission Model was introduced by Daganzo (1995) as a macroscopic representation of traffic flow capable of predicting the evolution of multi-commodity traffic flow over complex networks. According to Daganzo, CTM is aimed to improve the realism of traffic performance models base on which route choices and travel time predictions are made. The model built on the work of the LWR model (Lighthill and Whitham, 1955; Richards, 1956) and the triangular fundamental diagram (Newell 1993 I, II, III), providing the transportation community with a meaningful modeling tool for highway traffic at the time (Blandin *et al.* 2009).

Since then, CTM has received considerable attention and has been the subject of many research studies. The studies can be grouped into three broadly defined categories: (1) validating and improving the model performances, (2) improving and expanding the applications of the model and (3) using the model as performance evaluation tool for proposed theories and models.

Much work has been done to enhance the realism and capacities of CTM. Daganzo (1999) introduces a new version of CTM called Lagged Cell-Transmission Model (L-CTM), which allows variable cell lengths and adapts a non-concave flow-density. The study concludes that the lagged model is suitable to address particular roadway sections such as intersections and non-homogeneous highways. Laval and Daganzo (2005) introduced lane-changing algorithms that can be incorporated in CTM to improve realism, especially in particular traffic situations such as a port of entry (Cheu et al, 2009) or toll plazas. Ishak *et al.* (2006) propose several modifications to CTM which improves accuracy and realism of traffic flow representation and enhance the applicability of CTM for operational analysis of large-scale traffic networks. Szeto (2008) presented an enhanced lagged Cell-Transmission Model which resolved the L-CTM issue of generating unrealistic negative density in simulation network. The model was shown to also give more accurate solutions compared with L-CTM. More recently, Blandin *et al.* (2010) proposed a second order perturbed model of CTM which match empirical features of highway traffic more closely than the classic model.

Along with the theoretical development of CTM, a significant amount of field data has been used to validate and improve the practicality of this model particularly in highway applications. Muñoz *et al.* (2004) developed a semi-automated method for calibrating the parameters of a modified version of CTM. Muñoz *et al.* (2006) subsequently proposed a piecewise-linearized version of CTM called the switching-mode model (SMN). The authors prescribed parameter calibration methodologies that are computationally efficient and suitable for use in real-time traffic monitoring and control applications. Lu and Skabardonis (2006) exam the possibility of obtaining realistic shockwave value from NGSIM trajectory data. The finding of the study can contribute in improving the accuracy of input value of CTM simulation. Gomes *et al.* (2008) presented a complete analysis of the qualitative properties of CTM and validate the effectiveness of CTM in ramp metering management.

The studies demonstrate that practical, real-time application of CTM in operational use is plausible for traffic management on highway networks. All these studies and the successful implementation of the CTM paradigm in several simulators (e.g. Aurora, VISTA, TranSYT) demonstrate that CTM has great potential to be expanded for real-time applications modeling reliably traffic flows on urban networks.

Volumes of studies have been conducted to apply CTM in various transportation areas such as dynamic traffic assignment, signal optimization, emergency evacuation and simulations of various transportation modes. While detailed review of all these studies may not be relevant to the scope of this paper, the research work provides good references and exhibit good potential for the applications to be extended to urban context. In the next section, a review of the literature that focuses on applications of CTM in urban network context is provided.

2.4 Development of CTM in the Context of Urban Network

CTM was intended as a simulation model for highway network. In an attempt to extend CTM in modeling integrated freeway/surface street system, Lee (1996) proposes two enhancements: variable cell sizes and treatments of signalized intersections. Although preliminary results indicate generally consistency with results from NETSIM simulator, research work to improve applicability and to address some important limitations did not follow. Lo (1998; 1999; 2001) and Chang (1998) demonstrated the practicality in applying CTM to model signalized intersections by formulating signals in a binary manner. The algorithms presented have since been adopted in many studies (e.g. Lo and Chow, 2004; Zeng *et al.* 2005; Zhang *et al.* 2009) as a tool to evaluate performance of signal optimization plans.

Recent development in ITS technologies justify to the need of realistic travel time prediction model, especially in complex urban networks. Flötteröd and Nigel (2005) suggested it may be practical to extend CTM in fulfilling such demand and propose some potential approaches. In presenting a macroscopic model of traffic, Liu *et al.* (2008, 2011) described some key features occurring at signalized intersections such as queue evolution and blocking effects between different movements. The same considerations may serve to investigate the adequacy of CTM as an urban travel time prediction model.

Interaction between different modes of transportation has been the research focus of several CTM related studies. Lebacque *et al.* (1998) proposed a way to represent the effect of bus traffic in CTM. Tuerprasert and Aswakul (2010) presented M-CTM model to include effects of multi-class vehicles in CTM. Although the studies do not specifically address urban traffic, the work is relevant to the subject since urban traffic often consists of multiple classes of vehicles, namely transit vehicles.

Although many CTM based applications are proposed in the urban context, very few studies to-date provide thorough validation or critical analysis on the algorithm’s ability to capture urban traffic flows realistically. Much of the limitations of CTM remain unidentified and untreated, namely the lack of ability in representing the wide array of traffic control devices and the heterogeneous urban road configurations. Similarly, insufficient representation of the complex traffic dynamics in urban network, such as queue spillbacks and movement blockages, may cause unrealistic simulation results. Finally, lack of field data and calibration method specific to urban setup seem to be a factor preventing the validation of CTM as a simulation model for urban networks.

2.5 Conclusion

In this chapter, literature review focused on four topics related to the study is presented: (1) short-term travel time prediction of urban network, (2) characteristics of urban traffic flows, (3) development of CTM, and (4) development of CTM in the context of urban network. The review reveals that a short-term real-time travel time prediction method that is suitable for of large urban network scale can be valuable in producing the information required to assess the effectiveness of network traffic control policies. Further development is required since none of the methods presented in this chapter can incorporate all these features (*i.e.* short-term, real-time, data-driven travel time prediction on urban networks). Review on the development of CTM, a macroscopic simulator for highway traffic flows, indicates that there is a potential in extending the model to simulate traffic flows in urban networks. In the next chapter, a detailed analysis on the possibility and the potential challenges are presented.

CHAPTER 3 BACKGROUND

Review of the recent studies on travel time prediction modeling shows that the existing models do not sufficiently meet the criteria required to produce real-time short-term travel time prediction for a large urban network. The challenge remains in the difficulty of capturing the complex combined effect of interactions between a large number (and types) of traffic control devices and conflicting flows in a large scale. Building a model that is practical for operational use is another challenge. The model has to be simple enough to minimize the effort and expertise required to build, calibrate, and maintain on a regular basis, yet flexible enough to accommodate constant changes in the road capacities, road conditions, and management policies. Among the reviewed models, simulation-based approaches appear to have the biggest potential in addressing these challenges.

Microscopic simulation-based models have been shown to be able to capture more accurately complex urban traffic dynamics, albeit at a small controlled scale. On the other hand, a more simplistic nature of macroscopic simulation models makes them better fit for operational use in the context of a large urban network, only if they can provide sufficient details about the traffic dynamics to enhance their accuracy.

This study explores the possibilities of incorporating microscopic capabilities into a well-developed macroscopic simulation model, CTM, to meet the challenges of simulating traffics in complex urban networks. In this chapter, a brief review of the original CTM formulation is provided in the first section, followed by a discussion on the modification and the microscopic properties that may be incorporated to improve applicability of CTM in simulating traffic flows in urban networks, in the second part.

3.1 Cell Transmission Model

The review of the existing studies reveals that much development has been done to enhance CTM. However, in terms of urban network applications, the models presented in literature primarily use the original CTM formulation as the base. A recent study (Sezto *et al.*, 2009) cites and summarizes a collection of CTM formulations that are commonly used by researchers studying CTM in an urban context. In this section, CTM is presented generally based on Sezto *et al.* (2009). The only difference is that the notations presented here are modified to be consistent with the new proposed model so they can be easily compared.

CTM Representation of Traffic Network

In CTM, the basic building blocks representing homogeneous road segments in the network are *cells*. The advancement of traffic flow between two adjacent cells is facilitated by the use of *connectors*. The modeling parameters associated with the cells are used to derive the traffic density at each simulation update time, while the parameters associated with the connectors described the traffic flow. A triangular traffic flow fundamental relationship is assumed to describe the traffic density and flow at the cell level, where there is constant free-flow speed at low densities and constant wave speed at high densities. According to this assumption, length of cell i, L_i, can be determined by:

$$L_i = v_i^f \cdot \Delta t \tag{3.1}$$

Where

v_i^f = free flow speed designated for cell *i*

Δt = simulation time step

Consequently, the vehicle storage capacity of cell, X_i, can be determined by:

$$X_i = N_i \cdot L_i \cdot K^J \tag{3.2}$$

Where

N_i = Number of lanes in the road section represented by cell *i*
L_i = Length of cell *i* as determined by equation (3.1)
K^J = Jam density per lane

Ordinary Cell and Connectors

A basic road section (i.e. without junctions) can be represented by a series of interconnected cells, called *ordinary* cells. Ordinary cells are linked by corresponding ordinary connectors, as shown in Figure 1

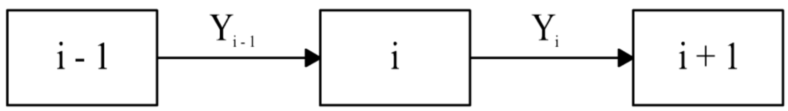


Figure 1: CTM, Ordinary Cells and Connectors

For each cell, the input connector and the output connector are used to represent the incoming traffic flows and the outgoing traffic flows, respectively, simulating the propagation of vehicles through the corresponding road segment. At each simulation time *t*, the status of ordinary connectors is updated by using equation (3.3), referred to as the flow advancing equation.

$$Y_i(t) = min\{x_i(t),\ Q_i(t),\ \ Q_{i+1}(t), \delta[X_{i+1}(t) - x_{i+1}(t)]\} \tag{3.3}$$

Where

$x_i(t)$ = Number of vehicles in cell i, at time t
$Q_i(t), Q_{i+1}(t)$ = Maximum flow, at capacity, of cell i and cell *i+1*
δ = Ratio of shockwave speed to free-flow speed (*w/v*)
$X_{i+1}(t) - x_{i+1}(t)$ = Effective available space or remaining storage capacity

Based on the connectors' status at time t, the cell occupancy at next update time, $t+1$, can be estimated by using equation. (3.3), referred to as the flow conservation equation.

$$x_i(t+1) = x_i(t) + Y_{i-1}(t) - Y_i(t) \tag{3.4}$$

Where

$x_i(t)$	=	Number of vehicles in Cell *i* at time *t*
$x_i(t+1)$	=	Number of vehicles in Cell *i* at the next time update *t+1*
$Y_{i-1}(t)$	=	Incoming flow from cell $i-1$, at time *t*
$Y_i(t)$	=	Outgoing flow from cell i into cell $i+1$

Uncontrolled Diverge Cells and Connectors

In CTM, traffic flow from a cell can diverge into a maximum of two diverge connectors, similar to vehicles that approach a freeway interchange, and they either continue on the main road or exit towards the off-ramp. The cell that models an exit junction is named a *diverge cell*, and the corresponding outgoing connectors are named *diverge connectors*. Figure 2 illustrates a CTM representation of a diverge section of a network.

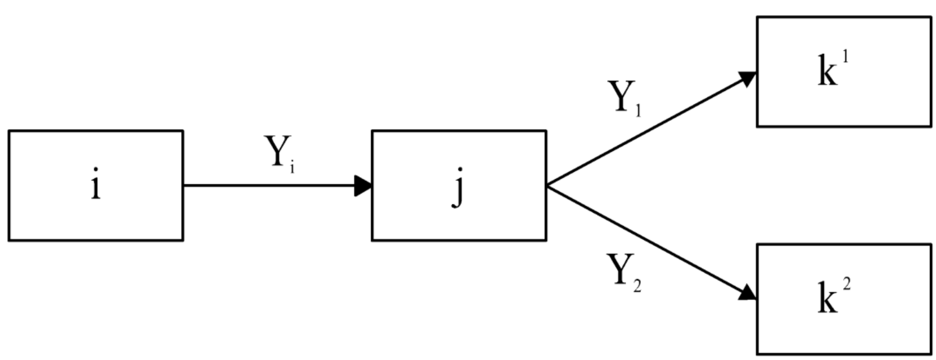


Figure 2: CTM Representation of Diverging Flows

Vehicles from the sending Cell *j* can flow into two different cells, Cell k^1 and Cell k^2. The splitting ratios are assumed to be known, so the inflows to cells k1 and k2, respectively, are:

$$Y_1(t) = \beta^1 Z_j(t) \quad and \quad Y_2(t) = \beta^2 Z_j(t) \tag{3.5}$$

Where

$Y_1(t), Y_2(t)$ = Inflows to Cell k^1 and Cell k^2, respectively
$Z_j(t)$ = Outflow from Cell *j*
β^1, β^2 = Proportion of vehicles going to Cell k^1 and Cell k^2

If either of the receiving cells (i.e. k^1, k^2) is unable to accommodate the expected inflow traffic, the entire outflow Z_j(t) is restricted. This implies that vehicles at diverge cell are served in the first-in-first-out sequence and when they are unable to advance to the one of the diverge cells, all vehicles that follow are prevented from advancing. The outflow Z_j(t) can be expressed as

$$Z_j(t) = min \begin{cases} \min\{X_j(t), Q_j\} \\ min\{\ Q_1(t), \delta[X_1(t) - x_1(t)]/\beta^2\} \\ min\{\ Q_2(t), \delta[X_2(t) - x_2(t)]/\beta^1\} \end{cases} \tag{3.6}$$

Signal Controlled Diverge Connectors

The previous diverge scenario is suitable to model traffic flows at interchanges on freeways, where no control devices are present. On the other hand, the signal controlled diverge connection assumes all traffic movements share the same green phase. The outflow capacity Q_j has a time varying capacity equal to saturation flow under green phase and zero capacity under red phase. If the movements do not share the same green phase, the model requires additional cells to represent green phase for each movement. Details of how a signal controlled approach can be modeled in CTM are shown in chapter 4.

Uncontrolled Merge Connectors

Figure 3 shows CTM representation of an uncontrolled freeway merge scenario. As in diverge cell, the merge cell algorithm permits the connection of two incoming connectors. Additional cells are required to model more than two movements merge at the same junction.

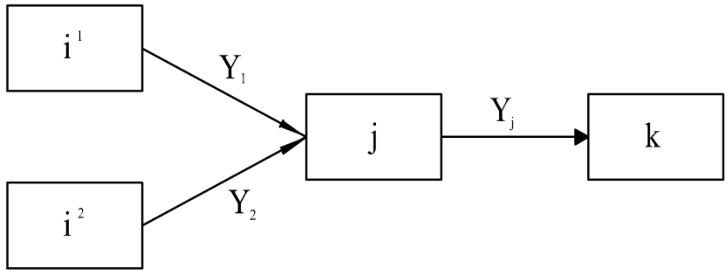


Figure 3: CTM Representation of Merging Flows

The cells immediately upstream the merging cell, j, are designated as sending cells, cell i^1 and i^2, respetivelly. The receiving cell is denoted as Cell j. The known proportions of traffic flows merging into Cell j are denoted as ρ^1 and ρ^2, where $\rho^1 + \rho^2 = 1$. The mathematic expression of the corresponding merging flows can be written as follows:

$$
\begin{aligned}
&if\ R_j(t) \geq S_1(t) + S_2(t)\ then \begin{cases} Y_1(t) = S_1(t) \\ Y_2(t) = S_2(t) \end{cases} \\
&if\ R_j(t) \leq S_1(t) + S_2(t)\ then \begin{cases} Y_1(t) = mid\{S_1(t),\ R_j(t) - S_2(t), \rho^1\, R_j(t)\} \\ Y_2(t) = mid\{S_2(t),\ R_j(t) - S_1(t), \rho^2\, R_j(t)\} \end{cases}
\end{aligned}
\tag{3.6}
$$

Where

$Y_1(t), Y_2(t)$	=	Actual outflows from Cell i^1 and Cell i^2 at time t
$S_1(t), S_2(t)$	=	Maximum possible outflows from Cell i^1 and Cell i^2 at time t
$R_j(t)$	=	Maximum possible inflow into Cell j at time t

$S_1(t)$ and $S_2(t)$ are defined as follows:

$$S_1(t) = \min\{x_i^1(t), Q_i^1(t)\} \tag{3.7}$$

$$S_2(t) = \min\{x_i^2(t), Q_i^2(t)\} \tag{3.8}$$

Where

$x_i^1(t), x_i^2(t)$	=	Number of vehicles in cell i^1 and i^2 respectively , at time t
$Q_i^1, Q_i^2(t)$	=	Maximum flow, at capacity, of cell i^1 and cell i^2

and $R_j(t)$ is defined as

$$R_j(t) = \min\{\, Q_j(t), \delta(X_j(t) - x_1(t))\} \tag{3.9}$$

Signal Controlled Merge Connectors

For signal controlled merge, additional proportionality factors, $\sigma_1(t)$ and $\sigma_2(t)$, are integrated into the equation 3.7 and equation 3.8, respectively, to represent the effect of signal phases. The rewritten expressions are given as follows:

$$S_1(t) = \sigma_1(t) \cdot \min\{x_1(t), Q_1(t)\} \tag{3.10}$$

$$S_2(t) = \sigma_2(t) \cdot \min\{x_2(t), Q_2(t)\} \tag{3.11}$$

Where

$\sigma_n(t)$ = 0 if the respective phase is red, and
$\sigma_n(t)$ = 1 if the phase is green

The maximum receiving capacity of cell j, $R_j(t)$, and the actual outflows $Y_1(t)$ and $Y_2(t)$ are determined according to equation (3.6) and equation (3.9) as for uncontrolled merge connectors.

Origin Cell

Origin cells are modeled through the same parameters as ordinary cells with the exceptions that there is no inbound connector, and the storage capacities are unlimited.

$$X_o(t) = \infty \tag{3.12}$$

The number of vehicles in a source cell, $x_o(t)$ can be determined either from a DTA algorithm, from simulation outputs, or from field data.

Destination Cell

Similarly to origin cell, destination cells are characterized by infinite storage capacity and are modeled through the same parameters as ordinary cells.

$$X_d(t) = \infty \tag{3.13}$$

3.2 Microscopic expansions to CTM

CTM was introduced as a macroscopic model to assist transportation planners estimating efficiently and reliably highway networks performance. Hence, by adopting the original CTM formulation for urban traffic simulation use one must consider the different characteristics between the highway and urban traffic. In this section, the study highlights some of the areas where such differences may be significant and modifications to the model may be required in order to produce realistic simulation results.

Traffic dynamics and control devices

The most distinctive characteristic of an urban network, compared with a highway network, is the frequent occurrence of flow interruptions due to conflicting flow movements and the effect of traffic control devices. In its current form, CTM addresses these flow interruptions in a binary, first-in-first-out manner. It lacks the capacity to simulate the effect of complex traffic dynamics such as lane changes, queue spillbacks, movement congestions and flow conflicts.

CTM also lacks the ability to represent the different types of traffic control devices common in urban networks, and the representation of complex signal phases for various movements cannot be easily implemented. Reliable simulation results can be obtained if CTM can account for the effect of these individual traffic features. Hence, CTM can benefit from some additional microscopic capabilities to achieve realistic simulation of traffic flows on urban highways.

This study attempts to improve CTM's capacity in simulating traffic control devices and various conflicting flows by incorporating the following specific characteristics: (a) a flexible and consistent method to represent traffic control devices and flow conflicts in CTM, (b) a more realistic approach to generate vehicle turning ratios for diverging movements, instead of using preset values, (c) addition of queue parameters to capture explicit output information about queuing behavior per movement throughout the network, and (d) addition of algorithms to represent effect of queue spillbacks and blockage by congested movements more realistically.

Non-homogeneous network conditions

Another aspect where urban networks are significantly different from highways is the non-homogeneous nature of the network. Roads in urban network are hardly homogenous. Traffic control policies (e.g. reverse direction at peak hours) and frequent operational road work (e.g. road maintenance, snow removal operations, etc.) can further modify or limit road capacities in a time-dependent manner. While the existing CTM formulation does allow changes in road capacities in a static manner, this study intends to incorporate time dependent road capacity in the proposed CTM framework.

A generic framework for operational usage

One of the main concerns about using microscopic simulation for the purpose of urban travel time prediction is the level of expertise and effort required in maintaining the model as the network becomes large and complex. In such a complex network, the large number of input parameters and calibrations required for the simulation results to be meaningful, not to mention realistic, might just prove to be impractical for operation use.

For example, a CTM cell is limited to have a diverge of two movements at a time, and the moments have to share the same signal phase. Use of multiple diverge cells is required to represent more diverging movements or signal phases. The addition of each diverge cell requires careful interpretation of cell capacity and calibration for the diverge ratio. This means to model one common four-way intersection with a number of signal phases requires a tedious interpretation and sufficient expertise of CTM underlying theory, which is somewhat unfeasible for typical traffic practitioners. The fact that each intersection can be interpreted and modeled in a variety of ways implies that the simulation model can be inconsistent if parts of a large network model are built by different users. The effect of such inconsistencies has not been studied, especially when the network is large and the effect can be compounded.

A CTM framework that requires less interpretation and manual adjustments should be considered for this model to become a practical tool for various transportation agencies and practitioners in general. Specifically, the proposed model must represent (a) traffic movements, (b) signal phases, and (c) various types of control devices in a generic and consistent manner. Equally important, when applied to a large-scale urban network, the proposed model should incorporate mechanisms to generate turn ratios base on demand and flow propagation at each intersection and eliminate the need to calibrate this parameter altogether.

Real-time simulation capacity

Increased microscopic capacities inevitably increase the requirement for computer resources. Studies have shown that CTM is suitable for real-time operational use in the highway contexts. In extending CTM for urban applications, it is desirable to retain its online capacity. Although the increase in computational requirement for real-time simulation in a large complex urban network may be difficult to assess at this stage, the approach is to maintain the architecture of the original CTM algorithm which is suitable for distributed computing environment.

Real-time model input and output capabilities should be considered in expanding CTM for urban use. The framework should be flexible to allow time-dependent values for its parameters. Implementation of real-time output parameters such as queue length or delay by movements can be beneficial additions to accommodate operational needs.

In the next chapter, a new CTM based framework/model taking into account the considerations discussed in this section is presented.

CHAPTER 4 CTM-URBAN, A GENERIC CTM BASED MODEL FOR URBAN NETWORKS

CTM-URBAN is a CTM based model proposed to simulate more realistically traffic flows in an urban network. New parameters and a modified formulation of the original model are introduced in this chapter to enable representation of complex urban network features and highly interactive traffic dynamics. While significant modifications are made, the algorithm remains compatible to the original CTM. The proposed model can be integrated into an existing CTM network (such as highway network) with minimal adjustment at the interfaces. This chapter presents the core algorithm of CTM-URBAN and provides discussion on how various components of CTM-URBAN can be practically implemented in simulations.

4.1 Definitions

The variables used in CTM-URBAN can be categorized into five general groups based on the function and the nature of the variable, as shown in **Table 1**. *Physical parameters* describe the physical layout and properties of the road section which remains unchanged during the simulation horizon. *Calibrated parameters* are field values to be collected to improve accuracy of the simulation. *Control parameters* provide CTM-URBAN the capacity to simulate the complex interactions between traffic movements, real-time road conditions, and various traffic management measures. *Algorithm generated parameters* are interim variables that are required by the algorithm and should not require manual input. Finally, *data driven parameters* belong to a special category of variables. While these parameters are generally simulation outputs from the algorithm, they can be replaced respectively by real-time data inputs (e.g. loop detector data) to transform CTM-URBAN to a real-time simulation tool.

Table 1: List of symbols used in CTM-URBAN

	Symbol	Description	Unit	Source
Physical	N_i	# of lanes within cell i	-	Network configuration
	m_j	# of movements allowed in a diverging/merging cell	-	Network configuration
	m	Movement number	-	Network configuration
	N_j^m	# of lanes allowed for each *m* in a diverging/converging cell	-	Network configuration
Calibrated	K^J	Max. density (jam conditions)	veh/ft/lane	Field observation/simulation
	Q_i	Saturation flow capacity of cell i	veh/hr	Field observation/simulation
	v_f	Free flow speed	ft/s	Field observation/simulation
	δ^F	Forward moving wave speed	mph	Field observation/simulation
	δ^B	Backward moving wave speed	mph	Field observation/simulation
	B_j	Split ratio at diverge cell j	-	Field observation/simulation
Control	Δt	Time increment	second	User input
	$\sigma_i(t)$	Signal/stop control variable	-	User input/algorithm
	$\alpha_i(t)$	Road capacity control	-	User input/algorithm
	$\delta_i(t)$	Wave speed ratio	-	User input
	$X_i(t)$	Cell capacity	veh	User input/algorithm
Algorithm generated	L_i	Cell length	ft	
	X_i^J	Jammed cell capacity of cell i	veh/cell	
	$y_j^m(t)$	Temporary flow assignment	veh	
	N_j^B	# of lanes occupied by estimated blocking movements	-	
	$C_j(t)$	Set of congested movements	-	
	$M_j^B(t)$	Set of blocking movements	-	
	$M_j^b(t)$	Set of blocked movements	-	
	$M_j^{LB}(t)$	Set of lane blocking movements		
	$\rho_j^m(t)$	Flow reduction ratio	-	
	$S_j^m(t)$	Queuing storage	veh	
Data Driven	$x_i(t)$	Cell occupancy	veh	Online data/algorithm generated
	$Y_i(t)$	Flow	veh	Online data/algorithm generated
	$\beta_j^m(t)$	Split/turn ratio	-	Online data/algorithm generated
	$x_j^m(t)$	Veh heading direction m	veh	Online data/algorithm generated
	$Y_j^m(t)$	flow for each direction m	veh	Online data/algorithm generated

More detailed definition and explanation of each variable can be found in the subsequent sections as they are introduced.

4.2 Formulation

As in the original CTM model, the network can be represented by a number of cells and connectors. The length of the cell is a function of free flow speed and time update increment (see Eqn. 3.1). Generally, the cells are considered to have same length, which implies that a common free flow speed is assumed on all the links in the network. Urban networks, however, inevitably contain different speed zones (e.g. school zones, residential vs. commercial roads, etc.) and thus different free flow speeds. Free flow speed v^f can also vary according to road geometric characteristics (e.g. 3-lane major arterial vs. 1-lane residential street, turn bay vs. through lane, etc). It is therefore necessary for the algorithm is capable of individualizing free - flow speed v^f for each cell. In Eqn. (4.1), CTM-URBAN introduces the cell dependent free-flow speed variable v_i^f. Therefore, the cell jammed capacity X_i^J becomes cell dependent.

$$L_i = v_i^f \cdot \Delta t \tag{4.1}$$

Vehicle flows propagate between adjacent cells according to the flow advancing equations and since different interconnected cells may be characterized by different free flow speeds, the network update time should be selected such that it does not allow for vehicles to skip cells during one update time step. In CTM-URBAN the update time step, Δt, is set to be 1 second, as this time resolution is generally sufficient for design of traffic signal timing. The notation $t + \Delta t$ is used interchangeably with $t + 1$ throughout this thesis. It is possible to increase Δt to reduce computational resource usage at the cost of simulation precision.

$$X_i^J = N_i \cdot L_i \cdot K^J \tag{4.2}$$

where N_i represents the number of lanes available in cell i and K^J represents the maximum density (jammed condition) per lane. Note that even though the time dependent parameter from Eqn. (3.2), $N_i(t)$, has been replaced by a time independent value, N_i that identifies the actual geometric characteristics in the field, special cases such as lane closures can still be accounted for through the control variable $\alpha_i(t)$. The purpose of this modification is to clearly distinguish between the physical parameters used to characterize geometric road configuration and the control variables to represent traffic management measures or time dependent changes in road operations.

4.2.1 Ordinary Cells and Connectors

Ordinary cells and connectors are used to describe section of roads that do not diverge or merge.

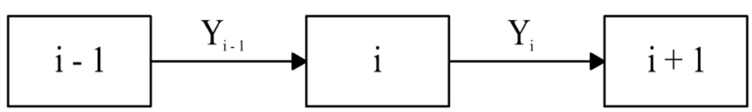


Figure 4: CTM-URBAN, Ordinary Cells and Connectors

Figure 4 shows a series of ordinary cells and connectors. The flows at each time step t can be updated as follows:

$$Y_i(t) = min\{x_i(t),\ \sigma_i(t)Q_i,\ \ \alpha_{i+1}(t)Q_{i+1},\ \ \delta_{i+1}(t)[X_{i+1}(t) - x_{i+1}(t)]\} \tag{4.3}$$

where $x_i(t)$, $x_{i+1}(t)$ represent the number of vehicles in cell i and cell $i+1$, Q_i and Q_{i+1}, are the flow capacities of cell i and cell $i+1$, and $X_{i+1}(t)$ is the storage capacity of cell $i+1$. These variables are similarly defined as in the original CTM.

The control parameters are new additions in the CTM-URBAN. The signal/stop control parameter, $\sigma_i(t)$, is introduced to account for flow capacity reduction due to traffic control devices. The road capacity control parameter $\alpha_j(t)$ is introduced to simulate reduction of road capacity due to real time road conditions such as traffic queuing, temporary lane closure, or traffic management policy.

$X_j(t)$ can be a function of X_i^J with a reduction factor (i.e. $\alpha_j(t)$) to represent storage reduction such as lane closure or accident. The term $\delta_j(t)$ is the shockwave travel speed ratio to describe dispersion of traffic from stop condition and under congested condition.

Following equation (4.3), the cell occupancy $x_j(t+1)$ at the next time intervalis updated with equation (4.4).

$$x_j(t+1) = x_j(t) + Y_{i-1}(t) - Y_j(t) \tag{4.4}$$

The sequence of updates will be repeated until *t* reaches the simulation time horizon.

4.2.2 Diverge Cell, Uncontrolled

A diverge cell is used to model the junction where one traffic movement is splitting into more than one movements (e.g. a freeway interchange, an turning movement at an intersection, an access lane into a parking lot, etc.). A diverge movement can be either controlled by traffic signs and/or signal or it can operate uncontrolled by this type of control devices but only through pavement markings. In this section, we consider the formulations for diverge uncontrolled by signs and signals.

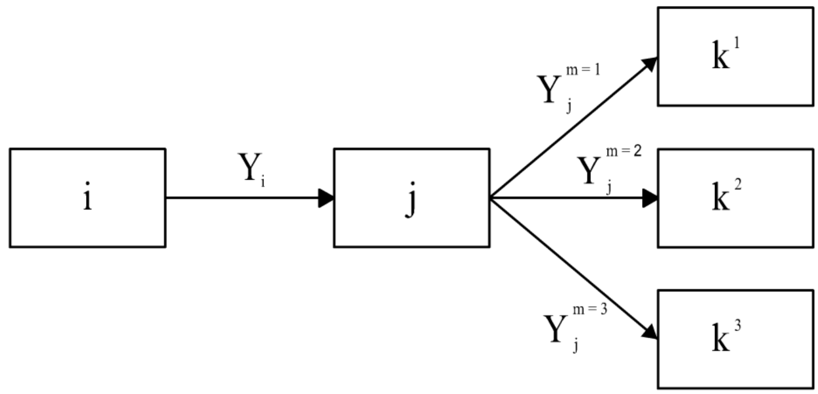


Figure 5: CTM-URBAN Representation of Diverge Flows

Figure 5 describes how diverge flows are modeled in CTM-URBAN. Cell i is an ordinary cell. Cell j is the diverge cell where there's one incoming flow $Y_i(t)$ and more than one outgoing flows $Y_j^m(t)$. There is no restriction on the number of vehicle movements that can be modeled in one diverge cell. Cell K^m is the notation to represent the beginning of diverging movements. With the exception of the notation, they are otherwise ordinary cells and the occupancies can be updated with equation (4.4).

Equation (4.5) updates the incoming flow $Y_i(t)$. The updated flow is then attributed to each movement based on the split ratio β_j^m or $\beta_j^m(t)$ in equation (4.6). Each movement in cell *j* is denoted by *m*. The number of lanes that vehicles can use for each movement *m* is denoted by N_j^m. The total number of movements in cell *j* is denoted by m_j.

$$Y_i(t) = min\{x_i(t),\ \sigma_i(t)Q_i,\ \ \alpha_j(t)Q_j,\ \ \delta_j(t)[X_j(t) - x_j(t)]\} \tag{4.5}$$

$$Y_i^m(t) = \beta_j^m(t) \cdot Y_i(t) \tag{4.6}$$

To calculate outgoing flow for each movement at time step t, equation (4.7) is used to generate temporary flows $y_j^m(t)$ based on the up-to-date cell traffic conditions. These values will be adjusted in the later part of the algorithm if traffic blockage due to congestion is detected.

$$y_j^m(t) = min.\{x_j^m(t),\ \sigma_j^m(t)Q_j^m,\ \alpha_{k^m}(t)Q_{k^m},\ \delta_{k^m}(t)(X_{k^m}(t) - x_{k^m}(t)\} \tag{4.7}$$

CTM-URBAN can simulate two types of traffic blockages: *movement blockage* (Figure 6) caused by congested movements blocking the entire road section, and *lane blockage* (Figure 7) caused by queuing at diverge junctions.

A movement blockage will cause reduction of outgoing flows at time step t, while a lane blockage will reduce the cell capacity in receiving incoming flow at time step t+1. The flowchart shown in Figure 9 describes how the algorithm detects the two types of blockages and subsequently reduces the flow or cell capacity with the use of equation (4.8) to equation (4.17).

Formulation for Movement Blockage

First, the algorithm identifies the occurrence of a movement blockage. A movement blockage is selected when congested movements occupy all available lanes in a road section, and as the result preventing other movements from advancing.

Congested movements can be detected by comparing the number of vehicles available to advance in cell $x_j^m(t)$ with the estimated outflow $y_j^m(t)$ at time t. If flow is smaller than the number of available vehicle, that movement is said to be congested, and the movement m belongs the set of congested movements *C(t)*.

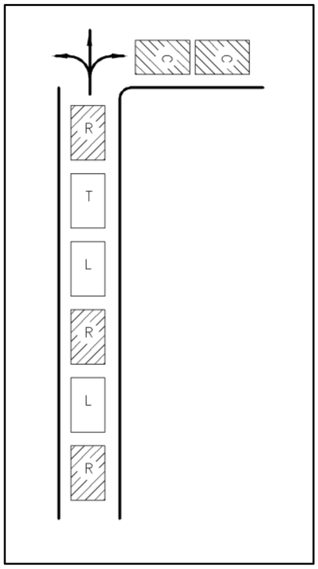


Figure 6: Example of a Movement Block

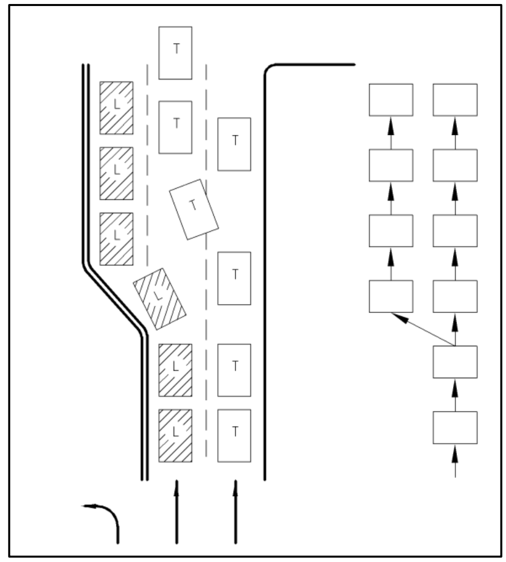


Figure 7: Example of a Lane Blockage

For each congested movement, the number of congested lanes N_j^m is added to the number of total congested lanes N_j^C:

$$if\ y_j^m(t) < x_j^m(t), \ \begin{cases} m \in C(t) \\ N_j^C \mathrel{+}= N_j^m \end{cases} \tag{4.8}$$

When the ratio between total congested lanes and the number of available lanes is at least one, a movement blockage occurs.

$$if\ \frac{N_j^C}{N_j} \geq 1, \qquad Movement\ Blockage\ occurs \tag{4.9}$$

The algorithm is able to capture stochastic occurrences of blocking movements, M^B, through equation $\sum_{\mathrm{m} \in m^B} N_j^m \ \geq \ N_j$ (4.10)

$M^B(t)$ **must** be generated according the following sequence:

1. Previously queued movements, $M^{LB}(t-1)$, as determined from the previous time update.

2. Previously blocking movement, $m \in M_j^B(t-1)$ and $y_j^m(t) = 0$

3. Randomly generated from the rest of the available movements:

$$random\ [C(t) - M^{LB}(t)] \tag{4.11}$$

All movements that do not belong to $M^B(t)$ are said to belong to the set of *blocked* movements $M^b(t)$. Blocking factors $\rho_j^m(t)$ are generated at this stage to simulate the reduction of flow that will be allowed to pass under the movement blockage conditions according to Eqn. (4.12) to Eqn. (4.14)

In the situation where none of the blocking vehicles in the preceding time step have advanced, none of the vehicles in the cell shall advance in this update. Essentially, the blocking factors $\rho_j^m(t)$ are set to zero for all movements. Set of blocking movements remains the same as in the previous update.

$$if \quad \begin{pmatrix} m \in M_j^b(t), AND \\ y_j^m(t) = 0\ where\ m \in M_j^B(t-1) \end{pmatrix}, \quad \rho_j^m(t) = 0 \tag{4.12}$$

$$M_j^B(t) = M_j^B(t-1) \tag{4.13}$$

Otherwise

$$\rho_j^m(t) \begin{cases} = 1, & if\ m \in M_j^B(t), \quad i.e. the\ blocking\ movements \\ \leq 1, & if\ m \in M_j^b(t), \quad i.e. the\ blocked\ movements \end{cases} \tag{4.14}$$

$$\rho_j^m(t) = Rand(0,1) \tag{4.15}$$

Finally, the blocking factor $\rho_j^m(t)$ generated by equation (4.15) is applied to estimated flow to establish the final outgoing flows, Y_j^m:

$$Y_j^m(t) = \rho_j^m(t) \cdot y_j^m(t) \tag{4.16}$$

Flow Advancing Equations

After the incoming and outgoing flows are determined, the status of the cell can be updated. CTM-URBAN introduces a new parameter, the storage variable, S_j^m. This parameter is used to capture more realistically the effect on traffic flow of frequently encountered queuing conditions at exclusive turning lanes when vehicle demand exceeds the turning lane storage capacity:

$$S_j^m(t+1) = S_j^m(t) + Y_i^m(t) - Y_j^m(t) \tag{4.17}$$

$$x_j^m(t+1) = min.\left\{S_j^m(t+1),\ \frac{N_j^m}{N_j} X_j\right\} \tag{4.18}$$

Finally, the occupancy of cell *j* can be calculated as the sum of occupancies by all movements:

$$x_j(t+1) = \sum_{m=1}^{m_j} x_j^m(t+1) \tag{4.19}$$

Accounting for Lane Blockage in CTM-URBAN

For each movement m, the algorithm verifies if the number of vehicles bearing that movement has exceeded the movement capacity.

$$\begin{gathered} if\ \ S_j^m(t+1) > x_j^m\ \ ,\ \ lane\ blockage\ occurs \\ m\ \in M^{LB}(t+1) \end{gathered} \tag{4.20}$$

Blocked lanes due to queuing conditions at downstream locations will reduce the flow capacity and thus cell capacity factor $\alpha_j(t+1)$ is calculated according to equation (4.21)

$$\alpha_j(t+1) = \frac{N_T - \sum N_j^m}{N_T}, \;\; where\; m \;\in M^{LB}(t+1) \tag{4.21}$$

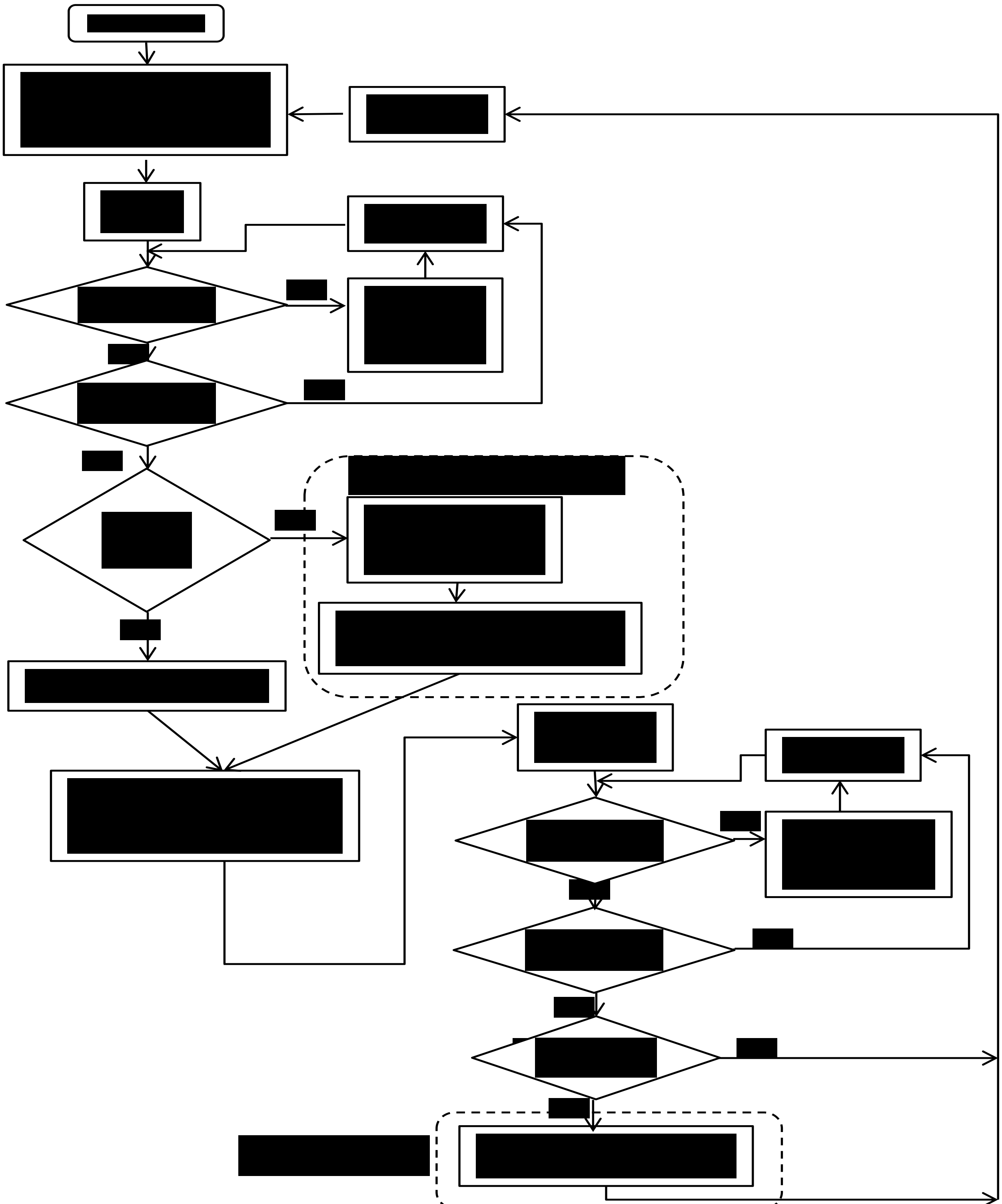


Figure 8: Flowchart of Diverge Algorithm in CTM-URBAN

4.2.3 Merge Cell, Uncontrolled

A merge cell is used to model traffic flows at roadway junctions where multiple vehicular flows merge into one (e.g. freeway interchanges, intersections, egress road from a parking lot, etc.). A merge junction can be controlled through signals and/or signs (e.g. intersections) or can be operated without the help of these control devices but only pavement markings (e.g. freeways). In this section, we consider the formulations for an uncontrolled merge.

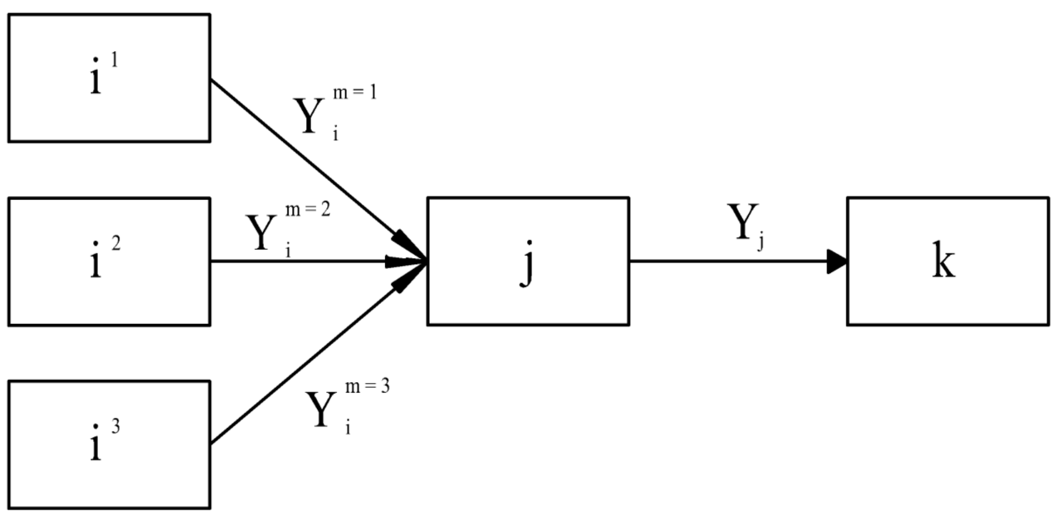


Figure 9: Merge Cell *j*

Figure 9 describes how merging flows are modeled in CTM-URBAN. Cell i^m is the notation to represent the end of the converging movements. With the exception of the notation, they are otherwise ordinary cells and the cell occupancies can be updated with Eqn. (4.4). Cell j is the converge cell where there can be more than one incoming flows $Y_i^m(t)$ and only one outgoing flow $Y_j(t)$. Cell k is an ordinary cell. There's no restriction on the number of movements that can be merged into one converge cell. To calculate incoming flow for each movement at time step t, Equation

(4.22)

(4.22) generates temporary flows $y_i^m(t)$ base on the current cell conditions.

$$y_i^m(t) = \ min.\{x_i^m(t),\ \ \sigma_i^m(t)Q_i^m\}$$

In equation (4.23) and equation (4.24), the temporary flow values generated by equation (4.22) are used to calculate the actual merging ratio $\gamma_j^m(t)$.

$$y_i^T(t) = \sum y_i^m(t) \tag{4.23}$$

$$\gamma_j^m(t) = \frac{y_i^m(t)}{y_i^T(t)} \tag{4.24}$$

The merging ratio is then used in the flow advancing equation (4.25) to produce the actual merging flows $Y_i^m(t)$. For uncontrolled flows merging from cells i^m, the values of signal factors σ_i^m are set to one. Alternatively, a constant value less than one can be applied if the reduction of road capacity due to merge can be observed and quantified.

$$Y_i^m(t) = \min\{x_i^m(t),\ \ \sigma_i^m(t)Q_i^m,\ \ \gamma_i^m(t)\alpha_j(t)Q_j,\ \ \gamma_i^n(t)\delta_j(t)[X_j(t) - x_j(t)]\} \tag{4.25}$$

By comparison, the original CTM proposes that the merging factor γ is assigned a fixed preset value. This assumption can significantly affect the accuracy of the operations around merging junctions because, in real-world, interactions between vehicles flows under uncontrolled conditions are expected to affect the merging ratios proportionally with the traffic demand. Equation (4.22) to equation (4.25) enable the merging factor γ to vary according to the available traffic volume. Using the merging factor γ in combination with the signal factor σ , CTM-URBAN provides the flexibility needed to simulate the real-world complex interactions between the traffic condition and the controlling devices in merging conditions.

4.2.4 Modeling of Traffic Control Devices

In CTM-URBAN, modeling of traffic control devices is done through the usage of one control parameter, σ, associated with each cell. Examples of the traffic control devices can be signals, stops, gates or traffic calming devices. Theoretically, sigma ranges between zero and one, inclusively. The specific value of σ can be determined in a number of ways according to the nature of the associated control device:

1. **Binary value**, as specified in the original CTM where a green light sets σ to 1 and a red light resets σ to zero. This approach is used if the simulation needs are those of a macroscopic approach and precision requirements are not very high.

2. **A continuous value as a function of conflicting flow volume**, applicable if the simulation is needed to capture the effect of opposing flows on the left turning vehicles on a permitted green phase. The value of σ can be determined at each time step according to conflicting volume base on research finding (e.g. van Hinsbergen *et al.*, 2008). Alternatively in a simplified approach, a pair of values represent the effect of congested or non-congested conflicting flow can be assigned instead of a continuous value.

3. **A continuous value as a function of merging flow volume**, such as in the case of a yield merge. The value of σ can be determined at each time step according to merging volume. In a simplified approach, a pair of values reflecting the effect of

congested and non-congested merging flow volume can be assigned instead of a continuous value

4. **A value based on the type of control device**, such as a sign-controlled intersection or a toll booth. σ can have empirical values based on the result of related studies (example: Chevallier and Leclercq, 2007).

5. **A reduction factor for a road configuration**, such as in the case of a non-signal controlled fork merge. If a reduction factor due to the road configuration can be determined by microscopic simulation or field observation, the value can be applied to σ in an uncontrolled situation to improve accuracy of the simulation.

6. **A reduction factor due to conflicting traffic flows of modes**, such as pedestrian and/or bicycles paths.

Note that the effect of above conditions can be combined in determining the final value of σ at each time step.

As mentioned in the problem statement, one goal of this study is to provide a generic formulation that can accommodate simulation of various types of control devices. A general description of how σ can be evaluated is considered appropriate to the scope. Detailed methods to determine an accurate value for each type of devices will be studied in future work

4.2.5 Intersection Cells

As in the original CTM formulation, a diverge cell cannot be followed directly by a merge cell. In intersections, however, it is common to have a diverged flow merging directly into another set of flows. An ordinary cell, named intersection cell, is added between the diverge and the merge cell to address such limitation. The cell capacity X_k^m of each intersection cell is a determined by equation (4.26). Figure 10 demonstrates the use of intersection cells in a typical CTM-URBAN intersection model.

$$X_k^m(t) = \frac{N_j^m}{N_j} X_j(t) \tag{4.26}$$

A source of inaccuracy which can be observed in both CTM and CTM-URBAN is that the travel time within the intersection is not considered. While the effect may be small, in the context of simulating a large network consists of many intersections, underestimating the travel time within intersections may become a factor affecting accuracy of travel time prediction.

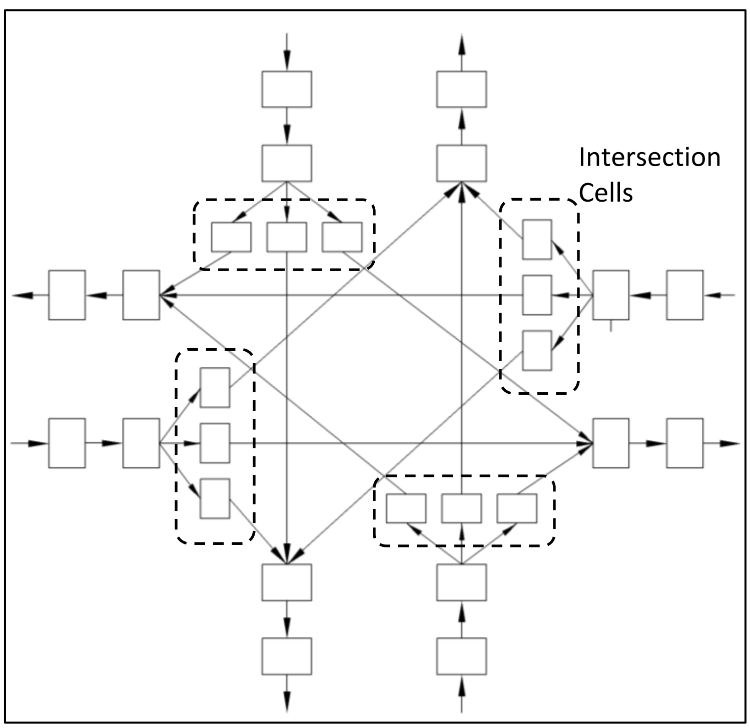


Figure 10: An example of CTM-URBAN representation of a typical four-way intersection

CHAPTER 5 CASE STUDY: A SIGNAL CONTROLLED INTERSECTION

In the previous chapter, a new intersection algorithm is introduced in CTM-URBAN as an improvement to the basic version of CTM (CTM-BASIC). The new intersection algorithm under the CTM-URBAN framework is expected to represent the traffic flow and queue propagation through signal controlled intersections more realistically compared to CTM-BASIC. A case study designed to evaluate the performance of both CTM and CTM-URBAN in terms of predicting the average travel time through a signal controlled intersection under various traffic conditions accurately is presented in this chapter.

In this case study, three different traffic scenarios representing various levels of downstream congestion within a signal controlled intersection will be simulated using CTM-BASIC, CTM-URBAN, and VISSIM, a leading commercial microscopic simulation package. First, a calibration procedure based on the VISSIM output, representing real-world data, is proposed. Next, the simulation results are compared to determine if CTM-BASIC can closely reproduce the travel time predictions generated by the microscopic simulator and if an improvement in accuracy can be observed from CTM-URBAN results.

The second half of the case study analyzes the effects of applying (1) a variable wave speed mechanism and (2) an optional dynamic input mechanism on CTM-URBAN. The simulation results are presented to show that notable improvement in accuracy can be observed by implementing these two additional mechanisms to CTM-URBAN. The findings are good examples of the flexibility in the proposed model/framework which allows easy implementations of future enhancements.

5.1 Experimental Setup

In the case study, CTM-BASIC, CTM-URBAN and VISSIM are configured to simulate one approach in a hypothetical four-way signal controlled intersection. The approach is 440 ft (134 m) in length and has two lanes. The intersection approach is followed by three downstream road segments and a signal is placed to control the movements: through (TH), left-turn (LT) and right turn (RT) movements. On the downstream road segments, two lanes are present for TH movement and one lane are presents for each LT and RT movements.

To account for various levels of congestion on different movements through this intersection, a virtual traffic light is placed at 44 ft (13.4 m) from the intersection on each downstream road. Phase combination of these signals will make up three scenarios representing possible traffic conditions in real-world intersections. Travel time from the beginning of the upstream road to the 132 ft (40.2m) mark of each downstream road, equivalent of 3 CTM cell-lengths, will be measured and designated as TH, LT, RT travel time respectively. Signal phases for the three scenarios are designed as shown in Table 2.

Table 2: Signal Phases in the case scenarios

Scenario	Main Signal Phase	LT Signal Phase	RT Signal Phase	Real-world Conditions
Case I	30s G. + 30s R.	Permanent G.	Permanent G.	Free-flow downstream
Case II	30s G. + 30s R.	5s G. + 25s R.	Permanent G.	Congested left-turn movement
Case II	30s G. + 30s R.	5s G. + 25s R.	5s G. + 25s R. (10s offset) (*i.e.* first full cycle begin at t=10s)	Left-turn and right -turn movements are congested. The offset in signal phase may create different levels of congestion on each downstream road

The simulation duration is 15 minutes. Traffic demands are entered for the first 12 minutes. During the last 3 minutes of the simulation no new vehicles are generated on the simulated approach to allow for network clearance and consistent evaluation of travel time for all models tested. Five travel demand levels are simulated, 1000, 1250, 1500, 1750, 2000 vehicles/hour respectively. Even though VISSIM is a microscopic model and allows modeling the impact of various vehicles types on the network performance, in this study all vehicles are considered passenger cars because CTM can't distinguish between different vehicle classes. This is not necessarily a limitation since the capacity analysis of a transportation facility is typically made based on passenger cars through means of equivalent passenger factors that are used to account for various traffic mix and geometric conditions (HCM 2000).

To account for stochastic variations in some input variable, 100 simulation runs are conducted for each scenario case, each demand level on VISSIM, CTM-BASIC, CTM-URBAN, and Dynamic CTM-URBAN. In the next section, several calibration steps are performed to ensure the parameters in all CTM models are corresponding to the VISSIM model in representing the experimental network. Performance evaluations of the CTM-BASIC and CTM-URBAN are based on the indicators shown in Table 3.

Table 3: Performance Indicators for the Case Study

Case	Target Characteristic	Indicator	Description
All Cases	Travel Time	Travel Time	Small relative errors (versus VISSIM results) exhibit in all scenarios and all demand levels indicate good performance.
Case II	Effect of Lane Blockage	TH/RT	The ratio of travel time captures the effect of LT lane blockage on the unblocked movements.
Case III	Level of Congestion	RT/LT	The RT signal phase is designed to cause heavier congestion compared with LT. The accuracy of this ratio indicates how well

the model captures the difference in the level of congestion downstream.

5.2 Calibration Procedures

As identified in Section 4.2, there are five parameters for CTM-URBAN (and similarly for CTM-BASIC) that require calibration. These parameters are identified as:

- free flow speed within the cell (v_f)
- max. density of the cell (K)
- saturation flow of the cell (Q)
- backward moving wave speed within the cell ( )
- turning ratio at the intersection (B)

The purpose of the calibration procedure is to ensure the values of these parameters are equivalent to the corresponding parameters in selected reference model, VISSIM.

In many urban networks in North America, a common speed limit for arterial roads is 30 mph (48.3 km/hr) and is used in this study as the value of the **free flow sped (v_f)** parameter in CTM models. In VISSIM where desired speed is given by a speed profile, a normally distributed speed profile with mean value of 30 mph (48.3 km/hr) is configured.

Max. density (K) represents the maximum number of vehicles per unit of distance observed under traffic jam conditions, sometimes it is referred to as the jam density. This density is a macroscopic parameter and it can be obtained from the space headway, which can be calculated based on model configuration values in VISSIM. In this study, *Wiedmenn 99* is selected as the underlying car-following model for all VISSIM simulations. The average standstill distance for this model is given as 4.92 ft (1.5 m). Average car length is set at 14.55 ft (126.4 m). From the two parameters, average space headway can be calculated as 14.55 ft + 4.92 ft = 19.47 ft (5.9 m). Cell length used in CTM models based on v_f is 44 ft (13.4 m). Consequently,

$K = \frac{1}{19.47\ ft} \times 44\ ft = 2.25$ vehicles per lane per cell (vplpc). The value 2.25 $vplpc$ is entered as the value of K in all CTM models. More details about the configuration of the car-following model can be found in VISSIM documentations.

Saturation flow (Q) represents the maximum flow rate of a given movement at which vehicles are discharged from queuing conditions at an intersection. This is not a direct input parameter of VISSIM because it depends on the characteristics of the vehicles and driving behavior, but it can be measured. A VISSIM model is setup to generate the data necessary to measure the saturation flow for through movements. The model consists of a one-lane 2000 ft (609.6 m)long road segment and a traffic signal placed at 1500 ft (457.2 m) downstream the road. Vehicles are generated to enter the road at a rate of 3600 vph. A 15-minute signal cycle begins with 5 minutes of red indication to allow for vehicles to accumulate at the stop line and during the remaining 10 minutes vehicles are released passed the stop line. A data collector is placed just after the signal to collect volume. An initial trial of 20 simulation runs reveal the flow rate stabilizes in the first 1.5 minutes after the signal turns green. Volume data collected from simulation second 390 through simulation second 810 are used to calculate maximum flow rate, which represents the saturation flow. To achieve a 95% confidence with an error smaller than 5% one hundred simulation runs were used, and the observed mean flow rate was 2231 vphpl. The value 2231 vphpl is used as Q for all CTM models.

Backward moving wave speed ( ) characterizes the queues forming at an intersection stop line, by showing how fast a queue travels upstream the intersection. This is not an input parameter in VISSIM but it can be obtained from individual vehicles trajectory data through regression analysis. First it is necessary to identify what parameters characterize vehicles in queuing conditions. In this study, vehicles are considered to join the queue if their travel speed is 3 mph or less. To maintain consistency with the previous calibrated parameters one hundred simulations runs are executed. In each simulation run, least-squares method is used to calculate the mean value of the wave speed. The position of the last vehicle in queue is plotted against time. An example of the scattered plots is shown in Figure 11. In the reference cases, the network length upstream of the signal is 440 ft (134.1 m), so data points occurred within 500 ft (152.4 m) from the signal are entered into regression model.

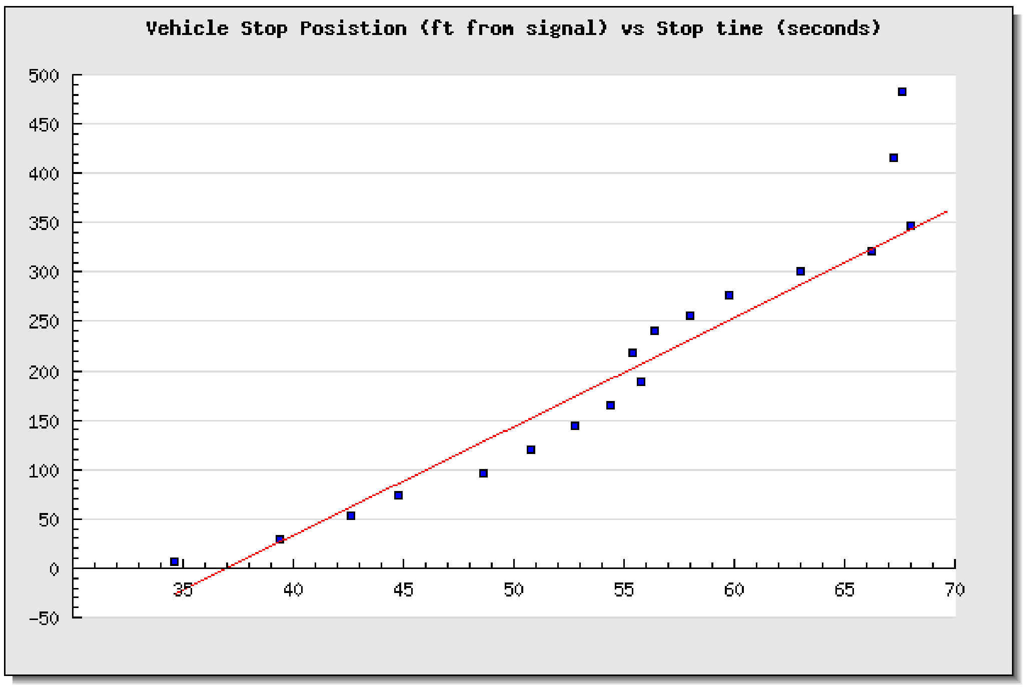


Figure 11: Scatter Plot Generated from VISSIM Data

A linear model is fitted through the data (as shown in Figure 11) and the coefficient of determination (R^2) is found to be 0.92, which indicates a good fitting of the linear model. The mean backward moving wave speed is determined to be at 7.4 mph (11.9 km/hr) with nearly 7% error at 95% confidence level.

The **turning ratio (B)** is an input parameter for VISSIM. The same number will be applied to both CTM-BASIC and CTM-URBAN. For case I and case II, $B_{TH} = 0.7, B_{LT} =$

$0.2, B_{RT} = 0.1$. For case III, $B_{TH} = 0.6, B_{LT} = 0.2, B_{RT} = 0.2$. Note in CTM-URBAN, turning ratio is not an input parameter, the ratio is considered as the demand turning ratio instead. The effective turning ratio is determined over time by the traffic conditions and is not an input value. The calibrated values used in CTM models are summarized in Table 4:

Table 4: Calibrated Values in CTM-BASIC and CTM-URBAN

Parameters	**Value**
free flow sped (v_f)	30 mph (48.3 km/hr)
Max. density (K)	2.25 plpc
Saturation flow capacity (Q)	2231 vphpl
Backward moving wave speed (w)	7.4 mph (11.9 km/hr)
The turning ratio (B_{TH}, B_{LT}, B_{RT})	Case I & II: 0.7:0.2:0.1 Case III: 0.6:0.2:0.2

5.3 Evaluation of CTM-BASIC & CTM-URBAN Simulation Results

In this section, simulation results based on the calibration procedures described in the previous section are presented for each scenario case. It is expected that CTM-URBAN should outperform CTM-BASIC in accurately predicting the average travel time through the designed intersection.

Performance Evaluation CTM-BASIC vs. CTM-URBAN

It can be seen in Figure 12 that under free-flow conditions that CTM-BASIC can reproduce closely the same travel time values as VISSIM at all tested traffic demand levels and for all three movements on the simulated approach. Overall, CTM-BASIC consistently underestimated travel time under free-flow conditions by 5% to 10 %, which is an acceptable range considering the simplicity of the macroscopic model. The smaller travel-time values can be explained by the fact that the implementation diverging mechanism in CTM-BASIC over-estimates the intersection capacity. The sum of lanes available in all cells just prior to the intersection becomes 4 lanes while the physical road contains only 2 lanes.

On the other hand, under the same free-flow traffic conditions (case I), it can be seen from Figure 12 that CTM-URBAN does not exhibit good accuracy in travel time predictions, except for low to medium traffic flow volumes. Travel times are overestimated by as much as 80% under heavy traffic flow on all movements. This significant discrepancy exhibited is not expected from the proposed model. A more detail examination on the causes of this error will be provided in a separate section.

In Case II scenario, the simulation results are more in line with the expectation. It can be seen in that when lane blockage occurs on the simulated intersection travel time estimates through CTM-URBAN are about 20%~40% below than VISSIM results on all movements. The errors are sizable but when compared to CTM-BASIC where the relative errors are generally above 50%, the results are significantly more accurate.

In Case III scenario, simulation results shown in Figure 14 indicate that CTM-URBAN is more consistent in predicting travel time when LT and RT downstream movements are congested causing a movement blockages and queue in the intersection approach. It can be seen that that travel time is inconsistently estimated when the traffic flow varies between 1000 and 2000 vph. Under medium and high traffic flows CTM-BASIC overestimates LT travel time by about 20% and if the travel demand is low it underestimates RT travel time by more than 20%. It shows that there is no consistency in the simulation results. On the other hand, CTM-URBAN generally underestimates the travel time at the level of 15% to 30%. Although the error is large, the consistency indicates there is room in improving the calibration procedure or the algorithm to obtain more accurate results.

Overall, it is inconclusive that the proposed CTM-URBAN improves CTM-BASIC in prediction of average travel time through a signal controlled intersection. While CTM-URBAN performs well in congested downstream conditions, the poor simulation results in the free-flow scenario indicate deficiencies preventing the expected performance of CTM-URBAN exist and needs to be identified in order for CTM-URBAN to be practical as a travel time prediction tool.

Hypothesis on the Causes of Unexpected Error

The simulation results from this study indicate there are deficiencies in the model that prevent CTM-URBAN from accurately predicting travel time, most notably under free-flow traffic condition. It can also be observed that CTM-URBAN exhibits contrasting behaviors in predicting congested and non-congested condition.

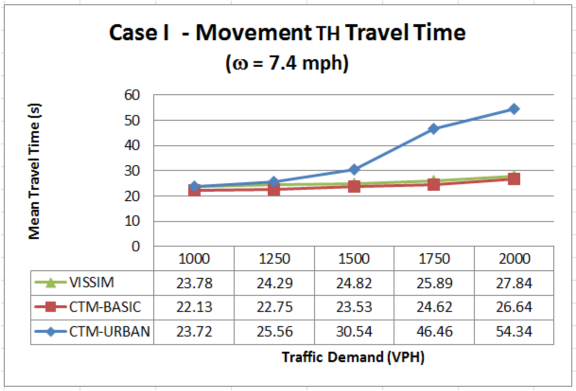


Figure 12 (a)

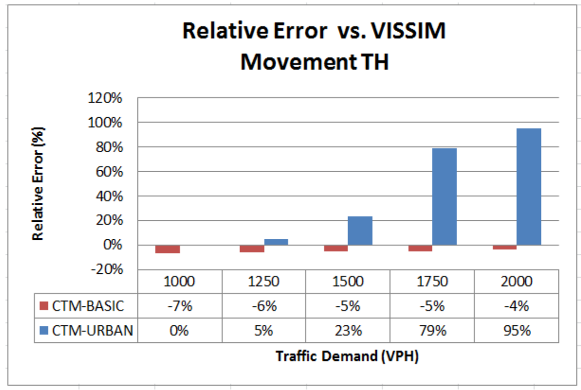


Figure 12 (b)

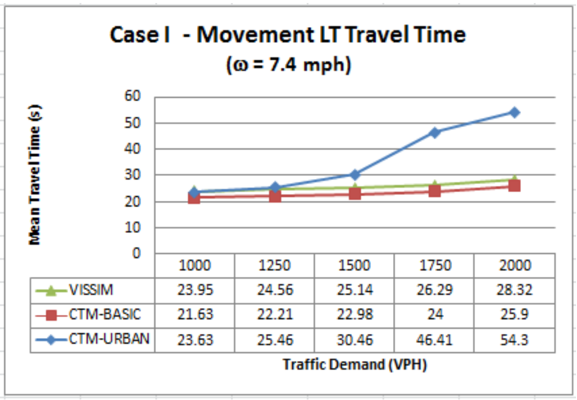


Figure 12 (c)

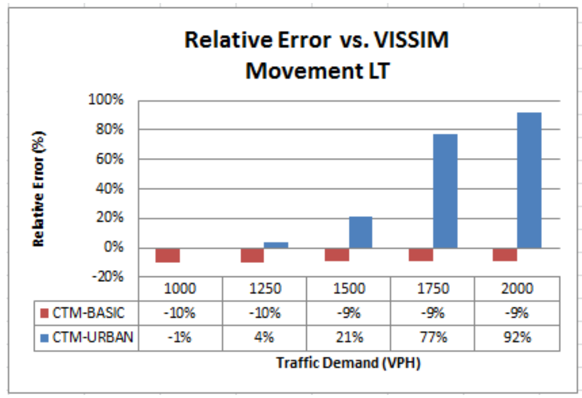


Figure 12 (d)

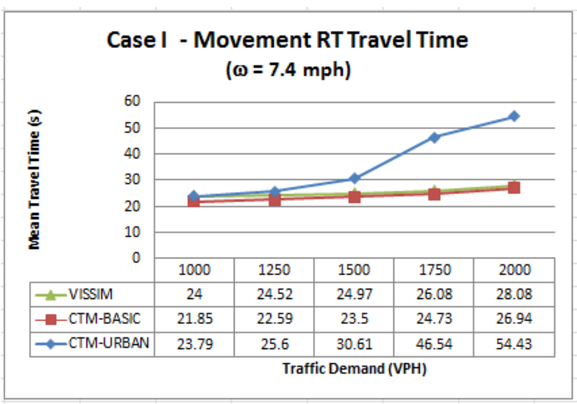


Figure 12 (e)

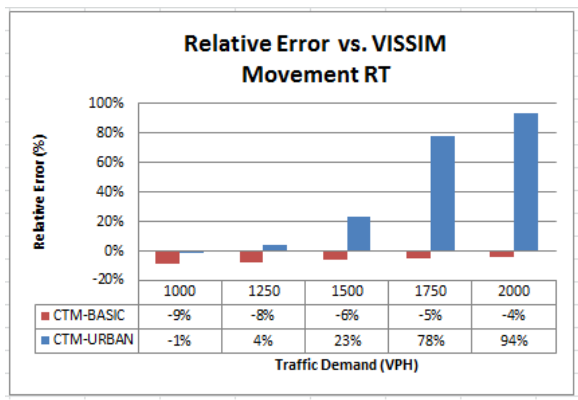


Figure 12 (f)

Figure 12: Travel Time Prediction for Each Movement under Case I Scenario

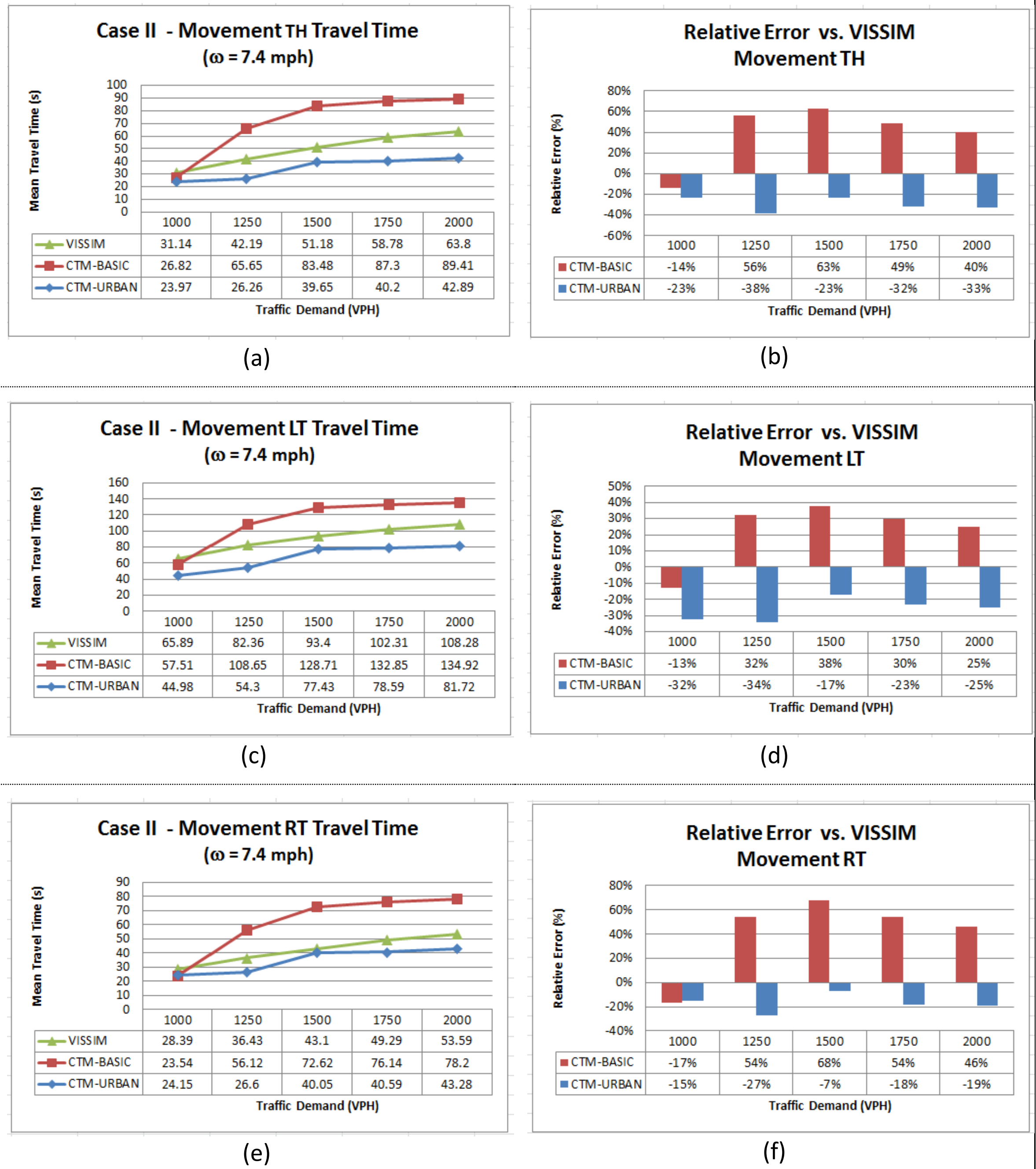


Figure 13: Travel Time Prediction for Each Movement under Case II Scenario

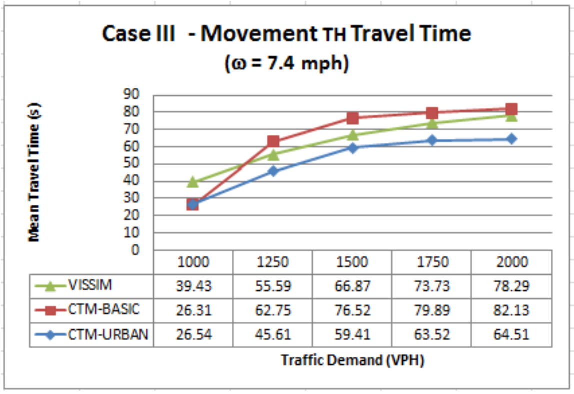


Figure 14(a)

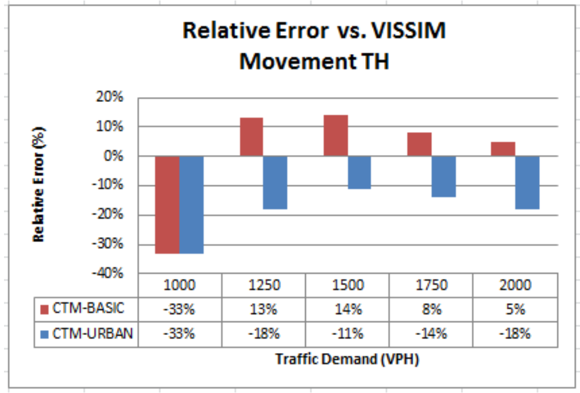


Figure 14

Figure 14**(b)**

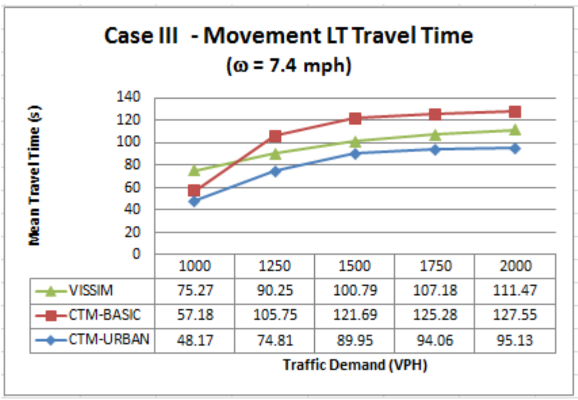


Figure 14(c)

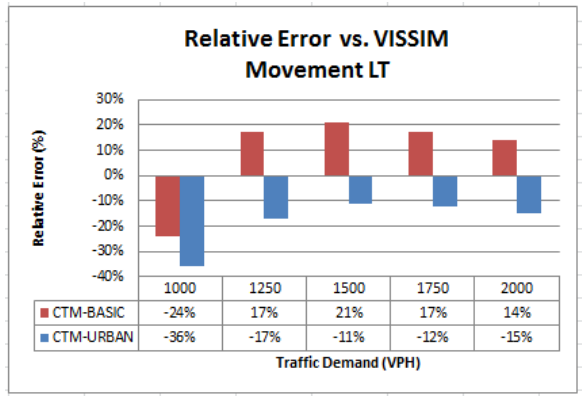


Figure 14(d)

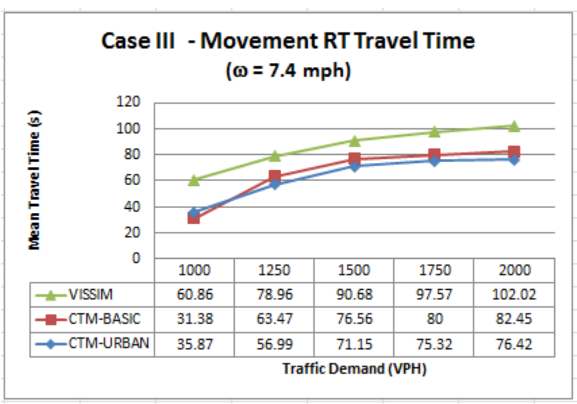


Figure 14(e)

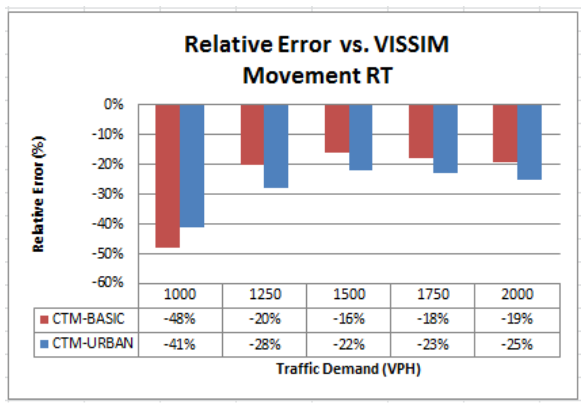


Figure 14(f)

Figure 14: Travel Time Prediction for Each Movement under Case III Scenario

In CTM-URBAN, the parameter that distinguishes congested and non-congested condition is the backward moving wave speed. A sensitivity test on the value of ω may indicate if a change in ω can influences pattern of accuracy in predicting travel time.

A range of ω values are applied to CTM-URBAN in performing case I simulation, and Figure 15 reveals that the accuracy of travel time prediction significantly improves when ω value is increased from 7.4 mph (11.9 km/hr) to 13 mph (20.9 km/hr) and ω values of 13 mph (20.9 km/hr) and 15 mph (24.1 km/hr) yield nearly identical results. The same test is applied to Case III simulations, but on the contrary, setting ω value equal to 13 mph (20.9 km/hr) produces the poorest travel time prediction. Instead, a scaled down ω value of 5.92 mph seems to produce the best simulation result. It appears that CTM-URBAN can be more accurate when different ω values are selected in simulating non-congested and congested conditions.

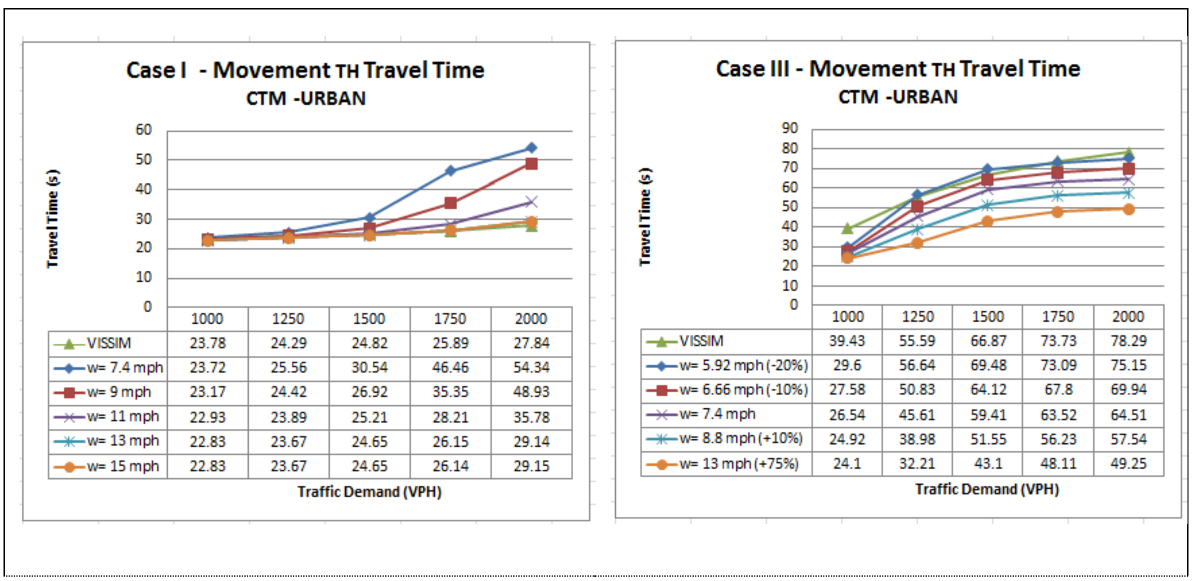


Figure 15: Results of Sensitive Analysis on CTM-URBAN

A possible explanation of this observation can be that backward moving wave speed varies with the level of congestion. A closer look at case III results seem to rule out this possibility. As demand input increased from 1250 vph to 2000 vph, TH travel times increase, indicating an increased level of congestion. It appears that results from one ω value consistently produce better prediction regardless of the level of congestion.

Another explanation is that perhaps more than one backward moving wave are present in the system and one wave speed can have more impact than another in congested or non-congested situations. A study (Akcelik and Besley 2002) on queue discharge behavior for signal controlled intersections may offer support for this explanation. In this study, two types of backward moving waves can be observed in queue discharging cycles, a queue formation wave and a queue departure wave. The queue departure wave speed surveyed at 11 isolated signal controlled intersections in Melbourne and Sydney is averaged at 13.6 mph. Liu *et al.* (2009) also support the view that multiple types of shock waves can be in a signal controlled intersection.

The findings can be used to explain what is observed in the sensitivities tests. CTM models in general can capture the occurrences of both the queue forming and queue discharging waves by definition of the algorithm, but with the same wave speed value. If the two waves travel at significantly different speeds, the choice of wave speed may influence the simulation outcome.

The proposed calibration procedure for obtaining the backward moving wave speed essentially identifies the queue forming wave speed. It is assumed this value is applicable to all backward moving waves occur in CTM simulations. The value is found to be 7.4 mph (11.9 km/hr). If the reported queue discharging wave speed of 13.6 mph is consistent with VISSIM simulation, the two wave speeds are significantly different.

In Case I where no downstream congestion is present, queue discharging is the primary mechanism that dictates travel speed. It is reasonable that the sensitivity test indicates the wave speed of 13 mph (20.9 km/hr) provides more accurate travel time prediction. In Case III where two downstream roads are congested, the queue forming mechanism in the downstream roads can be the primary factor that limits queue discharge on the upstream road. It is then reasonable that the queue forming wave speed of 7.4 mph (11.9 km/hr) produces more accurate travel time prediction in the sensitivity test.

Conclusion

The results of the study reveal that CTM-BASIC produces acceptable travel time prediction for non-congested conditions but cannot reproduce VISSIM simulation results with consistency in cases where downstream congestions are present. The relative errors are generally above 20%. This error range should be considered when applying CTM in urban networks.

CTM-URBAN exhibits an improvement to CTM-BASIC in terms of travel time prediction under congested conditions. The large prediction errors, compared with VISSIM results, in both congested and non-congested situations suggest that CTM-URBAN may require further adjustment to produce reliable simulation result. Examination of the CTM-URBAN simulation result concludes that by selecting appropriate backward moving wave speed for different case scenarios, simulation performance may be improved. A new experiment based on this conclusion is conducted and performance evaluation on the effect of the variable wave speed mechanism is presented in the next section.

5.4 Effect of Variable Wave Speed on CTM-URBAN

In this experiment, two different values of the backward moving wave speed (ω) are selected to simulate different case scenarios. For case I, ω is set to 13 mph (20.9 km/hr), equivalent of 1.75 times the calibrated backward moving wave speed of 7.4 mph (11.9 km/hr). For case II and III where downstream conditions are congested, ω is set to 5.92 mph, equivalent of 0.8 times the calibrated backward moving speed. The selection of the wave speed is based on the sensitivity test presented in the previous section. Same ω values as CTM-URBAN are applied to CTM-BASIC in each case. All other input parameters and case scenario remain the same as described in the previous section.

It is expected by implementing the adjusted ω values, there will be improvement in the accuracy of CTM-URBAN simulation compared with VISSIM results. The effect of adjusted ω values on CTM-BASIC outcome is unknown. Evaluation of the simulation performance is expected to assess if CTM-URBAN can potentially be calibrated to provide comparable results from VISSIM simulations.

Experiment Results

A comparison between the CTM-URBAN simulation results using the initial and adjusted ω value can demonstrate if the intended improvement in accuracy is tangible. Figure 16 (page 62) indicates a clear improvement in predicting TH travel time in Case I. The relative errors versus VISSIM results drop significantly to below 5% level. This trend is consistent in both LT and RT travel time predictions.

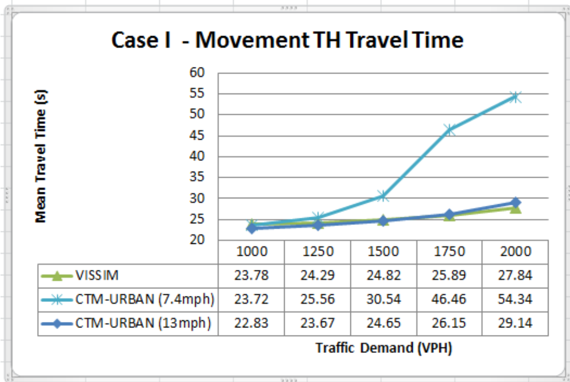


Figure 16(a)

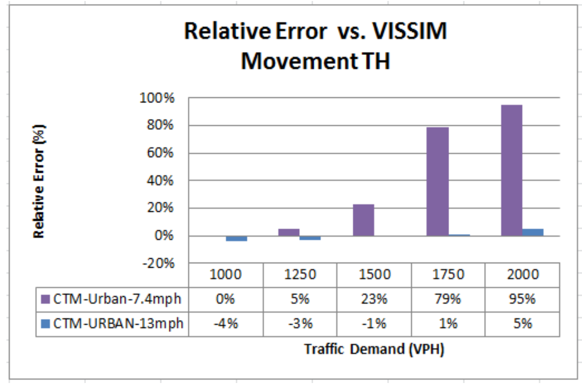
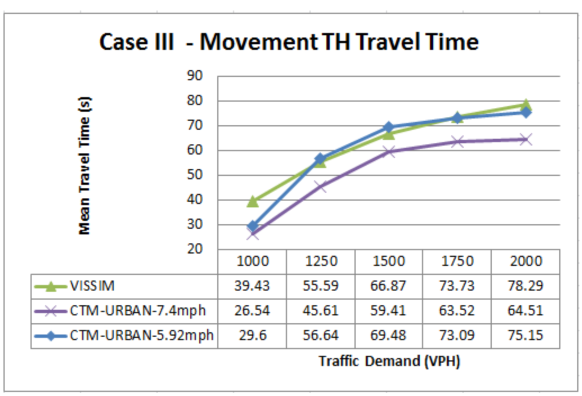


Figure 16(b)

Figure 16: Effect of Variable Wave Speed, Initial Test on Case I

Figure 17 presents the comparison of performance in travel time prediction between CTM-URBAN simulation results using initial and adjustable ω values of 5.92 mph (9.53 km/hr) for the simulation Case III. Significant improvement in accuracy can be observed in travel time prediction of TH movement and the same trend is observed for all movements in both Case II and Case III. It can be reasonable to conclude that the proposed change has achieved the intended purpose and it is meaningful to proceed with a closer analysis of CTM-URBAN simulation results.



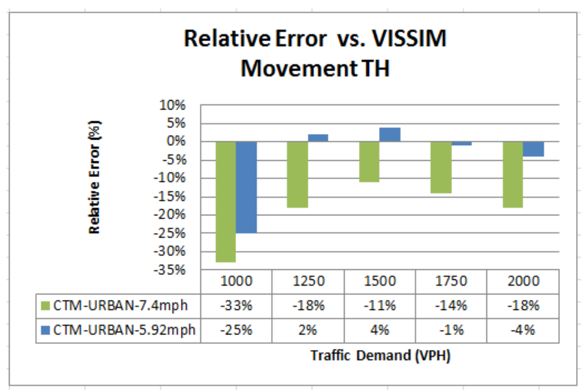


Figure 17: Effect of Variable Wave Speed, Initial Test on Case III

Effect of Variable Mechanism on CTM-URBAN Performance in Prediction of Travel Time

In Case I scenario, CTM-URBAN reproduces VISSIM simulation results closely. Figure 18 shows that CTM-URBAN predicts travel time under all preset demand levels in each movement within 5% relative error. The figure also demonstrates CTM-URBAN outperforms CTM-BASIC in predicting travel time under free-flow traffic condition.

In Case II scenario, CTM-URBAN results (as shown in Figure 19) exhibit a higher error level than in Case I. CTM-URBAN generally underestimates travel time in the 15% to 30% range compared with VISSIM results. This indicates that CTM-URBAN may be less effective in predicting travel time when lane blockage occurs due to congestion in particular downstream movement. It is unclear what causes contribute to the error with just the travel time indicator. A second performance indicator will be introduced in the next section to reveal the possible cause of the error. It should be noted that compared with CTM-BASIC results where errors which range from +40% to +70%, the proposed lane blockage mechanism in CTM-URBAN is clearly effective in correcting the tendency of CTM-BASIC to unrealistically overestimate travel time.

In Case III Scenario, CTM-URBAN produces mixed level of success in reproducing VISSIM results. As shown in Figure 20, errors at -30% can be observed in the prediction of travel time when the demand level is low (i.e. 1000 vph) in all movements. Aside from this, CTM- URBAN result is comparable to VISSIM results with errors under the 10% level. It is also clear that CTM-URBAN outperforms CTM-BASIC in Case III scenarios.

CTM-URBAN Performance in Prediction of Congestion Level

As observed in the analysis of travel time prediction, CTM-URBAN seems to be less accurate in simulating unbalanced downstream congestions causing lane blockages. A closer

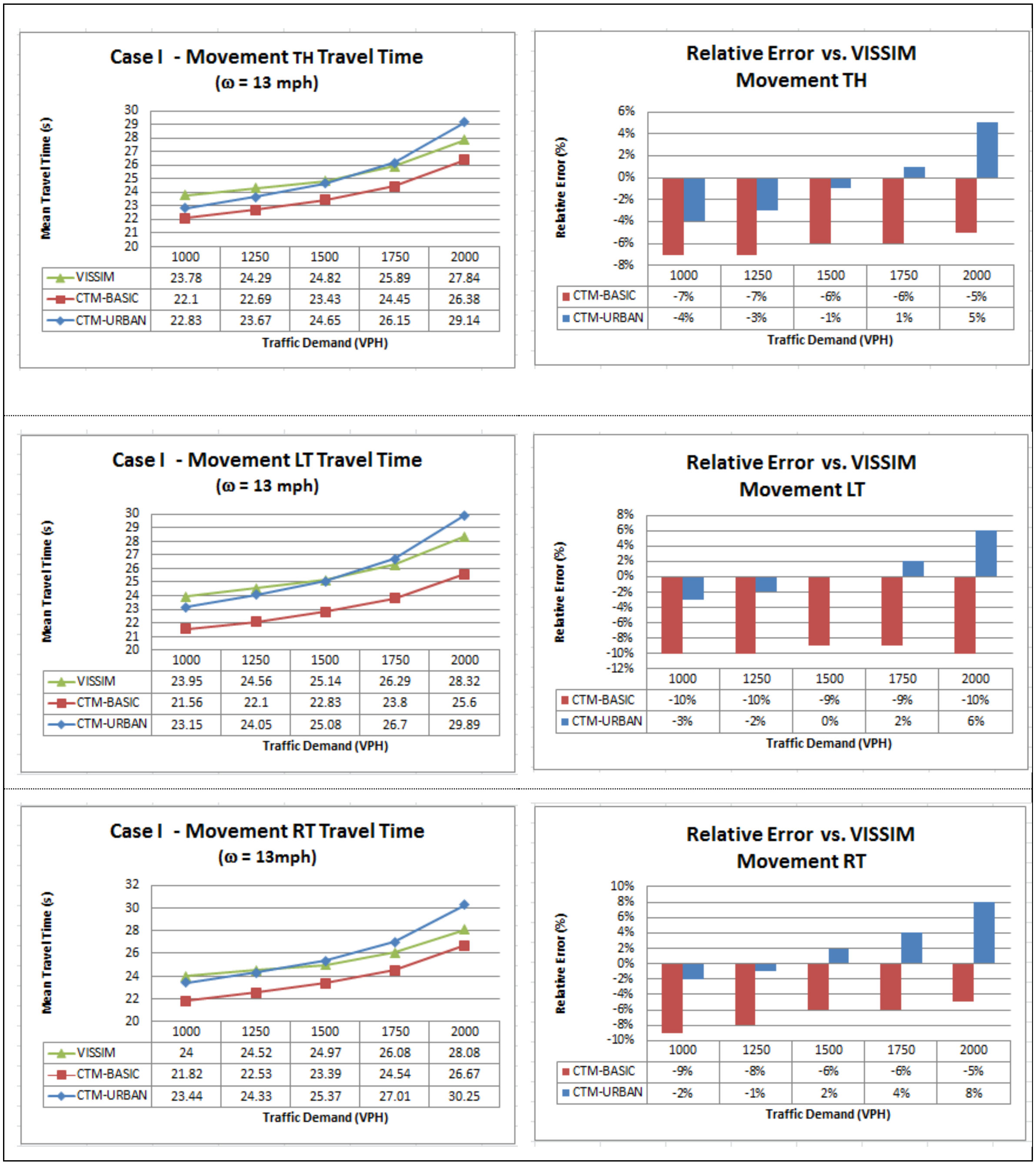


Figure 18: Case I Simulation Results, CTM-URBAN with Variable Wave Speed

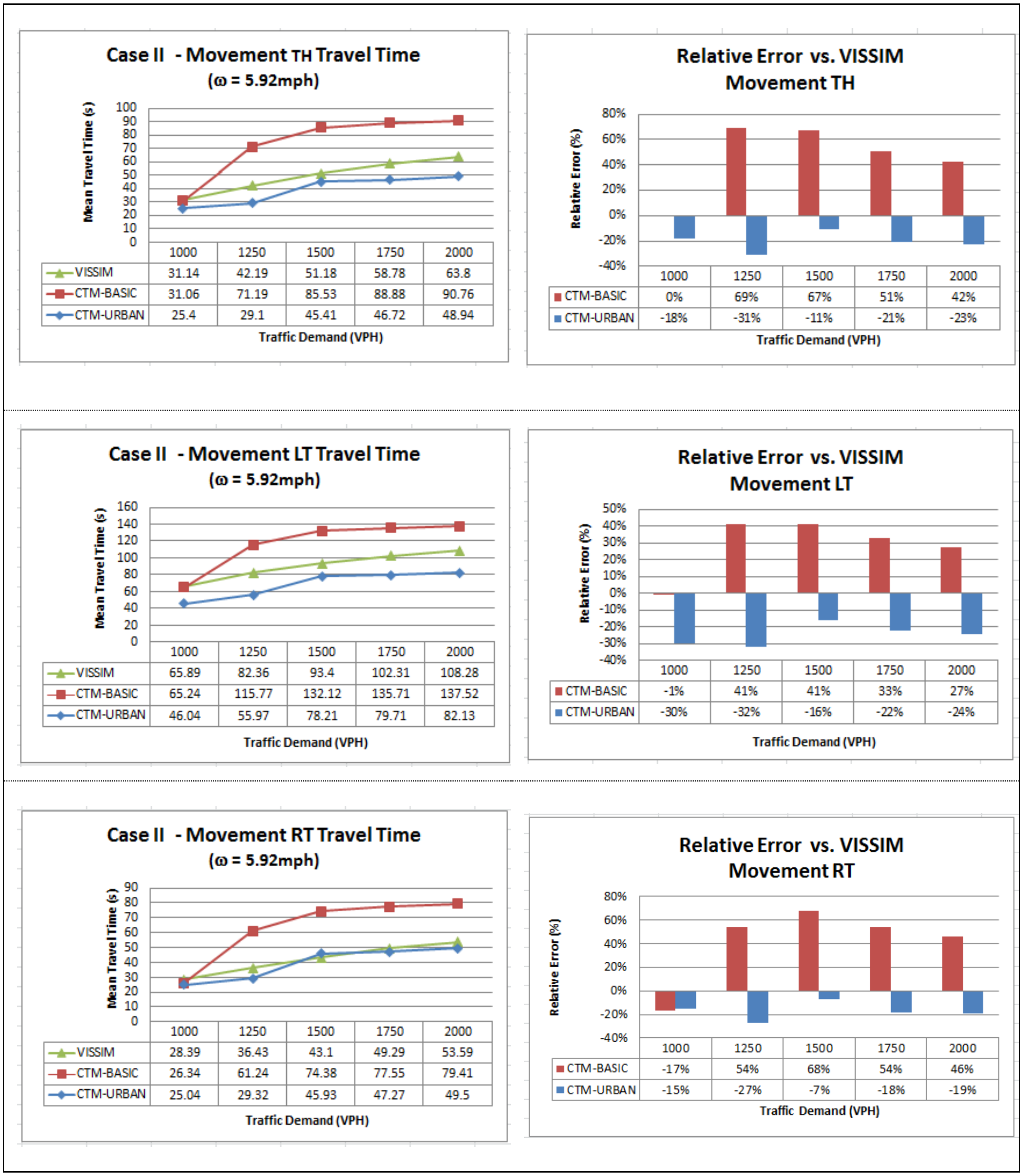


Figure 19: Case II Simulation Results, CTM-URBAN with Variable Wave Speed

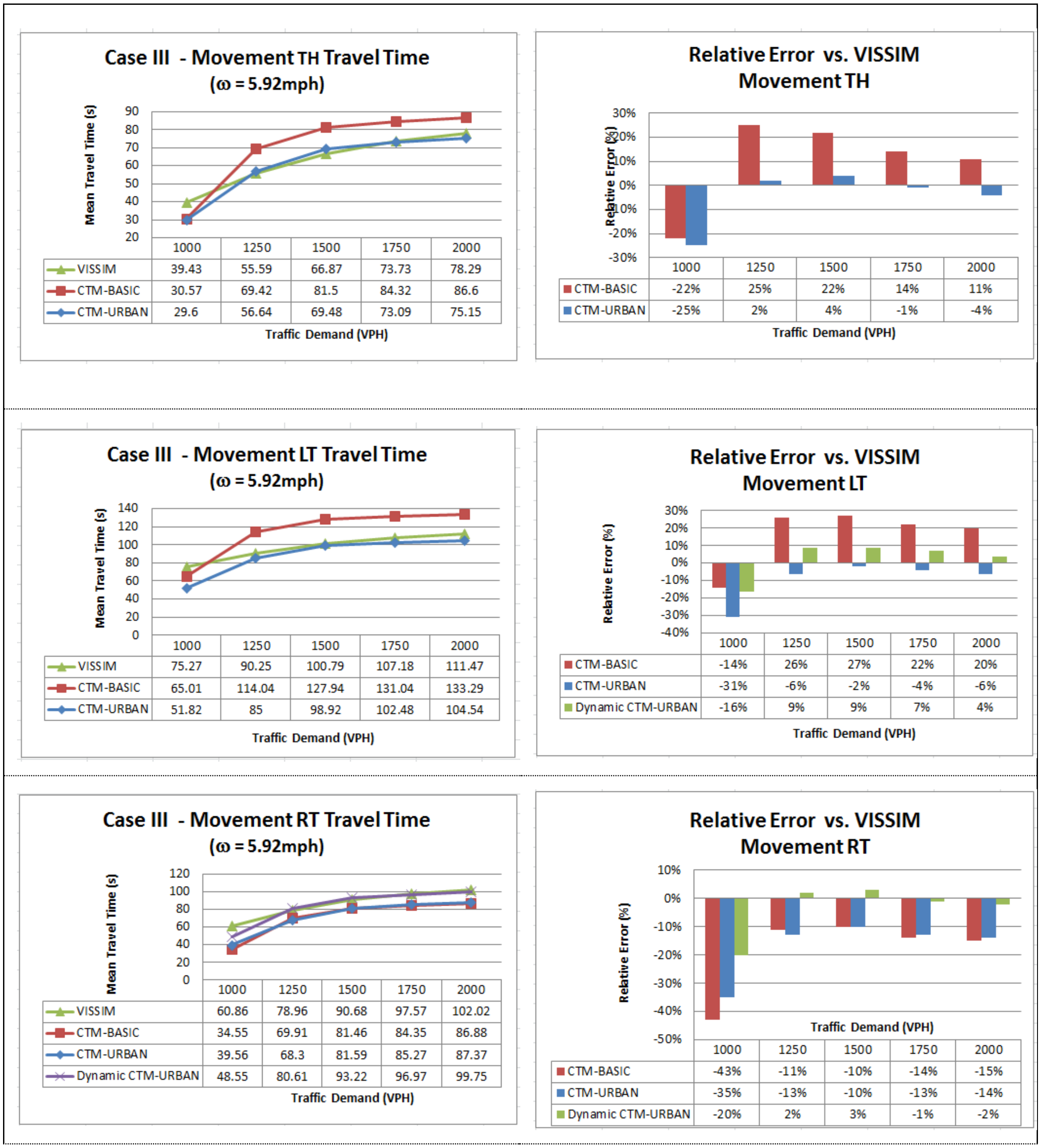


Figure 20: Case III Simulation Results, CTM-URBAN with Variable Wave Speed

look at the ability to predict congestion level may assist to identify the reason. The TH/RT travel time ratio shown in Figure 21 indicates VISSIM predicts a 10% to 20% higher congestion in the TH movement. CTM-URBAN does not capture this difference in the levels of congestion as the ratio is constantly close to 1.00. This can indicate that some delays in the TH movement are not captured. One possible cause of these delays is from TH vehicles merging from the queued left turn lane to the right lane. This merging delay is a not captured by lane blockage mechanism proposed in CTM-URBAN. Some improvements (on the lane blockage mechanism) to account of this delay should be considered in the future development of CTM-URBAN.

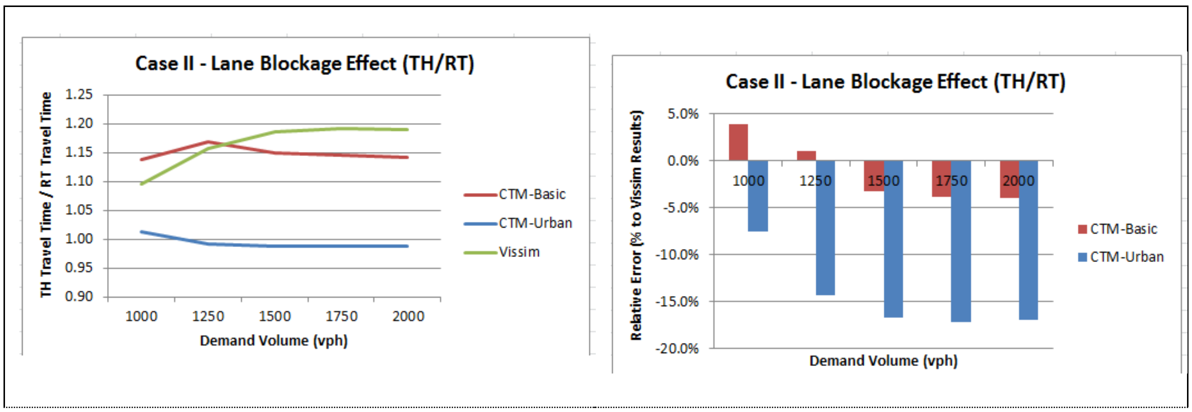


Figure 21: Case II Congestion Level, CTM-URBAN with Variable Wave Speed

In the Case III scenario (as shown in Figure 22), CTM-URBAN performs well in prediction the higher congestion level in RT movements. The errors are within 10% under all demand levels. This is consistent with the findings in travel time prediction results. CTM-BASIC performs poorly in this category exhibiting error at the 40% level.

Discussion on the dual-wave speed approach

The simulation results confirm that input of different wave speed values at non-congested and congested condition improve the realism of CTM-URBAN prediction. In real-life traffic, it is not practical to assess the congestion level and select an appropriate wave speed value prior to the simulation. One potential solution maybe to develop a mechanism where queue forming and queue discharge waves can be captured by CTM-URBAN with a dual-wave approach. Finally, it can be concluded that the limitation where only one wave speed can be applied in CTM-BASIC and CTM-URBAN hinders the ability of the models to predict of travel time in signal controlled intersections realistically.

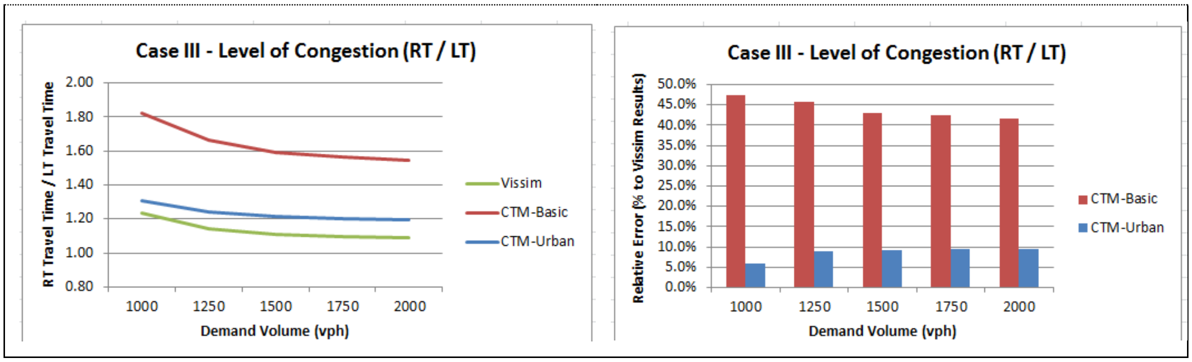


Figure 22: Case III Congestion Level, CTM-URBAN with Variable Wave Speed

Conclusion

The experiment results described in this section confirm the hypothesis that by selecting appropriate ω input values that correspond to the traffic congestion level, the ability of CTM-URBAN to predict movement travel time can be significantly improved in all case scenarios. CTM-URBAN provides simulation results comparable to the results generated by VISSIM simulator in both Case I and Case III.

In case II where one downstream congestion causes queuing in one lane, CTM-URBAN exhibits a 30% error level in travel time prediction. CTM-URBAN also fails to reproduce the difference in congestion level in Case II. This indicates there is potential for improvement in the lane blockage mechanism proposed in this study by incorporating a mechanism to reflect the delay due to the merging movements.

Simulation results from all case scenarios confirms that CTM-URBAN significantly improves the realism of CTM-BASIC in predicting vehicle travel time in a signal controlled intersection. The results also validate the claim that CTM-URBAN can produce satisfactory prediction of travel time in a signal controlled intersection. Both conclusions are based on the fact that the appropriate backward moving wave speed can be selected based on the congestion level prior to the simulation which is only practical designed experiments. Modification of the CTM-URBAN to reflect effects of multiple wave speeds under various congestion levels is essential to reproduce the same level of accuracy predicting travel time in real-life situations. A dual wave speed approach capturing the effects of queue forming and queue discharge waves is proposed as a potential enhancement for future studies.

5.5 Effect of Dynamic Demand Input on CTM-URBAN

In many practical traffic prediction studies or applications, supplied traffic information may contain information to derive time dependent turn ratio. Examples of these applications include microscopic simulator such as VISSIM, vehicle trajectory data such as provided by NGSIM project, Dynamic Traffic Assignment algorithms, and real-time loop detector data. In such cases, the time-based turn ratio may be used to improve accuracy of travel time prediction models.

An experiment is performed to evaluate the effect of incorporating this time based turn ratio input into CTM-URBAN, identified as Dynamic CTM-URBAN in this section. Simulation results are expected to show that Dynamic CTM-URBAN improves accuracy in travel time prediction compared with CTM-URBAN. All input parameters and case scenarios are identical to the configuration described in section 5.3 with the exception that VISSIM vehicle input data is extracted and processed to provide CTM-URBAN time-based demand ratio.

Simulation Results

In Case I where downstream traffic condition is non-congested, it can be expected that the addition of time-based turn ratio does not contribute to significant difference in travel time prediction if all other input parameters are identical. Dynamic CTM-URBAN simulation results (as shown in Figure 23) reveal there is a small increase in the error reported. The error may be trivial in terms assessing the overall quality in travel time prediction. In Case I scenario, Dynamic CTM-URBAN reproduces VISSIM travel time predictions well within 10% error.

In Case II scenario, Dynamic CTM-URBAN improves CTM-URBAN results from the error level of 30% to within 10% with the exception of RT movements under heavy vehicle demand. This finding indicates that a large portion of the error exhibited by CTM-URBAN in predicting travel time in lane blockage conditions may be attributed in the discrepancy of turning demand between static turn ratio and real turn ratio. The uncharacteristically high error reported in the RT travel time prediction may be explained by the hypothesis that the 5.92mph wave speed used to simulate Case II scenario does not accurately describe traffic conditions in the right turning lane where traffic conditions may be better described as non-congested. This hypothesis cannot be validated since different ω values cannot be applied in one simulation based on the current form of CTM-URBAN algorithm.

In Case III scenario where CTM-URBAN reproduces VISSIM results closely, Dynamic CTM-URBAN shows tendency to increase Case III travel time prediction by about 5% to 15%. The error reported seems to indicate a small improvement in accuracy but the difference is not conclusive.

In terms of predicting the downstream congestion levels, performance of Dynamic CTM-URBAN is not improved despite the additional information. The same conclusion drawn from

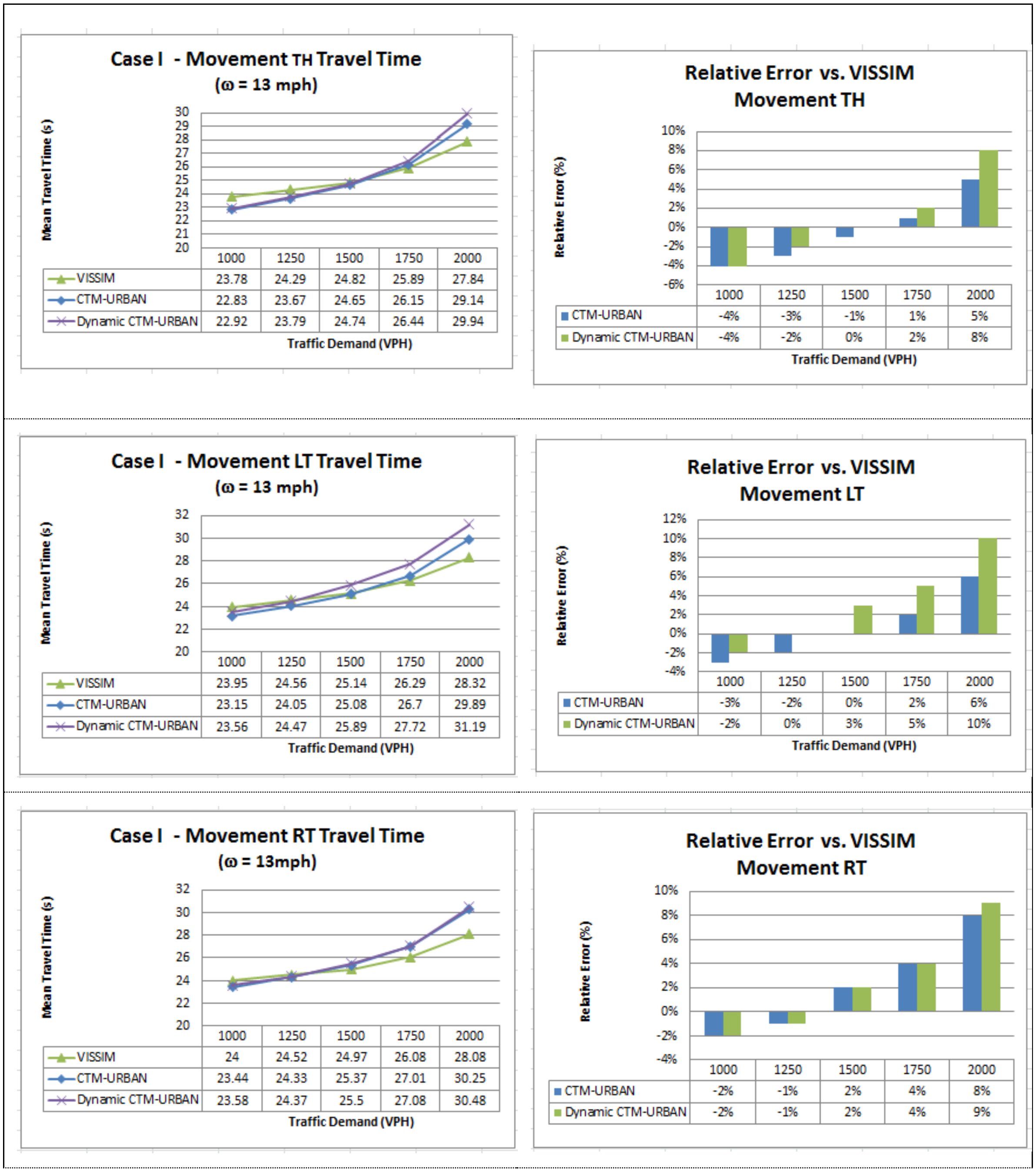


Figure 23: Case I Simulation Results, Dynamic CTM-URBAN

Figure 24: Case II Simulation Results, Dynamic CTM-URBAN

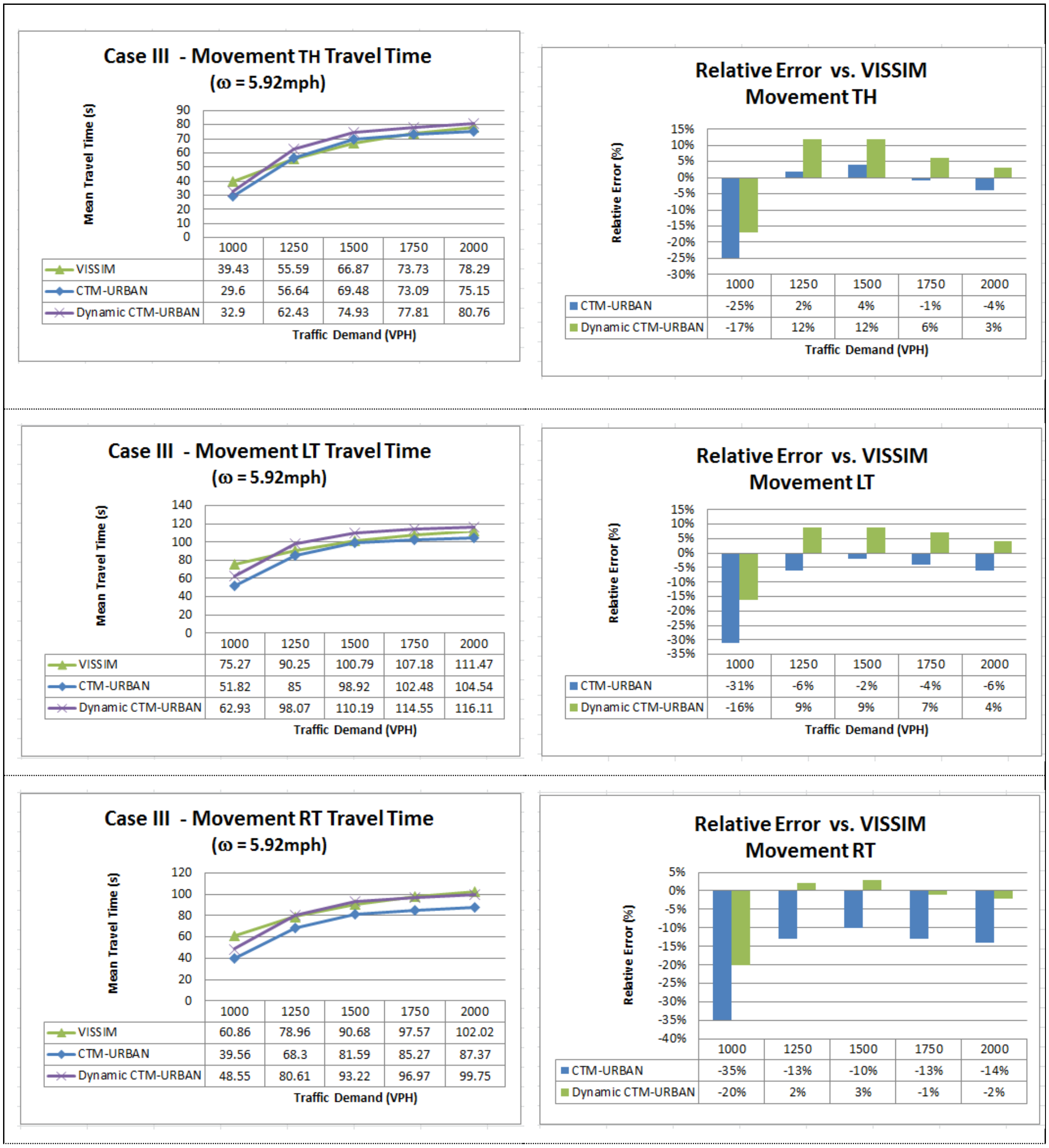


Figure 25: Case III Simulation Results, Dynamic CTM-URBAN

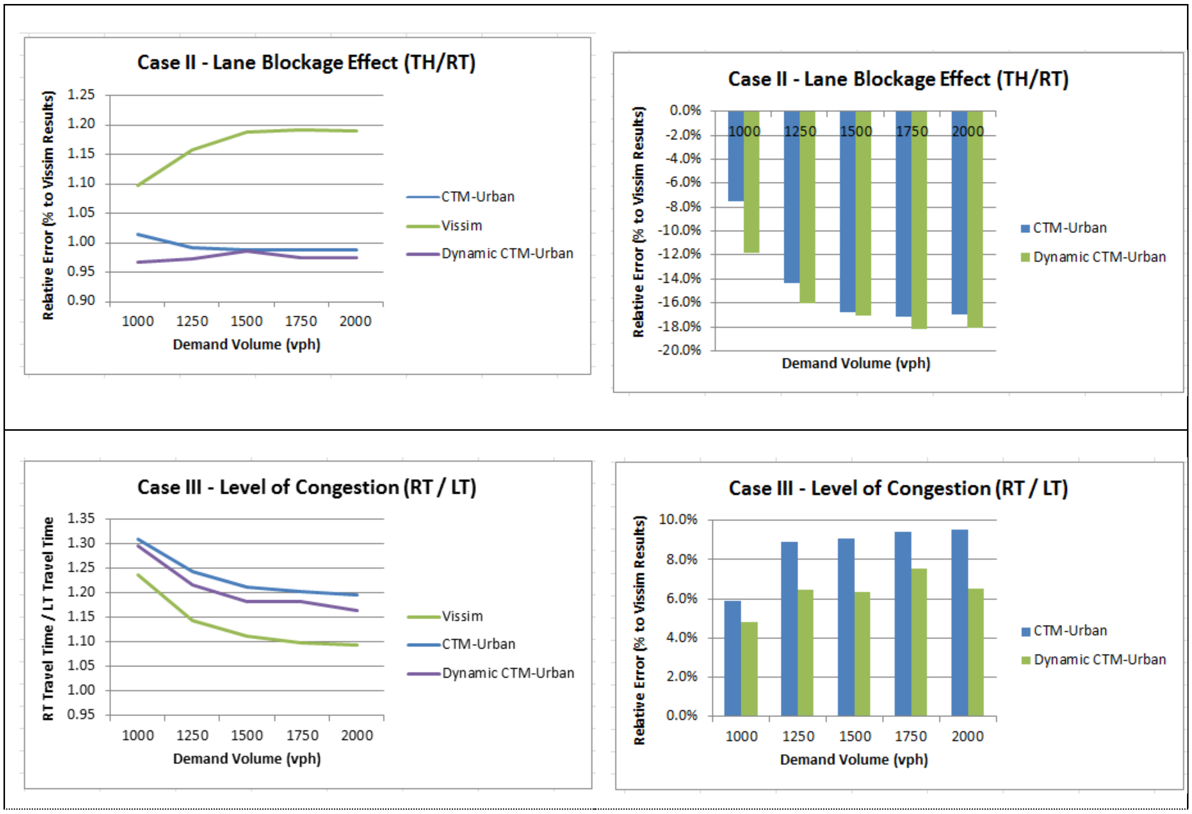


Figure 26: Prediction of Congestion Levels, Dynamic CTM-URBAN

previous section is confirmed that some vehicle merging behaviors observed in VISSIM is not considered in CTM-URBAN model.

Conclusion

Analysis of the experimental results confirms that the optional feature to incorporate time-based turn ratio information into CTM-URBAN can improve accuracy in travel time prediction. The improvement is most notable in Case II scenario. The increase in accuracy suggests that when time based demand information is available; the dynamic option is the preferred choice of CTM-URBAN.

5.5 Summary and Conclusion

In this case study, three different traffic scenarios representing various levels of downstream congestion within a signal controlled intersection are simulated using CTM-BASIC, CTM-URBAN, and VISSIM. In the first experiment, it is found that CTM-BASIC produces comparable simulation results to VISSIM simulator but the performance decreases under congested conditions. The error in travel time prediction are at 20% to 50% .

The proposed CTM-URBAN model improves CTM-BASIC in travel time prediction under congested conditions, but exhibit deficiencies in simulation under free-flow condition. An hypothesis on the cause of the error is that multiple wave speed may be in effect on the propagation of queues in signal controlled intersections. A variable wave speed mechanism is proposed to improve the accuracy of CTM-URBAN model and an experiment is conducted to confirm there is a potential improvement by incorporating the mechanism.

Additionally, an optional dynamic input mechanism on CTM-URBAN is tested on CTM-URBAN. The simulation results reveal notable performance improvement and the increase in accuracy suggests that when time based demand information is available; the dynamic option is the preferred choice of CTM-URBAN.

The findings of the case study indicate CTM-URBAN has the potential to become a reliable travel time prediction tool in urban networks where signal controlled intersections are common. Future enhancement and validations are still required to utilize CTM-URBAN as a practical simulator.

CHAPTER 6 CONCLUSION AND FUTURE WORK

6.1 Summary

The first chapter of this thesis introduces traffic simulators, identifies a problem statement with respect to the ability of the existing simulators to perform reasonably in real-time traffic applications and identified the objective of the thesis. The objective of this study is to develop a CTM-based simulator that accommodates traffic flow and various network features specific to urban roadways. In the second chapter the thesis provides literature reviews focused on four topics: (1) short-term travel time prediction of urban network, (2) characteristics of urban traffic flows, (3) development of CTM, and (4) development of CTM in the context of urban network.

The thesis continues to review the existing CTM algorithm, which was originally developed for simulation of highway traffic flows. The review identifies the limitations that prevent CTM to be applied in urban traffic flow simulations without modifications. It is believed that these limitations can cause CTM to generate unrealistic simulation results if applied in an urban context, specifically at signal-controlled intersections.

A new CTM-based model named CTM-URBAN is introduced to address the identified limitations and to provide a generic framework for future development of CTM in simulation of urban traffic flows. CTM-URBAN incorporates: (1) a new diverge algorithm that permits modeling of multiple movements and multiple signal phases; (2) a new mechanism to generate dynamic turn ratios instead of preset static values; (3) the ability to simulate lane blockage and full blockage at intersections which improves the realism of the simulation under congested traffic conditions; and (4) time-based input parameters allowing more realistic and flexible representation of various traffic condition and operation scenarios. All these features of CTM-

URBAN and other minor improvements make the simulator more suitable for real-time simulations compared with the basic version of CTM.

The accuracy of an urban traffic flow simulation model fundamentally depends on its ability to realistically predict travel time through a signal controlled intersection. Therefore, three case scenarios are designed to evaluate the capabilities of the original CTM algorithm and CTM-URBAN in predicting travel time through a signal controlled intersection under various demand and downstream congestion levels. The experimental results confirm that limitations identified with respect to the original CTM algorithm can be reproduced based on calibrated input values, and, therefore, direct application of CTM in urban traffic flow simulations it is not recommended.

On the other hand, the experiments demonstrate CTM-URBAN can generate more accurate travel time prediction through a signal controlled intersection under both non-congested and congested downstream conditions compared with the basic version of CTM. The improvement, however, is based on one importation assumption: the limitation of CTM-URBAN that allows only one input for the congestion wave speed can be overcome in future studies. In order for CTM-URBAN to be practical, it is essential that a dual-wave speed mechanism can be implemented in future studies. Validation of other proposed CTM-URBAN components can be continued after such mechanism is implemented. Several advantages of the proposed CTM-URBAN are summarized in the next section.

6.2 CTM-URBAN Advantages

CTM-URBAN offers advantages as a simulator of urban traffic flows at different levels. In terms of the proposed simulation framework, CTM-URBAN incorporates time-based parameters that increase the flexibility in representing the complex urban traffic flow and control scenarios. Also, the proposed framework introduces the possibility that components of the model (e.g. permitted flow, merging in lane blockage, etc.) can be developed and improved independently in a modular manner. This feature allows for faster development of the model while introducing a high degree of flexibility by permitting to toggle on and off specific features, as the user considers necessary.

In comparison with the original CTM algorithm, CTM-URAN provides these specific improvements. First, the new intersection algorithm is shown to provide more reliable and realistic simulation results. Second, the introduction of the algorithm-generated turn ratio for the diverge and merging cells reduces the calibration efforts considerably. This is one key advantage that will improve the applicability of CTM at large scale. Finally, the lane blockage algorithm introduced in this thesis is shown to correct the problem in CTM that will overestimate travel time through signal controlled intersections under partially congested downstream traffic conditions.

Overall, CTM-URBAN offers the advantage that it has the potential to fulfill all requirements described in the problem statements. It is demonstrated in the case study that CTM-URBAN is capable of providing **short-term travel time predictions**. CTM-URBAN is **data driven**, and the dynamic input feature provides the possibly for time-based data input. This and the fact that CTM-URBAN is simple and suitable for distributed computing environment make it possible to transform the model into a **real-time** simulator for **large scale urban** networks.

While additional features such as incorporation of dual wave speed mechanism will require additional research effort, the model exhibits the potential to become a practical tool for traffic management professionals. The model can be particularly suitable for the following applications:

- Impact evaluation on road closures due to repair work, maintenance operation, or events.
- Signal Optimization including actuated and adaptive signals.
- Validation of Dynamic Traffic Assignment models.
- Performance evaluation of existing network design.
- Evaluation tool for traffic improvement proposals.

There are still some major limitations that have to be overcome before the proposed model can be practical. The next section provides a discussion on these limitations.

6.3 Limitations

Although the design experiments confirmed that CTM-URBAN demonstrates improvement over the original CTM in terms of reliability and accuracy, the experiments also reveal two significant limitations of CTM-URBAN. First, it is found that use of only one backward moving wave speed input, corresponding to queue forming conditions, may hinder the prediction accuracy of CTM-URBAN under uncongested downstream condition. It is concluded that the model has to be modified to allow implementation of at least two wave speed values in order to provide realistic results. Second, a more accurate merging algorithm may be required to improve the lane blockage mechanism, as demonstrated in the case II scenario, to reflect the differences in congestion levels between the non-queuing movements. These two identified limitations prevent further calibration or validation of some proposed features of CTM-URBAN at this stage including (1) realism of representing permitted flow by the σ parameter, (2) benefits of full blockage factor (ρ), (3) accuracy of queue length estimation.

Other features are essential for CTM-URBAN to be truly applicable for simulations of urban traffic flow include:

- Simulation of stopped controlled intersections.
- Impact of vehicle composition (i.e. through vehicle equivalency representation)
- Multi-Mode Simulation (i.e. transit and pedestrian crossing)
- Integration of larger network

These characteristics of urban traffic flows are commonly encountered and a simulation tool can only claim practical if the impact of these characteristics is incorporated. The proposed model poses limitations, but the level of accuracy exhibited by CTM-URBAN under restricted conditions should provide encouragement for future development. Aspects of CTM-URBAN that can benefit from future work are described in the next section.

6.3 Future Work

Controlled experiments demonstrated in this thesis reveal some particular aspects where improvements are essential for CTM-URBAN to be reliable and accurate. One immediate improvement to be made on CTM-URBAN is definitely to incorporate ability to accept two or more input values for the (backward moving) wave speeds. It is clearly demonstrated that the input of one wave speed value is not sufficient for CTM-URBAN to represent the traffic flow dynamic through a signal controlled intersection. The study concludes at least two wave speed values should be implemented to represent the queue forming and queue discharge waves.

Once this feature is implemented and validated, it will be meaningful to validate the other proposed features (i.e. queue length estimation, full blockage, permitted movement, merging in lane blockage). Finally, experiments based on simulations of variable demand profile and downstream congestion conditions will evaluate CTM-URBAN's overall performance and realism in travel time prediction.

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