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**ON-LINE PERFORMANCE MEASUREMENT MODELS FOR URBAN  
ARTERIAL NETWORKS**

**Theodore Tsekeris**

*National Technical University of Athens  
Department of Transportation Engineering  
Athens, Greece  
E-mail: [fabtse@central.ntua.gr](mailto:fabtse@central.ntua.gr)*

**Alexander Skabardonis\***

*Institute of Transportation Studies  
University of California, Berkeley  
109 McLaughlin Hall, Berkeley, CA 94720-1720  
Phone: (510) 642-9166, Fax: (510) 642-1246  
E-mail: [skabardonis@ce.berkeley.edu](mailto:skabardonis@ce.berkeley.edu)*

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*\*Corresponding Author*

**ABSTRACT**

This paper addresses the problem of real-time estimation of urban arterial network performance. A number of analytical time-dependent models have been formulated and implemented for the on-line estimation of arterial link and system travel times. The proposed models provide alternative ways of incorporating the contribution of various network and operational characteristics to the travel time. The model inputs are volume and occupancy data from loop detectors, and signal control parameters. The models were tested on several real-life networks representing a wide range of configurations, demand patterns and control features. The results indicate that simple models appear promising in accurate measurement of link travel times. More complex models accounting for the randomness of delays at intersections improve the network-wide travel time estimates at the expense of data requirements and computational efficiency.

**KEYWORDS:**

Arterials, travel times, performance measurement, delays

## 1. INTRODUCTION

Transportation performance measures constitute an invaluable source of information for decisions related to infrastructure resource allocation, investment plan monitoring and project evaluation. The advent of Intelligent Transportation Systems (ITS) has even more increased the significance of obtaining timely and accurate transportation performance measures, which can be used for either optimizing traffic management strategies or informing travelers with respect to their optimal travel paths. Despite recent developments on the real-time measurement of freeway performance measures using routinely available loop detector data (1), no similar approaches exist for the performance measurement of urban arterial street networks. Existing methods typically encompass the calculation of traditional traffic engineering measures, including arterial link travel times or speeds, and Level of Service (LOS) based on historical data (2, 3). No current methodology exists that utilizes surveillance data to derive on-line performance measures.

Amongst various existing performance measures, as described in section 2, the average travel speed tends to be the most widely used. The average speed is usually decomposed into two components. First, the *running speed*, required to traverse an arterial link (link distance / free-flow speed), primarily affected by the relationship between traffic demand and capacity, the arterial design characteristics and the signal density. The second component refers to the *delay* experienced by vehicles at the downstream end of the link. The latter component has drawn particular attention during the last years, since it has been recognized that signal timing characteristics (green times, cycle length) and the quality of progression affecting the queuing delay are just as important as roadway characteristics in evaluating arterial performance (4). The application of Highway Capacity Manual (HCM) procedure as well as other approaches (5) has proven to provide inconsistent results under congested network conditions. On the other hand, several enhanced methods proposed in the literature, particularly emphasizing on interpreting and quantifying different delay characteristics (6), do not appropriately account for the needs of an on-line performance measurement system. These needs are related to reducing complexity, simplifying data requirements and increasing computational efficiency.

Existing performance measurements in real-time are typically restricted to the estimation of local intersection-based measures for signal timing parameter tuning or qualitative measures of performance (level of congestion) to provide collective traffic information, e.g., through changeable message sign (CMS) displays (7). However, this qualitative information cannot provide to drivers an accurate representation of the changes in actual traffic conditions, including dynamic speed and journey time variations along an urban arterial route.

The purpose of this paper is to propose and evaluate an on-line performance measurement system for realistic-size urban arterial street networks. The research is part of an ongoing large-scale project to develop an on-line performance measurement system for signalized arterials and networks (Arterial Performance Measurement System—*APeMS*) conducted by the University of California, Berkeley in cooperation with the Los Angeles Department of Transportation (LADOT). Section 2 of the paper discusses existing measures and methods for calculating arterial performance. In section 3, different methodological approaches for estimating the performance of arterial networks are formulated, and a new approach for consistent estimation of on-line arterial network performance is suggested. Section 4 provides the data and description of

the real-life arterial networks used in the testing of the alternative performance measurement procedures. Section 5 presents the results from the testing of the alternative methods. Section 6 summarizes the study findings, together with future possible research directions.

## **2. ESTIMATING ARTERIAL PERFORMANCE: MEASURES AND METHODS**

### **2.1 Measures of arterial performance**

This paper focuses on mobility-related performance measures, albeit other measures could also be well defined for the case of arterial networks so as to encompass wider economic, environmental and other concerns (8). The first major category of arterial network performance measures is the one related to the traditional LOS measures. These typically include the running time across a specific link section, some sort of delay time at the downstream intersection and the corresponding number of stops due to signals. More general, the average arterial link travel time has been widely used to incorporate the effects of both congestion at the running segment and progression at the downstream intersection. Other arterial network performance measures can include the estimation of queues at the intersections, the estimation of congestion (volume output / input) indexes during the peak period and travel time reliability (also referred to as variability and uncertainty) measures (9, 10).

### **2.2 Arterial performance measurement models**

Several alternative approaches for estimating urban arterial performance have been developed. These can be distinguished according to the definition of the arterial performance measure, as described above. In addition, these approaches can be referred to either *section-level* performance measures or *network-level* performance measures. The former case typically refers to the average travel time required by drivers to traverse a specific section, i.e. a particular (observed) segment of a road (arterial link), during a certain period of time. On the contrary, the latter case is associated with the estimation of the average total travel time that a driver departing from a specific origin experiences in order to reach the final (desired) destination. The network-level performance estimation usually involves some analytical or simulation-based procedure. Such procedures include analytical traffic flow models, mainly used for prediction purposes (11), statistical models, based on, e.g., state-space and Kalman filtering formulations (12), and neural networks (13). Furthermore, dynamic traffic assignment (DTA) models have been proposed that enable the representation of interactions between traffic demand and supply characteristics, and the impact of control interventions or incidents on network performance. Despite the behavioral underpinning of these models to support on-line dynamic traffic management systems, the extensive computational load involved for real-time applications and the extensive data requirements concerning users' behavior (14) render them irrelevant for the purpose of this paper.

The various section-based arterial performance measurement models presented below require as major input detector data, i.e. typical volume / occupancy measurements, without involving the need for use of advanced surveillance systems, such as probe vehicles or remote sensing technologies. One of the simplest methods includes the estimation of *space-mean* travel speed, based on the definition of the average length of vehicles and loop detectors. Other similar

approaches refer to the use of double loop detectors (speed traps) or some g-factor estimation method, similar to those employed for freeway travel time estimation (15). Another common method refers to the regression models, which may correspond to different categories, such as linear (3), non-linear (5) and Bayesian (16) models. Other methods found in the literature in this topic include dynamic input-output models (17), sandglass link travel time models (18), pattern-matching and vehicle signature analysis techniques (19, 20). Finally, the Bureau of Public Roads (BPR) travel time estimation technique (21) has been broadly used to calibrate various types of traffic models, although its results usually correspond to long-term averages rather than real-time expected values.

### 2.3 Criteria of model selection

A range of different factors should be considered for the selection of appropriate performance measurement models in urban arterial street networks. In the present context, the models will be implemented in a real-time dynamic traffic environment. This implies the need of considering the dynamic changes or adjustments of travel speed along different sections of a typical arterial link. Due importance should also be given to represent these changes in a way that is consistent with the principles underlying the traffic flow and queuing theory. Moreover, any proposed function should be compatible with the guidelines underlying the design and operation of the arterials, such as those of HCM according to the U.S. standards. The models should represent and interpret the complexity of the observed processes. However, they should also address the problem of minimum data requirements, ease-of-use and on-line computational burden for real-time operations. For the given problem, the time required for collecting and processing the data for a set of links should be smaller than the average arterial travel time along the route composed of these links.

Furthermore, any suitable model should provide robust results in cases of arterial networks with low detector sampling rates or different types of roadway designs. Such types of design can include short congested links, long semi-saturated links or a combination of them, and different network configurations, such as dense versus sparse networks, or radial versus grid networks. Another related issue concerns the procedures required for the model calibration. An on-line performance measurement model should normally require the least effort of re-calibration in regard to different sites and time periods. The existing regression models are typically site-dependent and require extensive re-calibration to be used for different locations or time periods. A last critical issue regards to the possibility of incorporating information relying on the engineering judgement and the knowledge of local network traffic conditions. In the next section, a model attempting to incorporate most of the above features is proposed, amongst other ones. The models investigated in this paper correspond to section-based measures, albeit they could also be well incorporated in DTA models to provide more efficient network-level travel time estimators.

## 3. PROPOSED ARTERIAL PERFORMANCE MEASUREMENT METHODS

This section presents a number of different analytical approaches for addressing the problem of real-time travel speed and time estimation in urban arterial networks. All methods are based on the use of section-based traffic information from inductive loop detectors. However, they employ

diverse assumptions concerning the constituent elements affecting the average time required for traversing a specific arterial segment. Such elements can refer to topological and / or operational characteristics of the arterial network, including the level of congestion, signal density and progression, as well as different types of delay experienced by travelers at the signalized intersections.

### 3.1 The spot speed model (SSM)

The first suggested solution approach is the so-called *spot speed* analytical model (SSM). This model, which is derived from the relationship between traffic flow  $q$  and occupancy  $o$ , calculates the speed at a specific section  $s$  of the link  $m$  during time interval  $\tau$  (of, e.g.,  $l_\tau = 15$  minutes length), in which the whole study period  $T = \{1, 2, \dots, \tau, \dots\}$  has been disaggregated. Then, the spot speed measure (in miles per hour or mph) is calculated as follows, in a time-dependent form:

$$u_m^{s,\tau} = \frac{\ell_E q_m^{s,\tau}}{1613 o_m^{s,\tau} N_m^s}, \quad \forall s \in m, \tau \in T \quad (1)$$

where  $\ell_E$  is the *average effective vehicle length*,  $N_m^s$  is the number of lanes at the section  $s$  of link  $m$  where the inductive loop detector has been installed, while  $q_m^{s,\tau}$  and  $o_m^{s,\tau}$  are the measured flow and occupancy values at this section. It is noted that the measures of  $q_m^{s,\tau}$  and  $o_m^{s,\tau}$  correspond to the cumulative value of flow and the average value of occupancy respectively over the whole length of time interval  $\tau$ . The  $\ell_E$  value is obtained from the following sum:

$$\ell_E = \ell_v + \ell_d \quad (2)$$

with  $\ell_v$  being the average length of vehicles and  $\ell_d$  the average length of loop detectors. In this paper, these average values were assigned as  $\ell_v = 4.27$  m (14 ft) and  $\ell_d = 1.83$  m (6 ft), that gives  $\ell_E = 6.1$  m (20 ft). It can be assumed that the spot speed estimate  $u_m^s$  provides a sufficient approximation of the average speed  $u_m$  across each link  $m$  of the arterial route  $R = \{1, 2, \dots, m, \dots\}$ . Also, route  $R$  is composed of  $n_m$  links, each of which is equipped with a total number of  $N_m^s$  single loop detectors, one on each lane approaching the downstream intersection. Then, the average arterial travel speed  $\bar{u}_R^\tau$  can be expressed as follows:

$$\bar{u}_R^\tau = \frac{\sum_{m=1}^M u_m^{s,\tau}}{n_m}, \quad \forall m \in R, \tau \in T \quad (3)$$

In turn, the average arterial route travel time  $\bar{t}_R^\tau$  is given as (in minutes):

$$\bar{t}_R^\tau = 0.06 \frac{L_R}{\bar{u}_R^\tau} \quad (4)$$

### 3.2 The BPR-based models

The second solution approach refers to the volume / capacity ratio-based method, having its origins at the well-known BPR-based model (21). The *standard BPR model* (SBPR) provides the average travel speed  $\bar{u}_R^\tau$  for an arterial route  $R$  as follows, in its time-dependent form:

$$\bar{u}_R^\tau = \frac{u_{mb}}{[1 + \alpha (q_c^\tau / c_c^\tau)^b]} \quad (5)$$

where parameters  $\alpha = 0.15$  and  $b = 4.0$ , while  $q_c^\tau$  and  $c_c^\tau$  correspond to the counted flow and the estimated capacity of the critical (link) segment of the arterial route (an explanation of the meaning of the critical segment is given below). The measure  $u_{mb}$  denotes the mid-block free-flow speed and can be obtained as follows (in mph):

$$u_{mb} = 0.79 u_L + 12 \quad (6)$$

where  $u_L$  is the speed limit (mph). In addition, Skabardonis and Dowling (22) proposed a new specification for the above model, based on an updated speed-flow relationship for signalized arterial facilities. According to this new model, known as *updated BPR model* (UBPR), the average travel speed  $\bar{u}_R^\tau$  can be expressed as follows:

$$\bar{u}_R^\tau = \frac{u_0^{\tau*}}{[1 + \alpha (q_c^\tau / c_c^\tau)^b]}, \quad (7)$$

where  $\alpha = 0.05$  and  $b = 10.0$ . The  $u_0^{\tau*}$  expresses the *adjusted free-flow travel speed*, which is calculated as follows:

$$u_0^{\tau*} = \frac{L_R}{L_R / u_{mb} + N_S (D^\tau / 3600)} \quad (8)$$

where  $N_S$  is the number of signalized intersections along the length  $L_R$  of the route. The measure  $D^\tau$  denotes the average time delay per signal of the route  $R$  and it is given on the basis of the signal delay equation of the HCM 1994 (4), as described in (22), by the following relationship:

$$D^\tau = 0.5 D_F^\tau C^\tau (1 - g^\tau / C^\tau)^2 \quad (9)$$

where  $g^\tau$  is the signal-specific effective green time (in seconds), given as  $g^\tau = 0.45 C^\tau$  (default) and  $C^\tau$  is the cycle length (in seconds). The default value of cycle length is here defined as  $C^\tau = 120$  seconds for all studied arterials and time intervals  $\tau$ . Based on the HCM 1994 (4), the parameter  $D_F^\tau$  is defined as follows:

$$D_F^\tau = \frac{1 - P^\tau}{(1 - g^\tau / C^\tau)} \quad (10)$$

The value of  $D_F^\tau = 0.90$  is used as default for all intervals here, based on the fact that all intersections of the studied route segments are coordinated signal-controlled with favorable progression. The *critical segment* of the given route is defined as the link segment with the maximum ratio between through volume and number of lanes. For the specified critical segment of each route, the *critical segment capacity*  $c_c^\tau$ , namely the capacity corresponding to this particular segment, is calculated (in vehicles per hour) for all time intervals of the study period as follows:

$$c_c^\tau = q_s N f_w f_{HV} f_{peak} f_{park} f_{bay} f_{CBD} \frac{g^\tau}{C^\tau} \quad (11)$$

The parameters of relationship (11) can be defined as follows (the values in the parentheses represent default values):

$f_w$	:	lane width factor (1.00)
$f_{HV}$	:	Heavy vehicle adjustment factor (0.98)
$f_{peak}$	:	Peak hour factor (0.90)
$f_{park}$	:	On-street parking adjustment factor (1.00)
$f_{bay}$	:	Exclusive left-turn bay or lanes adjustment factor (1.10)
$f_{CBD}$	:	Central Business District (CBD) adjustment factor (1.00)

The  $q_s$  measure corresponds to the ideal saturation flow rate, defined here as 1900 vehicles per lane per hour of green, while  $N$  denotes the number of through lanes at the critical section.

### 3.3 The uniform delay-based model (UDM)

The third approach is based on the estimation of the *uniform* (or regular) delay. The uniform delay-based model (UDM) assumes that vehicles arrive at the downstream intersection at some average arrival flow rate and can enter the intersection at the saturation flow rate when the light is green. The average arterial travel time  $\bar{t}_R^\tau$  can be expressed here as follows (in minutes):

$$\bar{t}_R^\tau = t_R^0 + d_u^\tau \quad (12)$$

where

$$t_R^0 = 60 \frac{L_R}{u_{mb}}, \quad (13)$$

$$d_u^\tau = \frac{0.5 C^\tau [1 - (g^\tau / C^\tau)]^2}{60 [1 - (g^\tau / C^\tau) \min(X, 1)]} D_F^\tau \quad (14)$$

and

$$X = (q_c^\tau / q_s N) / (g^\tau / C^\tau) \quad (15)$$

The  $t_R^0$  term expresses the *free-flow travel time*, while the term  $d_u$  expresses the *average uniform delay* during the average cycle length along interval  $\tau$ , as adjusted to include the signal progression effect.

### 3.4 The overflow delay-based model (ODM)

The *overflow delay-based model* (ODM) incorporates both the concepts of adjusted free-flow speed  $u_0^{\tau*}$ , as it is given in relationship (8), and critical segment capacity  $c_c^\tau$ , estimated in relationship (11). Assuming a time interval of 15-minutes length, the analytical relationship that provides the inverse of the average arterial travel speed  $\bar{u}_R^\tau$  (in hours per mile) can be described as follows, in its time-dependent form:

$$\frac{1}{\bar{u}_R^\tau} = \frac{1}{u_0^{\tau*}} + \left\{ 0.25 l_\tau \left[ (X-1) + \sqrt{(X-1)^2 + \frac{8J_D^\tau X}{c_c^\tau l_\tau}} \right] \right\} \quad (16)$$

where  $J_D$  is a delay parameter that is given as follows:

$$J_D^\tau = \frac{2c_c^\tau}{l_\tau} \left( \frac{1}{u_c} - \frac{1}{u_0^{\tau*}} \right)^2 \quad (17)$$

The measure  $u_c$  denotes the speed (mph) at capacity. The time interval length  $l_\tau$  in relationship (16) is expressed in hours. The first component in (16), i.e. the inverse of the adjusted free-flow speed, accounts for the effects of signal density, arterial link characteristics and congestion on the mid-block running speed. The components included in the bracket are principally related to the delay at the signalized intersection. The first component in the bracket accounts for the effect of capacity changes due to the signal-induced delay and oversaturated conditions in the area close to the downstream signalized intersection.

The second component in the bracket accounts for the effects of random delay variations at the end of the intersection queue. This type of varying delay is usually referred to as *overflow queuing delay* and it refers to both short-term (due to random variations in arrivals) and long-term (due to oversaturated conditions at upstream signalized intersections) variations in queuing delays. This last component was first proposed by Akcelik (23), as a modification of the

Davidson's (24) travel time function. The single parameter that should be fitted in the ODM is the delay parameter  $J_D$ . The capacity speed  $u_c$  and, hence, parameter  $J_D$ , can be estimated using the signal delay equation of the HCM as follows:

$$u_c^\tau = \frac{L_R}{3600 \frac{L_R}{u_{mb}} + 1/2 D_F^\tau C^\tau \left(1 - \frac{g^\tau}{C^\tau}\right) + 900 l_\tau \sqrt{\frac{4 f_{cs}}{l_\tau c_c^\tau}}} \quad (18)$$

where  $f_{cs}$  is a calibration term that is equal to  $f_{cs} = 12$  for coordinated signalized arterials.

### 3.5 The generalized delay-based model (GDM)

The generalized delay-based model (GDM) estimates the average arterial travel time and speed using both concepts of uniform and random intersection delays. According to it, the average arterial travel time  $\bar{u}_R^\tau$  can be expressed here as follows (in minutes):

$$\bar{t}_R^\tau = t_R^0 + d_u^\tau + d_o^\tau \quad (19)$$

where

$$d_o = 15 l_\tau \left\{ (X - 1) + \sqrt{(X - 1)^2 + \frac{8 \kappa I X}{c_c^\tau l_\tau}} \right\} \quad (20)$$

The  $\kappa$  factor incorporates the effect of the signal controller on delay. For pretimed signals, as those of the tested arterial networks, a value of  $\kappa = 0.5$  is used. The term  $I$  denotes the upstream filtering or metering adjustment factor. The  $I$  value reflects the way that upstream signals decrease the variance in the number of arrivals per cycle at the downstream intersection. Based on the corresponding HCM 2000 (25) look-up table (Chapter 15), the  $I$  value is obtained for specific ranges of the degree of saturation  $X$  for the through movement at the upstream intersection. The first two components of the GDM are the same to those used in the uniform delay-based model in equation (12). The third component  $d_o$  expresses the incremental delay due to random and overflow queues, similar to the model proposed by Akcelik (23) and described in equation (16).

## 4. ARTERIAL NETWORK DATA

The proposed models were implemented using real-life field detector data for the morning peak period of five different arterial networks. These include the Lincoln Boulevard (*LIN*) at Marina Del Rey in Los Angeles, the Fairfield Parkway (*FAIR*) in Fairfield, CA, the M street (*MST*) in Washington, D.C., the Ygnacio Valley (*YGN*) in Walnut Creek, CA and the Silk Lake network (*SIL*) in Los Angeles. Table 1 provides the detailed characteristics of each arterial network. These characteristics refer to the configuration type (linear or grid), the number of links  $n_m$  and signalized intersections  $N_s$ , and the type of flow information, regarding to the measurement of

only through or mixed (through and turning movement) flow. Other information includes the signal density  $D_s$ , the maximum speed limit  $u_L$  and the ‘true’ network-wide (for all routes  $R$ ) average travel speed  $\bar{u}^*$  and time  $\bar{t}^*$ , as computed by CORSIM model (see Section 5). The signal density  $D_s$  is given as:

$$D_s = \frac{1}{n_R} \left( \frac{L_R}{N_s} \right), \quad (21)$$

where  $n_R$  refers to the total number of arterial network routes. In the case of grid arterial network,  $D_s$  is considered as the ratio between the number of intersections  $N_s$  and the total length of arterial network links. In order to allow a more detailed analysis of the performance of the SBPR, UBPR, UDM, ODM and GDM, each arterial link  $m$  has been here considered as a single individual route  $R$ , that is  $n_m = n_R$ . In other words, each individual link  $m$  of the arterial network is considered to be a critical segment. By definition, the travel speed and time measurements carried out by the SSM are also applied at the level of each individual link  $m$  (see 3.1).

Particular attention has been given on evaluating the performance of the proposed models based on the individual characteristics of each network as well as the availability of traffic signal timing information. The green times and cycle length at each signal are typically provided in real-time by the Transportation Management Center (TMC). However, the on-line availability and accuracy of this information cannot be always ensured in practice for various reasons. Such reasons include the hardware requirements and the computational burden imposed for collecting and processing the timing information in real-time, particularly under the implementation of complex adaptive traffic control strategies in extended arterial networks. All tested networks are operating under a fixed coordinated traffic control regime.

## 5. COMPUTATIONAL EXPERIENCE

### 5.1 Set up of experiments

In this paper, the CORSIM microscopic traffic simulation model was used to provide the ground-truth arterial link travel speeds and times. The measure of the overall quality of the calibration procedure that was used here is the *GEH* statistics of the UK Highways Agency (26) and is calculated as follows:

$$GEH = \sqrt{\frac{(q_m^\tau - \hat{q}_m^\tau)^2}{(q_m^\tau + \hat{q}_m^\tau)/2}} \quad (22)$$

where  $q_m^\tau$  and  $\hat{q}_m^\tau$  refer to the measured and estimated (by CORSIM) link volumes at a specific section of link  $m$  during interval  $\tau$ . If the GEH values are less than 5 for more than 85% of the measurement locations, then the simulation output can be considered as providing a sufficient representation of the actual traffic conditions in the arterial network. After calculating in an

iterative way the traffic demand and turning movements for each intersection of the tested arterial network sites and imputing any missing detector data, the CORSIM simulation results showed a satisfactory convergence between the observed and simulated traffic counts at the selected measurement locations.

Due to reasons mentioned above, the availability of signal timing information was also considered for each test network. The model predictions were first obtained using the actual values of effective green times and cycle length. In addition, the sensitivity of each model was investigated under the hypothesis of unknown signal timings. In the latter case, a constant effective green time split ratio equal to the HCM default value of  $g/C = 0.45$  was assumed for each interval  $\tau$ . Given that the detector data is available for time intervals of  $l_\tau = 15$  minutes, the number of intervals  $\tau$  considered for each case was set equal to four, except of the *LIN* case, where a total study period of 2 hours was considered, i.e. eight 15-minutes intervals.

## 5.2 Presentation and analysis of the results

The comparison of the relative performance of the various algorithms is carried out on the basis of the output average travel speeds and times of the CORSIM micro-simulation model. As mentioned above, the outputs were obtained after an iterative process so as to ensure that the criterion described in (22) is satisfied for each test network. First, the network-wide relative average error (*RAE*) of each model output was calculated for each arterial site. The *RAE* measure is calculated as follows:

$$RAE = \frac{\bar{t} - \bar{t}^*}{\bar{t}^*} \quad (23)$$

where  $\bar{t}$  corresponds to the network-wide average arterial travel time as estimated by each model. Table 2 provides the *RAE* values of each model, using actual signal timing information. The performance of the proposed models is found to vary according to the characteristics of each arterial test network. The GDM appears to provide the best travel time estimates, in terms of the *RAE*, for the case of urban networks, i.e. the *LIN*, *MST* and *SIL*. The ODM (particularly for the *FAIR* network) and the UDM models demonstrate the best performance for the case of suburban arterial networks, with speed limit  $u_L \geq 40$  mph and average arterial travel speed  $\bar{u}^* \geq 20$  mph.

The SSM demonstrates the largest variations in the *RAE* amongst the different test sites. These results can be probably attributed to the fact that signal control parameters have no effect on the model output. Both SBPR and UBPR models appear to underestimate network travel times, albeit the latter model provides significantly lower *RAE* values, in comparison to the former one. This improvement can be attributed to the updated speed-flow relationship accounted by the UBPR model and the congestion effect incorporated in the adjusted free-flow speed  $u_0^{\tau*}$ . The UDM also systematically tends to underestimate travel times, but it provides considerably lower *RAE* values in comparison to the UBPR and, particularly, the SBPR model.

Table 2 also shows the statistical performance of the average arterial travel time estimates by model and test site. The statistical analysis examines the difference of the mean values of arterial travel times produced by CORSIM and each model using two-sided  $t$ -test statistic (27). The percentages below the  $RAE$  values in Table 2 indicate the confidence level to which the models' results are significantly different from the corresponding CORSIM results. The GDM produces travel times with the least significant differences (at the lowest confidence levels < 80.0%) from the CORSIM travel times, in comparison to the other models for all test sites. Similar is the behavior of the ODM, except of the case of the grid network  $SIL$  (with confidence level 95.0%). On the other hand, the performance of the SSM is considerably reduced, resulting statistically significant differences even at the highest levels of confidence, for the case of urban linear networks ( $LIN$  and  $MST$ ). The UBPR model and, particularly, the SBPR model are associated with the largest statistically significant differences between the model and the CORSIM results.

Furthermore, the variations in the estimated arterial travel times are investigated at the level of each individual link for each test site. For this purpose, the link-based mean absolute relative error  $(MARE)_m$  is also calculated to demonstrate the ability of each model to capture errors in the estimated delays at intersection level. The  $(MARE)_m$  is given as follows:

$$(MARE)_m = \frac{1}{n_m^+} \left( \sum_{m=1}^M \frac{|t_m^\tau - t_m^{\tau*}|}{t_m^{\tau*}} \right), \quad \forall \tau \in T \quad (24)$$

where  $t_m^\tau$  and  $t_m^{\tau*}$  correspond to the estimated and 'true' travel time along link  $m$ , while  $n_m^+$  refers to the number of links traversed by positive flows, i.e.  $q_m^\tau \neq 0$ . Figure 1 illustrates the relative performance of each model, in terms of the link-based  $(MARE)_m$ . The largest variations in  $(MARE)_m$ , with respect to the various models and sites, are observed in the  $LIN$  network, but these variations are considerably smaller in comparison to those observed in  $RAE$  values. The GDM produces the smallest  $(MARE)_m$  values for the grid-type network  $SIL$ . The UDM provides the best estimates for the linear networks with the highest speeds, i.e.  $LIN$  and  $FAIR$ . On the other hand, the UBPR model provides the best estimates for the linear networks with the lowest average travel times  $\bar{t}^*$ , i.e.  $MST$  and  $YGN$ . These results probably suggest the redundancy of the incremental delay information provided by the ODM and the GDM for linear-type networks, which increases the errors of delay estimates at each individual intersection. However, as it was shown earlier, the models accounting for the randomness in the delay estimation appear to increase the accuracy of the overall (network-wide) performance measures.

Another set of experiments to evaluate the relative performance of the models was carried out through considering unavailability of actual field signal timing information. In this case, the models fed with the default signal timing values, i.e. effective green time ratio  $g/C = 0.45$  and cycle length  $C^\tau = 120$  seconds. Figure 2 demonstrates the sensitivity of each particular model, in terms of the percentage increase of  $RAE$ , under the assumption of using the above default signal timing parameters. The SSM has not been included since its results are not affected by the signal

timing plans. The SBPR model appears to be almost fully insensitive to the change in signal timing parameters. Furthermore, the GDM and the ODM in sequence demonstrate the smallest sensitivity with respect to the changes of signal timing. Namely, the consideration of the randomness in delays appears to improve the robustness of the network travel time estimation under the absence of knowledge on the actual values of signal control parameters. On the contrary, the UBPR model and, in particular, the UDM show the largest changes in the estimated travel times. As it was expected, the magnitude of these changes increases for the cases of most congested arterial networks, namely the *MST* and the *YGN*. These results may provide insights in the suitability of the application of each model under different levels of signal timing availability and arterial network traffic characteristics.

## 6. SUMMARY AND CONCLUSIONS

This paper provides a first attempt to address the problem of real-time estimation of urban arterial network performance. A number of different analytical time-dependent models have been formulated for the on-line estimation of arterial travel times and applied in various real-life test networks. The suggested models provide alternative ways of incorporating the contribution of various network and operational characteristics to the estimation of the average arterial travel time. The model input requirements refer to typical detector data (volume / occupancy) and signal control parameters. The test networks have been suitably selected so as to provide insights about the impact of network layout and traffic demand size on the performance measurement.

The model results manifested considerably varying levels of accuracy with respect to the ‘true’ travel times. In particular, the aggregation of the estimated travel times at the network level and changes in the available signal timing information should be taken into account to fully evaluate the accuracy and robustness of the proposed models. The generalized delay model (GDM) and, at a lesser extent, the overflow delay model (ODM) demonstrated the most promising modeling approaches, in terms of the average total travel times and the statistical significance of the difference of the means, for the on-line performance measurement of urban arterials.

The models accounting for the randomness at intersection delays (ODM and GDM) appeared to provide improved network-wide travel time estimates and increase the output robustness when existing signal timing information departs from the actual (optimal) one. On the other hand, conceptually simpler models, without incorporating randomness effect, demonstrated the most promising behavior on measuring travel times at a finer level of detail, i.e. at each individual link. Further research on the topic should be undertaken to enable the representation of more complex factors influencing travel times, such as platoon dispersion effect. The implementation of the suggested models on realistically large-scale urban street networks could provide additional insights on issues of computational efficiency and tractability.

The work reported in this paper is part of an ongoing large-scale project to develop an on-line performance measurement system for signalized arterials and networks (Arterial Performance Measurement System—*APeMS*). The project involves real-time acquisition of surveillance data from the Los Angeles ATSAC signal system with over 3,000 signalized intersections. Currently, the most promising of the proposed models are being applied on portions of the Los Angeles ATSAC network, and the models’ results will be compared with field measurements.

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**Table 2.**        ***RAE* and statistical performance (*%* significance of difference of the means in comparison to CORSIM results using two-sided *t*-test statistic) of the model results using actual signal timing information**

**Table 1. Characteristics of the arterial networks of the tested sites**

Network	Type	Area	Number of links	# Signalized nodes	Flow info.	$D_s$	$u_L$	$\bar{u}^*$ (mph)	$\bar{t}^*$ (minutes)
<i>LIN</i>	linear	urban	12	7	through	0.24	35	12.63	16.40
<i>FAIR</i>	linear	suburban	10	6	through	0.56	50	36.61	14.50
<i>MST</i>	linear	urban	14	8	mixed	0.10	30	15.95	5.40
<i>YGN</i>	linear	suburban	12	7	through	0.24	40	24.10	7.50
<i>SIL</i>	grid	urban	30	11	through	0.25	30	18.80	23.30

**Table 2. RAE and statistical performance (% significance of difference of the means in comparison to CORSIM results using two-sided *t*-test statistic) of the model results using actual signal timing information**

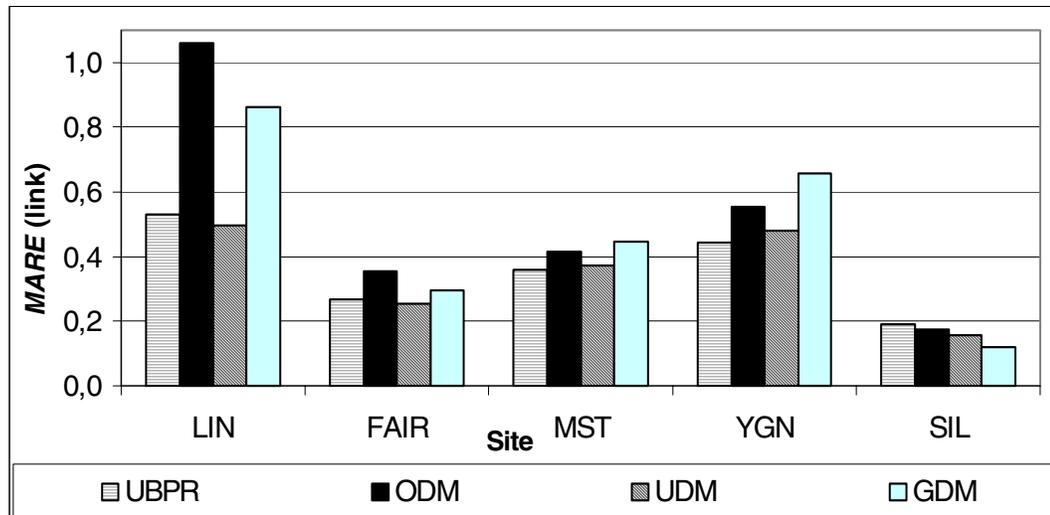
NETWORK	SSM	SBPR	UBPR	UDM	ODM	GDM
<i>LIN</i>	106.9 (99.9%)	-70.2 (99.5%)	-49.7 (95.0%)	-41.6 (95.0%)	26.6 (< 80.0%)	-6.9 (< 80.0%)
<i>FAIR</i>	18.2 (< 80.0%)	-37.6 (99.0%)	-25.5 (98.0%)	-21.9 (95.0%)	4.9 (< 80.0%)	-16.4 (< 80.0%)
<i>MST</i>	-35.5 (100.0%)	-55.2 (99.0%)	-24.0 (95.0%)	-16.2 (< 80.0%)	-6.6 (< 80.0%)	-4.5 (< 80.0%)
<i>YGN</i>	118.3 (90.0%)	-42.9 (99.0%)	-25.7 (95.0%)	-9.8 (< 80.0%)	-9.9 (< 80.0%)	16.8 (< 80.0%)
<i>SIL</i>	-19.4 (< 80.0%)	-43.6 (99.9%)	-15.2 (98.0%)	-10.3 (90.0%)	11.1 (95.0%)	2.8 (< 80.0%)

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**Figure 1.**  $(MARE)_m$  values of the models for different sites

**Figure 2.** Sensitivity of the models to changes in the signal timing information

**Figure 1.**  $(MARE)_m$  values of the models for different sites



**Figure 2. Sensitivity of the models to changes in the signal timing information**

