

# Traffic Adaptive Control for Oversaturated Isolated Intersections: Model Development and Simulation Testing

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**Abstract:** Traffic adaptive control for oversaturated intersections (TACOS) is a hybrid optimization and rule-based strategy that addresses weaknesses of existing adaptive control strategies by having attributes such as: (1) the information used for decision-making is not dependent on forecasts; (2) intersection utilization is used explicitly in the objective function; (3) phase sequencing is optimized; and (4) operational anomalies are detected and responded to. A new intersection simulator that emulates NETSIM, INTEGRATION, and TACOS was developed to compare TACOS with pretimed and actuated control strategies. Demand scenarios consisted of light to heavy flow, cyclical arrivals, and arrivals with an upstream incident. Throughput-to-demand ratio, speed, delay, queue time, and percent stops were examined. Traffic adaptive control for oversaturated intersections showed significant improvements over pretimed and actuated control in terms of all examined measures of effectiveness under all flow scenarios. Demanding parameter specifications required in other adaptive control strategies are unnecessary in TACOS.

**DOI:** 10.1061/(ASCE)0733-947X(2004)130:5(1)

**CE Database subject headings:** Traffic control; Intersections; Simulation; Optimization; Traffic signals.

## Introduction

Over the past 2 decades there have been significant efforts to develop efficient and robust signal control systems. Although the main challenge changed from controlling near-saturated conditions to oversaturated conditions, the methods for meeting the new challenge did not change accordingly. For instance, the latest generation control has some characteristics that enable decentralized, adaptive, acyclic operations, but also it has inherited some characteristics that may cause poor performance in oversaturated conditions, such as estimation and prediction-induced errors, limited selection of objective functions, absence of optimization of phase sequence, and lack of self-correction procedures. The aim of the research presented herein was to develop and evaluate a real-time traffic adaptive control strategy for isolated, oversaturated intersections (TACOS). Strategies like TACOS are no longer theoretical and simulated constructs. They can be implemented using the new generation of open system architecture controllers, e.g., ATC 2070 (ITE 2000).

This paper consists of an overview of past research, a description of TACOS, and results from simulation tests of TACOS against pretimed and actuated control. Throughout this paper “traffic control strategy” refers to algorithms for the control of a single signalized intersection.

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Note. Discussion open until February 1, 2005. Separate discussions must be submitted for individual papers. To extend the closing date by one month, a written request must be filed with the ASCE Managing Editor. The manuscript for this paper was submitted for review and possible publication on September 4, 2002; approved on August 14, 2003. This paper is part of the *Journal of Transportation Engineering*, Vol. 130, No. 5, September 1, 2004. ©ASCE, ISSN 0733-947X/2004/5-1-8/\$18.00.

## Literature Review

Adaptive control strategies can be categorized into two groups: optimization based and rule based. Optimization-based strategies include a computational process to optimize the total performance, which is usually delay or a combination of delay and stops. Optimization-based models include optimization policies for adaptive control (OPAC) (Gartner et al. 1991), real-time, hierarchical, optimized, distributed, and effective system (Head et al. 1992), real-time traffic adaptive control logic (Memon and Bullen 1996), and vehicle-specific adaptive control logic (Kamyab et al. 1996).

Optimization-based strategies do not guarantee that an overall optimal control is obtained since they are based on a large number of short-term optimizations (Bang 1976). Lin (1988) asserts that true optimal signal operation cannot be achieved regardless of the level of sophistication of the control strategy. Rather, optimization represents a process of searching for a better course of action.

In rule-based strategies, decision making depends on preset rules only, as manifested in signal control at isolated intersection (SCII) (Elahi et al. 1987, 1992), and generalized adaptive signal control algorithm project (Owen and Stallard 1999). Rule-based models can estimate total performance. However, performance is not optimized but it is compared with predetermined thresholds for making short-term decisions.

Stepwise adjustment of signal timing (Lin 1988), and signal priority procedure for optimization in real time (Yagar and Han 1993) are examples of optimization and rule-based hybrid strategies.

The main weaknesses of adaptive control strategies include: estimation and prediction-induced errors, limited selection of objective functions, no optimization of phase sequence, and lack of self correction.

### *Estimation and Prediction-Induced Errors*

Adaptive control strategies typically rely on estimated and predicted flow conditions and detectors placed far enough upstream

of the stop line are needed to provide the data. Even when the inputs are accurate, the embedded demand estimation and prediction models tend to introduce errors into the information that is used to make signal timing decisions. Lin et al. (1987) indicated that adaptive control strategies are so vulnerable to these errors that reliance on arrival information provided directly by detectors is more desirable. A robust traffic control strategy is least susceptible to or minimizes the effects of detector errors, detection errors, and forecasting errors.

### Limited Selection of Objective Functions

The objective function of adaptive control strategies typically is limited to delay or a function of delay and stops. Each intersection is a spatially limited resource. This limitation is ignored by strategies that do not explicitly address the question: "Are the resources used as effectively as possible to discharge traffic demand?" Throughput in the objective function has seen limited use and testing. Li and Gan (1999) indicated that for pretimed signal control, objective functions that are designed to maximize traffic throughput and minimize queue sizes produce better optimal timing plans. When formulating a real-time control policy for oversaturated arterials, Lieberman et al. (2000) observed that signal timings aimed to maximize system throughput improved delay and speed significantly compared with results of optimal signal timings produced by *SYNCHRO*, *PASSER II*, and *TRANSYT-7F*.

### Absent Optimization of Phase Sequence

The maximization of the efficiency of a signalized intersection should include the optimization of both green time and phase sequence, rather than the optimization of green time alone. Most adaptive control techniques neglect or are incapable of optimizing the sequence of phases. As a result, in multiphase operations, current adaptive control does not perform as efficiently as in two-phase operations. For instance, OPAC produced inferior performance for an eight-phase dual ring operation compared to a two-phase operation (Gartner et al. 1991). Phase sequence optimizing SCII had no such problem (Elahi et al. 1987, 1992). However, SCII's determination of an "optimal" phase sequence on a cycle-by-cycle basis is not real-time adaptive so it created the same phase sequence repeatedly in oversaturated conditions.

### Lack of Self-Correction Procedure

Existing adaptive control strategies focus on finding the optimal green time required to discharge expected arrivals detected by upstream detectors. The resultant green may be inadequate due to the randomness of vehicle discharge (Li and Prevedouros 2002). Accumulation of this error can hamper the performance of adaptive control. Incidents on approaches can also cause blockages which can remain undetected in the absence of stop line detection. Therefore, the inclusion of a self-correction procedure in the decision-making process is important.

In summary, a desirable adaptive strategy should have the following characteristics:

1. Use reliable information in decision-making process by avoiding forecasts;
2. Use throughput and intersection utilization in the objective function;
3. Optimize both timing and phase sequencing; and
4. Detect operational anomalies and respond to them.

## Traffic Adaptive Control for Oversaturated Intersections Processing Logic

The development of TACOS consisted of three building blocks. The first building block was the development of an adaptive control strategy that incorporates the four desirable features listed above. The second building block was the development and testing of intersection simulator NETSIM, INTEGRATION, TACOS (NIT) which is able to simulate isolated intersections with pre-timed, actuated or TACOS signal control. The third building block was the evaluation of TACOS.

Traffic adaptive control for oversaturated intersections is a hybrid optimization and rule-based control strategy. The objective function for optimization is based on the throughput of the whole intersection per unit of time. Traffic adaptive control for oversaturated intersections is not limited by the traditional concepts of cycle length and green splits. It can choose any phase among candidate phases and give this phase a nonfixed green time based on preset rules and optimization objectives. As a result, the signal timing produced by TACOS is acyclic. The TACOS decision making is based on the estimation of arrival information supplied by detectors without future demand forecasts. These features are detailed below.

The decision-making process of TACOS takes place at the end of each green based on real-time information on queues. Each decision basically consists of two elements: choice of phase among all candidate phases and duration of green for the chosen phase. Each decision is made based on preset rules and optimization objectives. The main rule used in TACOS is that the waiting time (WT) of the vehicle at the stop line must not exceed a user-determined duration,  $WT_{max}$  (usually 30–180 s). The maximum waiting time can be different for each lane depending on its characteristics (through or left turn movement, major or minor street, etc.) This provides the engineer with some degree of direct control over delays.

The choice set of signal phases used in TACOS is similar to the standard National Electrical Manufacturers Association set but without a fixed sequence. The optimization process consists of the following four steps.

### Step 1: Estimation of Critical Queue for Each Candidate Phase

The critical queue is the longest queue on those lanes served by the same phase at the end of each green. It can be obtained by

$$N_p = \max\{\max(N_l)_M\} \quad (1)$$

where  $N_p$  = estimated number of vehicles in the critical standing queue of candidate phase  $p$  at the end of each green (veh); and  $(N_l)_M$  = estimated number of vehicles in the standing queue on lane  $l$  of movement  $M$  at the end of each green.  $N_l$  is estimated by Eq. (8).

### Step 2: Calculation of Phase Duration for All Candidate Phases

The phase duration consists of green time ( $G$ ), yellow time ( $Y$ ), and all red time (AR). The rationale of determining green time in TACOS is that it should be long enough to discharge the critical queue and arrivals joining the critical queue. The next green time  $G_p$  for phase  $p$  can be determined as

$$G_p = SULT + (N_p + NA_p)h \quad (2)$$

where  $SULT$ =start-up lost time (s);  $NA_p$ =estimated arrivals joining the critical queues of phase  $p$  when the critical standing queue is discharging (veh); and  $h$ =saturation headway (s/veh).

$NA_p$  can be estimated from the arrival rate during the effective red time; e.g., according to the Highway Capacity Manual (TRB 2000)

$$NA_p = \frac{SULT + N_p h}{r_{cr}} N_p \quad (3)$$

where  $r_{cr}$ =effective red time of critical standing queue (s);  $r_{cr} = AR + R_{cr} + SULT$ ;  $R_{cr}$ =red time for critical standing queue (s); and  $R_{cr}$ =zero for the discharging movement.

Before accepting  $G_p$  as final for the candidate phase, three checks are conducted:

1.  $G_p$  must not be less than the preset minimum green time  $G_{min}$ . If  $G_p < G_{min}$ , then  $G_p = G_{min}$ ;  $G_{min} \geq 7$  s is suggested.
2.  $G_p$  must not exceed the preset maximum green time  $G_{max}$ . This is because long greens hamper the ability to respond to fluctuating demand.  $G_{max} = 30 - 60$  s is suggested but specific approaches (e.g., approaches affected by a railroad crossing) may have longer  $G_{max}$ . The traffic analyst can evaluate performance with various  $G_{max}$  settings by using NIT.
3. When a pedestrian actuation has occurred, the green time must satisfy the pedestrian crossing time PED, i.e., as defined by the Highway Capacity Manual (TRB 2000). If  $G_p < PED$ , then  $G_p = PED$ .

User settings of yellow and all red are attached to all movements in expiring phases except for overlapping movements in the current and chosen phases.

### Step 3: Estimation of Discharge Volume if Candidate Phase is Selected

This estimate is obtained by

$$v_p = \sum_M \sum_l ((N_l)_M + (NA_l)_M) \quad (4)$$

where  $v_p$ =estimated number of vehicles that can be discharged if the candidate phase  $p$  is selected.

If  $(N_l)_M$  is the critical standing queue of this candidate phase,  $(NA_l)_M = NA_p$ . If  $(N_l)_M$  is not the critical standing queue of the candidate phase,  $(NA_l)_M$  is obtained by

$$(NA_l)_M = G_p (N_l)_M / (r_l)_M \quad (5)$$

where  $(r_l)_M$ =effective red for lane  $l$  of movement  $M$ .

### Step 4: Selection of Optimal Phase Among Candidate Phases

The selection of the optimal phase from the candidate phase set must maximize intersection utilization.  $E_p$  was created to do this

$$E_p = \frac{v_p}{G_p} \quad (6)$$

where  $E_p$ =efficiency of intersection utilization for candidate phase  $p$  (vehicle/s).

The TACOS calculates  $E_p$  for all candidate phases at the end of each green and the candidate phase with the largest  $E_p$  is chosen

$$\max\{E_p\} \quad (7)$$

The TACOS' processing logic is as follows:

1. Estimate  $N_l$  for each lane based on the detector information at the end of green.
2. Is  $WT_{max}$  rule violated? If no, go to 3.1. If yes, go to 4.1.
- 3.1 Calculate  $G_p$  for each candidate phase.
- 3.2  $G_p$  subject to  $G_{min}$ ,  $G_{max}$ , and PED rules.
- 3.3 Calculate  $E_p$  for each candidate phase.
- 3.4 Select phase with max  $E_p$ . Go to 5.
- 4.1 Calculate  $G_p$  for the phases where the rule is violated.
- 4.2  $G_p$  subject to  $G_{min}$ ,  $G_{max}$ , and PED rules.
- 4.3 Select phase with max  $WT_{max}$ . Go to 5.
5. Display Y+AR for nonoverlapping movements; continue green for overlapping movements.
6. Display green for chosen phase.

In computer simulation tests of TACOS, the decision-making process occurs at the end of the green because it is instant. In reality, however, the controller needs to start the decision-making process at the end of green minus  $\theta$  s, depending on intersection complexity, and detection and processor speed. In most cases  $\theta$  is likely to be shorter than 2 s.

### Acquisition of Demand Input

The required demand data for TACOS are the queue lengths on each lane on every intersection approach at the end of each green. A method for estimating queue lengths based on the use of advanced detectors is described below. An advanced detector detects the presence of vehicles and provides continuous counting; such detectors are currently available in the market. Advance detectors can start, pause, and terminate the counting as the controller commands.

A typical three lane approach is used in the sample loop layout herein. Inductive loop detectors are assumed although other types of detectors may also be suitable. Lane 1 is an exclusive left turn lane with length  $L_{LT}$ . Lane 2 is the through lane adjacent to the exclusive left turn lane. Lane 3 is through and right turn lane. Two detectors are needed for each lane, at a minimum. Detectors named "1" are placed at the stop line and detectors named "2" are placed at the end of the left turn bay or at  $L_{max}$  for the through lanes. Different  $L_{max}$  can be specified for each lane depending on the prevailing lane utilization. For through lanes,  $L_{max}$  can be the distance between the stop line and an upstream intersection or a busy upstream source or sink. For left turn lanes,  $L_{max}$  can be equal to the length of the left turn bay. When the  $L_{max}$  of Lane 2 is less than or equal to  $L_{LT}$  of Lane 1, the method described below applies, otherwise, a more complex estimation is required [Eqs. (10)–(12)].

At the end of  $t$ th green for the subject lane  $l$  there are  $m_{t,l}$  vehicles between Detectors 1 and 2 [ $m_{t,l}$  is estimated by Eq. (9)]. Detector 2 counts the new arrivals over time. The exact number of vehicles between stop line and Detector 2 is the sum of  $m_{t,l}$  and the new arrivals until the next green. Assuming that Detector 2 counts  $ma_{t,l}$  new arrivals until the  $(t+1)$  green serving this lane starts, the queued vehicles on lane  $l$  can be estimated by

$$N_{t,l} = m_{t,l} + ma_{t,l} \quad (8)$$

At this time, Detector 1 starts to count the departing vehicles and Detector 2 continues to count the new arrivals. When the  $(t+1)$  green ends, Detector 2 counts  $NA_{t+1,l}$  more arrivals during green and Detector 1 counts  $md_{t+1,l}$  departures during green. Thus, the number of vehicles between the two detectors on lane  $l$  is

$$m_{t+1,l} = m_{t,l} + ma_{t,l} + NA_{t+1,l} - md_{t+1,l} \quad (9)$$

As a result of this iterative calculation, the controller is aware of the number of vehicles that did not clear the last green and will consider those vehicles at the next phase selection and green estimation. This estimation does not apply to busy, exclusive RT lanes with RTOR.

When the  $L_{max}$  of Lane 2 is greater than  $L_{LT}$  of Lane 1, the estimation of the through queue on Lane 2 is more complicated because left turn vehicles also actuate Detector 2 on Lane 2. The estimation for through vehicles on Lane 2 can be conducted based on the real-time percentage of left turning vehicles that passed Detector 2 on Lane 2

$$N_{t,2} = m_{t,2} + ma_{t,2}(1 - P_{t,LT}) \quad (10)$$

where  $P_{t,LT}$  = percent of left turn vehicles of  $ma_{t,2}$  after  $t$ th green

$$P_{t,LT} = \frac{ma_{t,1}}{ma_{t,2}} \quad (11)$$

When the  $(t + 1)$ th green ends, the number of vehicles between the two detectors in Lane 2 can be calculated as

$$m_{t+1,2} = m_{t,2} + (ma_{t,2} + NA_{t+1,2})(1 - P_{t,LT}) - md_{t+1,2} \quad (12)$$

The timetable of commands sent from the TACOS controller to the detectors is as follows:

- The controller sends commands only at the beginning and the end of a phase;
- Detector 2 (located upstream) is initialized to 0 at the end of the current phase and it counts continuously until it is reinitialized; and
- Detector 1 (by the stop line) is initialized to 0 at the beginning of the phase and counts only during the current phase, that is  $G + Y + AR$ .

The ability to detect the presence of a standing vehicle is important. The detection of a standing vehicle at Detector 2 indicates that the queue has exceeded  $L_{max}$  and Detector 2 should continue counting when the standing vehicle begins to move.

One stop line and one upstream detector on each lane are the minimum requirement for TACOS. In reality, additional detectors are needed to detect the demands reliably, such as pedestrian buttons to detect pedestrian crossing demand and stop line detectors in tandem to detect vehicles that stop too far ahead of or behind the stop line. These detector configurations and features are available at several signalized intersections with actuated controllers.

The controller's knowledge of the number of vehicles that have discharged during green can also be used for incident detection. For example, if green is given but no vehicle or fewer vehicles than expected discharge, an incident or other operational failure may have occurred.

### NETSIM/INTEGRATION/Traffic Adaptive Control for Oversaturated Intersection Simulator

A new intersection simulation software, *NIT*, was developed and tested because existing simulation models cannot execute the TACOS strategy. The *NIT* emulates NETSIM and INTEGRATION and was designed to be able to simulate the intersection operation under pretimed, actuated, and TACOS control. The *NIT* is a microscopic, stochastic, interval-oriented traffic simulator. The *NIT*'s car-following model, lane-changing logic, simulation mechanism, and MOE estimators are presented below.

#### Car-Following Model

Microscopic car-following models generally classify a vehicle as independent or follower. The speed of the subject vehicle is a key

factor. The NETSIM calculates the vehicle's speed by estimating its acceleration, whereas INTEGRATION uses the speed-headway relationship. Important elements of these two methods that were adopted in *NIT* are presented below.

The NETSIM updates the vehicles sequentially in the simulation (Aycin and Benekohal 1999). First, the leader is moved and then the follower is placed at a position satisfying the design constraints of the model. That is, the model determines a vehicle's speed and position after updating its leader for the present time step. The vehicles in NETSIM are updated by the following equations of motion:

$$V_{i+1}^{t+\Delta t} = V_{i+1}^t + a_{i+1}^t \Delta t \quad (13)$$

$$X_{i+1}^{t+\Delta t} = X_{i+1}^t + V_{i+1}^t \cdot \Delta t + a_{i+1}^t (\Delta t)^2 / 2 \quad (14)$$

where  $V_{i+1}^{t+\Delta t}$  = speed of  $(i + 1)$ th vehicle at time  $t + \Delta t$ ;  $i$  =  $i$ th vehicle, which is the leader;  $i + 1 = (i + 1)$ th vehicle, which is the follower;  $t$  = beginning time;  $\Delta t$  = time interval;  $a_{i+1}^t$  = acceleration rate of  $(i + 1)$ th vehicle at time  $t$ ; and  $X_{i+1}^{t+\Delta t}$  = position of  $i$ th vehicle at time  $t + \Delta t$ .

The leader is first brought to its new position when the simulation time is advanced by one time step. The follower is then moved to a certain location such that if the leader vehicle decelerates to maximum deceleration limits, the follower will be able to stop without colliding with the leader.

The INTEGRATION involves the vehicle's acceleration only when simulating the queue discharging process. In all other cases, the vehicles are governed by the following equations of motion:

$$V_{i+1}^{t+\Delta t} = f(X_i^t - X_{i+1}^t) \quad (15)$$

$$X_{i+1}^{t+\Delta t} = X_{i+1}^t + V_{i+1}^t \Delta t \quad (16)$$

The follower's speed is a function of the distance headway between it and the leader. This function is based on a link-specific microscopic car-following relationship that is calibrated macroscopically to yield the appropriate target aggregate speed-flow attributes for that particular link (Van Aerde and Associates Ltd. 2000). The macroscopic calibration of the microscopic car-following relationship ensures that vehicles will traverse that particular link in a manner that is consistent with that link's capacity (CAP), free flow speed (FFS), speed at capacity (SAC), density at capacity (DAC), and jam density (JD).

*NIT* updates vehicle positions using NETSIM's equations of motion [Eqs. (13) and (14)] sequentially from follower to leader so that the follower's condition is determined by the simultaneous condition of the leader. When the leader's state of motion affects the follower's reaction, the following two cases are recognized.

#### Case 1

If the leader's speed is equal to or smaller than a speed threshold, e.g., the leader rests or is in a standing queue, and the follower's speed is greater than the speed threshold, the follower will apply a deceleration at the rate of

$$a_{i+1}^{t+\Delta t} = -(V_{i+1}^t)^2 / (X_i^t - X_{i+1}^t - L_{veh}) / 2 \quad (17)$$

where  $L_{veh}$  = length of vehicle.

This rate is constant when the follower approaches the leader unless the leader vehicle changes its state of motion, e.g., the leader is in a discharging queue. If the speeds of both the leader and follower are smaller than the speed threshold and the leader's speed is greater than the follower's, the follower will accelerate at the rate of maximum comfortable acceleration. This acceleration causes the follower to catch up with the leader when both are in a

discharging queue. The default of the threshold speed is 9 ft/s, which is the queue threshold speed of NETSIM.

### Case 2

If the leader's speed is larger than a speed threshold, the follower's acceleration is set to zero and the follower's speed is calculated based on the front-bumper to front-bumper distance of the two vehicles. Using zero acceleration is based on the fact that vehicles traveling in uncongested conditions do not change their acceleration significantly.

The speed of the follower is determined by a 2-order polynomial speed–distance headway relationship, which is calibrated by the link's FFS, SAC, DAC, CAP, and JD as follows:

$$V_{i+1}^{t+\Delta t} = A + B/(X_i^t - X_{i+1}^t) + C/(X_i^t - X_{i+1}^t)^2$$

$$A = \text{FFS} \quad (18)$$

$$B = \frac{(\text{SAC} - \text{FFS}) \times \text{JD}^2 + \text{FFS} \times \text{DAC}^2}{(\text{DAC} \times \text{JD}^2 - \text{JD} \times \text{DAC}^2)}$$

$$C = \frac{-\text{FFS} - B \times \text{JD}}{\text{JD}^2}$$

In summary, NIT calculates the acceleration of the vehicle only when specific conditions are satisfied. It can use different methods to determine the subject vehicle's speed based on its leader's state of motion. This treatment is a more realistic representation of the difference of driver behavior in congested and uncongested conditions.

### Lane Changing Logic

The NETSIM and INTEGRATION model both discretionary and mandatory lane-changing (Aycin and Benekohal 1999; Van Aerde and Associated Ltd. 2000). The motivation for discretionary lane changing is similar in both models, that is, to maximize the subject vehicle's speed. Discretionary lane changes in INTEGRATION are performed if speed increases when changing from the current lane to the target lane. Discretionary lane changes in NETSIM are performed to bypass a slow or heavy vehicle, to avoid a collision with the leader, to join a shorter queue at the intersection, or to vacate a blocked lane. Mandatory lane changing is attempted when the vehicle is in an unacceptable lane due to lane channelization, lane drop, lane closure, or in order to get onto an appropriate lane, i.e., for performing the intended turning movement downstream.

The NIT assumes that there are no discretionary lane changes. This assumption is reasonable for the intended use of NIT (at near and oversaturated conditions) because vehicles traveling on intersection approaches seldom make lane changes to achieve speed gains under congested conditions. This assumption may require relaxation when NIT is expanded to networks. The NIT allows lane changes only if a vehicle's direct downstream lane is unacceptable, e.g., the left-turning vehicle has to change to the exclusive left-turn lane because its direct downstream lane is for through movement only.

### NIT's Simulation Mechanism

An object-oriented approach (programmed in C++) was utilized in developing NIT. The program scans the traffic system and summarizes MOEs at each interval. Five types of classes were used: link, volume, signal, detector, and vehicle. The NIT implements three steps at each interval:

1. Updates the signal based on information from the controller if the simulation clock is at the beginning of a second;
2. Generates new vehicles at the beginning of each lane of origin node based on user-defined volume parameters; and
3. Updates existing vehicles in the network based on car-following and lane changing logic.

Measures of effectiveness (MOE) for each lane are necessary to evaluate the performance of different signal control strategies. Link-based, approach-based, and intersection-wide MOEs can be derived from lane-based MOEs by using weighted aggregation. The lane-based MOE estimators of NIT include a throughput estimator, a speed estimator, a delay estimator, and a queue estimator. Due to space limitations these estimators are not presented herein; they are detailed in Li (2002).

Several comparisons of performance among NIT, TSIS/NETSIM, and INTEGRATION were conducted to validate NIT. Test results generally showed that NIT was capable of producing MOEs that were close to those from TSIS/NETSIM and INTEGRATION. In fact, the differences between NETSIM and INTEGRATION were larger than the differences between NIT and either NETSIM or INTEGRATION. The tests of NIT are detailed in Li (2002).

### Evaluation of Traffic Adaptive Control for Oversaturated Intersections

Traffic Adaptive Control for Oversaturated Intersections was evaluated against pretimed and actuated control strategies using three increasingly elaborate intersection configurations and various demand patterns (Li 2002). Only the test results using the most complex intersection are included herein. The MOEs used in the evaluation were: (1) network throughput-to-demand ratio, (2) network speed, (3) network delay, (4) network queue time, (5) percent stops, and (6) total green time for each movement. The best control strategy is the one that provides a high throughput-to-demand ratio, high speed, low delay, queue time, and stops under all traffic flow conditions.

The purpose of the tests was to investigate the basic properties and abilities of TACOS. Two simplifications were applied: no right turn on red and no pedestrian demand. [TACOS and NIT readily accept pedestrian demand as was discussed under Eq. (2)]. Pretimed signal timings were optimized with *TRANSYT-7F* using "delay and stops" as the objective function. For the actuated control phases and phase timing, vehicle extension intervals of 2, 3, and 4 s were tried and the value that produced the best performance in terms of speed and delay was used to compare actuated control with TACOS control. The phase flags for the actuated signal timing were set as: vehicle recall=ON, double entry=ON, simultaneous gapout=ON, lag=ON, all the rest=OFF. In addition to presence detectors at the stop line, all lanes have passage detectors 15 m upstream of the stop line. These detectors place calls when the phase is active. For TACOS, the value of  $WT_{\max}$  was set to 120 s. The TACOS detectors were placed at the stop line, at a location 65 m upstream of the stop line for the through lanes, and at the upstream end of the left turn bay on each of the left turn lanes. Multiple traffic demand conditions were examined as follows:

#### Test 1: Low, Moderate, and High Demand (with Randomness)

Five 30 min volumes, 20, 40, 60, 80, and 100% of the highest volume were used, resulting in five separate simulations for each

**Table 1.** Results of Tests 1, 2 and 3

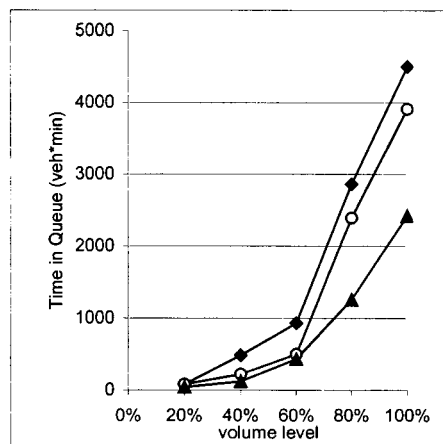
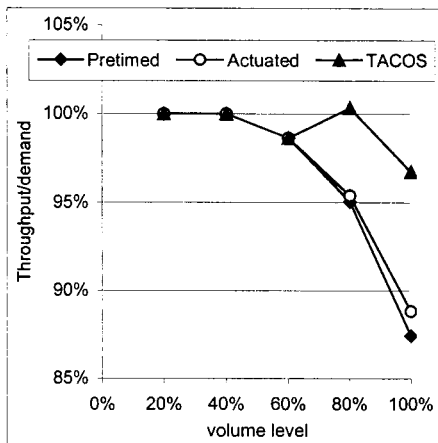
MOE	Controls	Test 1	Test 2	Test 3
Throughput-to-Demand Ratio	Pretimed	100%	100%	95%
	Actuated	100%	100%	97%
	TACOS	100%	100%	99%
	TACOS vs. Pretimed	0%	0%	4%
	TACOS vs. Actuated	0%	0%	1%
Speed (km/h)	Pretimed	20.7	18.4	14.9
	Actuated	28.1	24.5	19.3
	TACOS	30.3	26.5	24.3
	TACOS vs. Pretimed	46%	44%	63%
	TACOS vs. Actuated	8%	8%	26%
Delay (sec/veh)	Pretimed	49.3	53.6	73.6
	Actuated	23.2	31.4	49.0
	TACOS	19.0	26.5	29.1
	TACOS vs. Pretimed	-61%	-51%	-60%
	TACOS vs. Actuated	-18%	-16%	-41%
Time in Queue (veh * min)	Pretimed	932	1170	1561
	Actuated	501	697	1063
	TACOS	435	568	592
	TACOS vs. Pretimed	-53%	-51%	-62%
	TACOS vs. Actuated	-13%	-19%	-44%
Percent stops	Pretimed	76%	81%	83%
	Actuated	76%	80%	80%
	TACOS	69%	73%	72%
	TACOS vs. Pretimed	-9%	-10%	-13%
	TACOS vs. Actuated	-9%	-9%	-10%
Green on EB-LT (sec)	Pretimed	598	598	598
	Actuated	405	395	427
	TACOS	357	396	387
	TACOS vs. Pretimed	-40%	-34%	-35%
	TACOS vs. Actuated	-12%	0%	-9%
Green on EB-TH,RT (sec)	Pretimed	606	606	606
	Actuated	582	597	620
	TACOS	651	668	589
	TACOS vs. Pretimed	7%	10%	-3%
	TACOS vs. Actuated	12%	12%	-5%

Note:

Test 1 = uniform arrivals and volume at 60% level.

Test 2 = platooned arrivals for EB and WB TH movement; arrival cycle = 2 min.

Test 3 = EB arrivals with upstream incident.



of the three control strategies tested. The TACOS' sensitivity to  $G_{\min}$ ,  $G_{\max}$ , and  $WT_{\max}$  was examined as part of this test using the 80% level of volume. The 75 and 125% values of the base settings for  $G_{\min}$  and  $G_{\max}$ , as well as three values for  $WT_{\max}$  equal to 120, 150, and 180 s were tested.

### Test 2: Cyclical, Platooned Arrivals

This scenario was based on the 60% level of volume. The eastbound and westbound through flows arrived in platoons of 2 min cycles.

### Test 3: Flow Anomalies

This scenario was based on the 60% level of volume. The eastbound traffic flow included an upstream incident.

The results of Tests 1, 2 and 3 are summarized in Table 1. The comparison with Test 1 shows that cyclical arrivals and flow anomalies significantly worsen performance in terms of all MOEs examined. The TACOS produced significant improvements over the pretimed and actuated control strategies for throughput, speed, delay, queue time, and stops. The last two blocks in Table 1 show the total green time for eastbound left turn movement and through movement, respectively. The total green time shown indicates that TACOS made larger changes to the green time of these movements which, in turn, indicates that TACOS was more responsive to traffic demand. Further inspection of the throughput-to-demand

ratio and time in queue for Test 1 (graphs in Table 1) show that TACOS produced consistently significant improvements over pretimed control under all flow conditions. The TACOS produced significant improvement over actuated control under all flow conditions in terms of all MOEs except for percent stops under 100% level of volume, where TACOS produced a result that is comparable with the actuated control result. This is an expected outcome because actuated control, which responds to individual arrivals, tends to produce fewer stops.

The TACOS' phase sequence optimization is presented in Table 2. Phasing did not follow a fixed sequence. Tests 2 and 3 produced more phases than Test 1 because TACOS was able to respond to their special demand patterns. Table 2 includes a graphical illustration of the first ten phases for Test 2.

Sensitivity analysis revealed that TACOS is not particularly sensitive to  $G_{\min}$  and  $WT_{\max}$  but it is quite sensitive to  $G_{\max}$ . Smaller  $G_{\max}$  produced higher speed, lower delay, and time in queue. This is because the decision-making process of TACOS occurs at the end of each green and the shorter maximum green time caused it to react to real-time traffic conditions more promptly.

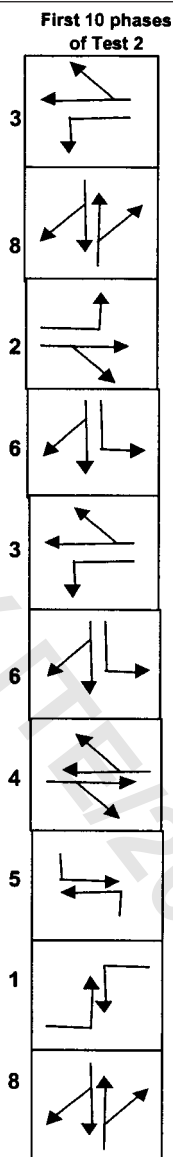
### Conclusion

This paper presented the basic theory and part of the evaluation of a new adaptive control strategy. The TACOS is a hybrid optimi-

**Table 2.** TACOS Phase Sequence in Tests 1, 2 and 3

Phase sequence	Test 1	Test 2	Test 3
1	1	3	8
2	8	8	3
3	6	2	8
4	4	6	6
5	5	3	2
6	1	6	8
7	8	4	6
8	4	5	3
9	8	1	8
10	5	8	2
11	3	4	5
12	2	8	8
13	8	1	3
14	4	6	8
15	5	4	6
16	1	5	8
17	8	8	2
18	4	3	3
19	8	1	5
20	5	8	8
21	3	2	6
22	2	6	6
23	8	3	3
24	6	2	2
25	3	5	8
26	2	8	8
27	5	4	2
28	8	8	3
29	4	1	5
30	1	6	2
31	6	4	6
32	4	5	4
33	8	8	7
34	1	2	1
35	4	3	2
36	5	8	8
37	8	5	4
38	6	8	1
39	3	4	5
40	2	1	8
41	8	8	4
42	2	6	8
43	8	4	1
44	3	5	5
45	6	1	4
46	2	8	8
47	5	4	6
48		8	1
49			2
50			8

Phases recorded after 300 sec. initial simulation period.



zation and rule-based adaptive control strategy that addresses, at least in part, weaknesses of existing adaptive control strategies by having the following attributes:

1. The information used for decision-making processing is more reliable because it is not dependent on a forecasting model;
2. Intersection utilization is used explicitly in the objective function;
3. Phase sequencing is optimized; and
4. Detection of operational anomalies and ability to respond to anomalies have been incorporated.

In the course of developing TACOS, an approach for the estimation of queue length on each lane of intersection approaches was devised. The estimation is made by using measurements from advanced detectors that provide simultaneous presence and count data.

A new intersection simulator, NIT, was developed in order to evaluate TACOS. The NIT's car-following model, lane-changing logic, simulation mechanism, and method of estimating MOEs were a combination of methods employed in TSIS/NETSIM and INTEGRATION.

The TACOS was compared with pretimed and actuated control strategies under three flow scenarios using NIT. The flow scenarios consisted of light to heavy flow, cyclical arrivals, and arrivals with an upstream incident. A comprehensive list of MOEs including throughput-to-demand ratio, speed, delay, queue time, percent stops, and total green time per movement was examined. The TACOS showed significant improvements over pretimed and actuated control strategies for all MOEs under all flow scenarios. In all cases, TACOS produced the best performance using the same parameter settings. However, demanding parameter specifications which are required in other adaptive control strategies are unnecessary in TACOS. Overall, the simulation results indicated that TACOS is a promising improvement for adaptive traffic signal control.

Additional simulation tests on intersections with different levels of complexity of geometry, phasing, and demand (including pedestrians, emergency vehicle preemption, etc.) are planned. Laboratory comparisons with other adaptive control strategies and expansion of TACOS for network applications merit additional effort. Field tests using the ATC 2070 controller would provide the ultimate ground for evaluation and fine tuning of the signal control strategy. Network expansion of TACOS is a longer term endeavor because of the combined complexities of signal coordination and the extensive changes to NIT in order to handle network modeling.

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