Link-Journey Speed Estimation for Urban Arterial Performance Measurement Using Advance Loop Detector Data under Congested Conditions

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Abstract: Travel speed ties directly to travel time, so it is an important measure for quantifying arterial performance. However, accurately estimating link travel speed for urban arterials is difficult because of traffic fluctuations and stop-and-go conditions caused by signal control. This research proposes a two-step empirical approach to effectively estimate the link-journey speeds using only advance loop detector outputs. The first step is to estimate the spot speed on the basis of advance loop measurements using Athol's algorithm. The robust regression technique can be used to calibrate the speed estimation parameter (or g-factor) in Athol's algorithm. The second step is to use the proposed simplified speed estimation model to estimate the link speed using only the calculated loop-spot speed without any knowledge of signal timing plans. Traffic operations in the central business district of the City of Bellevue, Washington, are simulated in the VISSIM traffic simulation model. The test results show that only 50 cycles of data are needed to calibrate the g-factor in loop-speed estimation and the same datasets can be used to calibrate the proposed link-speed model. Using this model, the average mean absolute error over the study links is reduced from 4.24 to 1.51 mph. With proper calibration, this average error can be further reduced to 0.91 mph. The results are encouraging and satisfactory. The results also show that the accuracy of speed estimation may be further increased when more data are applied for calibration. **DOI: 10.1061/(ASCE)TE.1943-5436.0000429.**

CE Database subject headings: Travel time; Traffic speed; Urban areas; Traffic congestion; Data analysis.

Author keywords: Link-journey speed (link speed); Link travel time; Speed estimation; Arterial performance measurement; Loop detector.

Introduction

Travel time is one of the most desired operational and system measures of effectiveness (MOEs) for evaluating the performance of freeways and urban arterials (Martin et al. 2003). Travel time can be obtained using several techniques including, e.g., license plate matching, probe vehicles, traffic loop detector data—based travel time estimation (Turner et al. 1998). Among these techniques, estimating travel time from traffic loop detector measurements is considered one of the most feasible and cost-effective solutions to quantifying traffic system performance because these sensors have been permanently installed to collect fundamental traffic data like volume and occupancy. Inductive loop detectors (or loop detectors) are by far the most widely deployed type of traffic point sensors in the existing infrastructure system and serve as the standard form of traffic detection in many transportation agencies (Kell and Fullerton 1991; Klein 2001; Wang and Nihan 2003; Klein 2006). However, as point detectors, loop detectors cannot directly measure travel time. Hence, extensive research studies have been conducted and many travel speed models have been developed for freeway operations (Ruimin et al. 2006). Compared with freeway travel-time estimation, urban arterial link travel-time estimation is more challenging because of the severe traffic fluctuations and stop-and-go conditions imposed by signal control. Moreover, an arterial network usually has many possible routes. Route or section speed estimation may not be informative for most drivers to capture a timely overview of the arterial network (Ban et al. 2009). Link-journey speed (or link speed) is a more comprehensive and useful MOE, which allows engineers to compare intuitively the performance on the same or different links, whereas the link travel time is suitable for comparing only the performance on the same route or link. Provided the length of each link on an arterial, link travel time can be calculated easily using link speed.

Average link speed or travel time can be modeled by using the volume and/or occupancy data retrieved from the loop detectors. Such speed/travel time modeling approaches include linear (Turner et al. 1996), nonlinear (Zhang 1999), Bayesian (Frechette and Khan 1998; Park and Lee 2004), and K-NN (Robinson and Polak 2005). Some studies (e.g., Skabardonis and Geroliminis 2008) have derived delay models in which the travel time is equivalent to free-flow travel time plus the delay caused by external factors, such as traffic control or interaction between vehicles. Some researchers specifically focused on the control-delay estimation because control delays are the major contributors to arterial delays

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Note. This manuscript was submitted on February 15, 2011; approved on August 16, 2011; published online on March 27, 2012. Discussion period open until April 1, 2013; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Transportation Engineering***, Vol. 138, No. 11, November 1, 2012. © ASCE, ISSN 0733-947X/2012/11-1321-1332/$25.00.

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(e.g., Engelbrecht 1997; Fambro and Rouphail 1997; Sharma et al. 2007; Zheng et al. 2009; Ban et al. 2009).

Overall, the arterial travel time or speed estimation research can be categorized into three levels: microscopic, mesoscopic, and macroscopic. The microscopic models estimate/predict travel times on the basis of high-resolution second-by-second data or cycle-by-cycle data (Liu and Ma 2009; Li 2009; Zheng et al. 2009; Skabardonis and Geroliminis 2008). Even though these techniques can effectively capture the fluctuations of traffic, they may not be suitable for practical implementation and require higher data capacity from the supporting infrastructure, resulting in higher costs. As for the macroscopic models, the well-known Bureau of Public Roads (BPR) model (BPR 1964) has been used by many planning agencies for decades. Recently, Tarko et al. (2006) proposed a simple macroscopic model for predicting link speeds on urban streets. This model is derived from the HCM-based delay model and does not require the information of traffic-signal timing. However, it requires volume information from side streets crossing over the main road. Because of coarse data output, macroscopic models may not be suitable for the advanced transportation management systems (ATMS) and advanced traveler information systems (ATIS) applications, which require timely updates.

To combine the benefits of microscopic and macroscopic models, the mesoscopic models, a level between microscopic and macroscopic, have been gaining researchers' attention (Gault and Taylor 1977; Sisiopiku and Rouphail 1994; Zhang 1999; Xie et al. 2001). This type of model is commonly used for short-term performance measurement in arterial networks at a level suitable for ATIS and ATMS use. In the past decades, several regression-based travel-speed models have been developed, such as the British model (Gault and Taylor 1977), Illinois model (Sisiopiku and Rouphail 1994), and Iowa model (Zhang 1999). After reviewing these link-speed models, Xie et al. (2001) proposed a calibration-free, HCM-based Singapore model that requires only the detector and signal outputs. They showed that the Iowa model has the best performance among these models but the Singapore model provides satisfactory results without calibration efforts. Nevertheless, the Singapore model requires data from both system and advance detectors, whereas the Iowa model requires only data from advance detectors. Most existing infrastructure has only advance detectors, usually located approximately 100 ft (30.48 m) from the stop bar. Hence, it is more desirable to develop a more generalized approach that uses only the advance detector outputs to estimate link speed.

On the basis of the literature review, most existing arterial travel-time models require knowledge of the traffic-signal timing plans implemented on the network (Ban et al. 2009). It would be cumbersome to retrieve either current or historical signal timing data, especially for actuated or adaptive signal control. Therefore, the objective of this study is to develop a simple yet effective approach for estimating link speed using the advance loop detector data without the knowledge of signal timing.

The paper is organized as follows. First, the test bed and traffic simulation setup is explained. Next, a speed-conversion method is proposed to solve the practical problem frequently encountered when calculating speeds using the advance loop detector outputs. Then, a simplified speed-estimation model is proposed to overcome the speed-overestimation problem commonly seen in practice. Following that is an evaluation of the models, including a discussion about the advantages, errors, and constraints of the proposed model. Finally, the paper will conclude by identifying the model's potential, practicability, and future work.

Simulation Modeling

Test Bed

The central business district (CBD) area in the City of Bellevue, Washington, was selected as the test bed for the simulation-model development. As of June 2010, 603 advance detectors are able to collect cycle-by-cycle volume and occupancy data and push the data back to the traffic management center (TMC) in real time. The test bed represents a typical city roadway network in which each roadway link is equipped with loop detectors in a standard configuration, including one set of advance detectors and presence detectors. Each advance detector is located approximately 100–120 ft (30.48–36.58 m) from the stop bar.

As shown in Fig. 1, both directions of two major corridors in the network, 112th Avenue and 8th Street, are selected as the test corridors. Eighth Street is a major corridor connecting Interstate 405 and Bellevue Way Avenue. 112th Avenue is another major north-south arterial that serves as the alternative route for I-405. It usually carries less traffic than 8th Street. Compared with 112th Avenue, 8th Street has complicated traffic characteristics and also serves as a major corridor for most transit services. Moreover, the intersection approaches on 8th Street have a variety of lane layouts, e.g., dedicated right- and left-turn lanes and links on 8th Street have more side streets along the corridor. These factors may cause more weaving traffic and are more likely to result in erroneous detection, such as missing count, from the detectors located in the through lanes. Another challenge is that both corridors run semiactuated, coordinated control with a cycle length equal to 140 s. Different signal-timing plans are used in different periods of day in response to traffic-demand changes.

Simulation Model

Many traffic-simulation software packages have been developed for intelligent transportation systems (ITS) application evaluation and verification. In this research, VISSIM 5.2 is used to model the entire test bed. VISSIM is one of the microscopic behavior-based traffic simulation software packages that can simulate and analyze traffic operations under a board range of scenarios. Moreover, it is also useful for collecting the MOEs to evaluate the various alternatives under consideration. In VISSIM, driver behaviors are modeled following the work published by Wiedemann (1974 and 1991). Individual vehicle behaviors can be simulated independently. Many simulation studies have been conducted using VISSIM. Gomes et al. (2004) developed and calibrated a VISSIM model for simulating a congested freeway. Moen et al. (2000), Bloomberg and Dale (2000), and Tian et al. (2002) investigated the performance of VISSIM by comparing it with CORSIM, a traffic simulator developed by the Federal Highway Administration (FHWA). They concluded that VISSIM performed favorably. Park and Schneeberger (2003) also showed the effectiveness of VISSIM to simulate the coordinated actuated signal system.

The simulation model of the central business district (CBD) is provided and calibrated by the City of Bellevue. The model is designed for afternoon peak hours and calibrated using the ground truth volume count data collected during 2009–2010. The model was calibrated following the calibration procedure developed by Dowling et al. (2004). Below is a summary of the calibration process applied to this simulation model.

1. The simulation mode was calibrated with field travel-time data. Probe vehicles ran 10 times on seven major corridors during afternoon peak hours. The hourly travel-time errors are less than 1 min.

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Fig. 1. Two study corridors, 112th Avenue and 8th Street, in CBD area of Bellevue, Washington

2. The turning-movement count error is within 5% for critical intersections.
3. The hourly volume was converted to the GEH statistics indicated by the FHWA standard. A total of 95% of the links has a GEH statistic <1, showing that the model meets the requirement.

Datasets

The goal of the research is to use the data from the advance detector and estimate link speed. To capture the speed data when the vehicles are crossing over the advance detectors, the data detection points (in VISSIM) are placed on those advance detectors in all through lanes at each intersection approach for each link. As for link travel-time collection, the definition of link by Zhang (1999) is adopted. The definition of link is "a section of road spanning from the exit corner of one intersection to the exit corner to the immediate downstream intersection." The ground truth link speed is calculated as

$$S_J(t) = \frac{L_k}{TT(t)} \tag{1}$$

where L_k = link length for link k; and $TT(t)$ = ground truth link travel time for time interval t. The link travel time should be composed of cruise time and signal delay (Xie et al. 2001).

Both loop data–calculated speed and travel-time data are collected every cycle. Cycle-based data are found to adequately capture the average effect of each link for each cycle and can be easily aggregated on the basis of a specified period. Three datasets—Dataset 1, Dataset 2, and Dataset 3—are generated using different simulation random seeds. Dataset 1 is generated by only one simulation run (50 cycles after 30-min warm-up period). The second and third datasets are generated by 10 simulation runs (500 cycles). Datasets 1 and 2 are used for the model calibration process, whereas Dataset 3 is used for the model-verification process.

Link-Speed Estimation

To estimate the link speed using single-loop detector outputs, the writers propose a two-step empirical approach. The first step is to calculate the spot speed on the basis of a traditional estimation model with the help of a speed-conversion procedure. The second step is to develop a simplified link-speed estimation model based

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solely on the input of spot speed measured at advance loop detectors.

Loop-Data–Based Spot-Speed Estimation

The Athol's speed estimation formula (Athol 1965), also called the g-factor approach, is used to calculate the spot speed at the advance detector locations. This approach has been widely used in the freeway (Wang and Nihan 2000, 2003) and arterial speed estimation (Zhang 1999). The loop-spot speed for time interval t is defined as

$$S_L(t) = \frac{N(t)}{T \cdot o(t) \cdot g(t)} \tag{2}$$

where t = time interval index; N = interval traffic volume; o = occupancy (percentage of time a loop is occupied by vehicles per interval); T = time length per interval; L = mean effective vehicle length; and g = speed-estimation parameter (often called g-factor) determined by the effective vehicle length. L and g are related by $g(t) = 1/L(t)$. In practice, however, g is considered constant assuming the traffic composition does not change temporally and spatially. For example, Washington State Department of Transportation (WSDOT) uses $g = 2.4$ for their freeway applications (Ishimaru and Hallenbeck 1999). For arterial applications, Zhang (1999) used a constant effective length of 20 ft to determine $g = 2.63$, assuming traffic is composed only of passenger cars. In these study corridors, g is mostly affected by the buses and rarely by trucks. g is assumed to be only site-dependent to simplify the estimation process. After removing the time dimension of g, Eq. (2) is redefined as

$$S_L(t) = \frac{q(t)}{o(t) \cdot g} \tag{3}$$

where $q(t)$ = flow rate (veh/h) in time interval t. In this case, g is considered a site-dependent constant that requires calibration. According to Eq. (3), the ground truth loop speed or the effective vehicle length is needed to accurately calibrate g. According to the empirical evidence found by Guo et al. (2009), the ground truth $S_L(t)$ measured from dual-loop detectors follows a linear relationship with q/o ratio with an error term $\varepsilon(t)$ as follows:

$$\frac{q(t)}{o(t)} = gS_L(t) + \varepsilon(t) \tag{4}$$

In Eq. (4), the slope of the linear regression line, g, should pass through the origin. The linear model in Eq. (4) can be easily solved if the ground truth $S_L(t)$ is known. For freeway loop detectors, the ground truth spot speed can be retrieved from dual-loop detectors and used for model calibration (Guo 2009). For arterial applications, dual-loop detectors are rarely seen in practice. Alternatively, "instantaneous spot speed" data can be collected using speed guns when a vehicle is crossing over the loop detector (Dowling 1996).

The average, instantaneous spot speed $S_I(t)$ for each time interval t is defined as

$$S_I(t) = \frac{\sum_{n=1}^{N} u_n}{N(t)} \tag{5}$$

where u_n = instantaneous spot speed of the nth vehicle measured by the speed gun when the advance detector is initially occupied by the vehicle in time interval t; and $N(t)$ = interval traffic volume.

Although the speed estimated from single-loop measurements is often regarded as "spot" or "point speed" in many previous studies (e.g., Han et al. 2010; Zhang 1999), it is different from the spot speed in a strict academic perspective. The reason is that a loop detector has a physical length and its occupancy measurements correspond to a travel distance of the effective vehicle length. Speed measured by radar sensors can be regarded as spot speed (Dowling and Cheng 1996). Essentially, the average instantaneous speed $S_I(t)$ and the single-loop data calculated speed $S_L(t)$ are not equal.

To explain the discrepancy between $S_I(t)$ and $S_L(t)$, assume that a vehicle is a particle traveling from the beginning of the loop detector toward the end of the detector. $S_I(t)$ can be regarded as the average speed when the particle is measured at the moment of entering the detector, whereas the $S_L(t)$ is the average mean speed when the particle is crossing over the entire link during time interval t. In other words, $S_I(t)$ is regarded as a special case of time mean speed (TMS) and $S_L(t)$ is regarded as a special case of space mean speed (SMS) when vehicles are traveling on a link with a length equivalent to the effective vehicle length L. On the basis of the theoretical relationship between TMS and space mean speed (SMS) (Han et al. 2010; Dowling and Cheng 1996), TMS is always no lower than SMS as proposed by Wardrop [please see May 1990]

$$\text{TMS} = \text{SMS} + \frac{\sigma_{\text{SMS}}^2}{\text{SMS}} \tag{6}$$

where σ_{SMS}^2 = variance of SMS. The time mean speed and space mean speed are identical when all vehicle speeds are equal. Their discrepancy increases with the increase in vehicle speed variance. Because of the traffic signal effect, vehicle speeds observed by advance loops during a time period are not identical. This implies that the measured $S_I(t)$ should always be higher than $S_L(t)$. The discrepancy between $S_L(t)$ and $S_I(t)$would be larger at the advance detectors where vehicles suffer from control delay. A speed-conversion procedure is required to convert $S_I(t)$ to $S_L(t)$ for the calibration process in Eq. (4).

Speed Conversion

Using Link 1-1 as an example, the relationship between q/o and instantaneous spot speed, $S_I(t)$, is illustrated in Fig. 2(a) using Dataset 2. The data points are located in two groups. The first group, circled by the longer-dashed line, shows that $S_I(t)$ has a linear relationship with q/o ratios. The second group, circled by the shorter-dashed line, does not show any relationship between $S_I(t)$ and q/o, but shows that these data points occur with high occupancy. The cause of the second data group is that during a high congestion period, vehicles tend to occupy the loop detector for a long time period and few vehicles can pass the detector, resulting in low $S_L(t)$, whereas the average instantaneous speed, $S_I(t)$, for these passing vehicles could still remain higher than 10 mph, as indicated by data points at the bottom of Fig. 2(a). Once the high-occupancy data points are removed, the linear relationship can be easily determined. This linear relationship is consistent with the relationship between q/o and $S_L(t)$ except that the regression line does not pass the origin.

Locating g-Factor Line

In the preliminary analysis, the threshold of occupancy of 10% is used. Fig. 2(b) shows the data points with occupancy lower than this 10% threshold. An ordinary least squares technique (Faraway 2005) is applied to retrieve this linear relationship between $S_I(t)$ and q/o. As expected, the linear regression line does not pass the origin. It is reasonable that $S_I(t)$, theoretically, should be higher than zero because the speed gun measures a vehicle speed sample at the moment when it is crosses over the advance detector.

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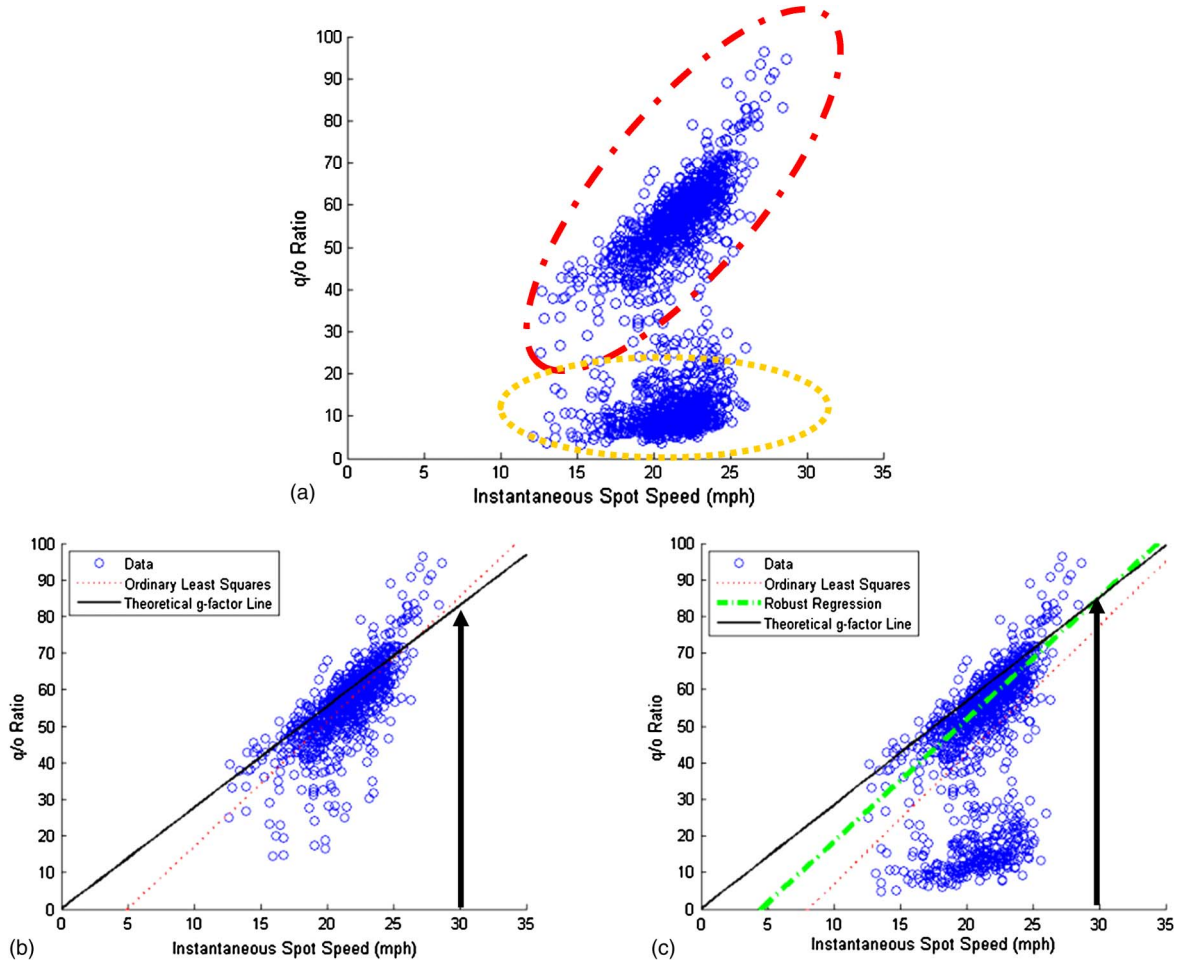

Fig. 2. Example of speed conversion at Link 1-1: (a) raw data comparisons between $S_I(t)$ and q/o; (b) filtered data when occupancy <10%; and (c) effect of robust regression when occupancy <30%

To reconstruct the linear relationship as identified by Eq. (4), the radar gun reading is assumed to be identical to the loop measurement as vehicles are crossing a short distance at a very high speed. In other words, vehicles tend to keep constant speeds as they pass over a loop detector at a fast speed. Thus, it is assumed that $S_I(t)$ and $S_L(t)$ are equal when the average vehicle speeds reach a speed limit (30 mph used in this study's routes). Fig. 2(b) shows the regression line intersect with the vertical black arrow line when the speed limit is 30 mph. The solid black line passing through the origin and the intersection is the g-factor line. The slop of the g-factor line is the g being calibrated in Eq. (4) for this specific location.

Remedies for Incorrect Occupancy Thresholding

Least squares regression performs favorably if the errors are normally distributed (Faraway 2005). Unfortunately, the occupancy threshold is not always constant. A fixed occupancy threshold may not exclude all high occupancy data points. As observed in this study's datasets, the occupancy threshold values are site-dependent. Setting inadequate occupancy thresholds may result in more "noise" or outliers. Fig. 2(c) demonstrates the data points when the occupancy threshold of 30% is applied. In this case, traditional ordinary linear regression suffers from the outliers, resulting in a biased g-factor line. Hence, the robust linear regression technique is adopted. In this research, the linear regression technique adopts iteratively reweighted least squares with a bi-square weighting function (Holland et al. 1977). Fig. (2c) shows the result of robust regression in a longer-dashed g-factor line, which is robust to the outliers (high occupancy data points).

Another remedy for outliers is to determine the threshold on the basis of the percentile of the q/o ratios. In this study, the 30th percentile is used to capture enough high q/o ratio samples for regression analysis. Table 1 shows the g-factor calibration results. All of the g-factors are smaller than 2.63, indicating that the average vehicle length is longer than 20 ft. Columns 1 and 2 show the calibrated g-factors using Datasets 1 and 2, respectively. On the basis of the paired two sample t-test (Hines 2003), the g-factors calibrated by using different datasets are not significantly different at $p = 5\%$ significance level ($p - \text{value} = 0.40$). Therefore, the g-factors calibrated by Dataset 1 (50 cycles) are suitable for the speed-estimation process.

Simplified Link-Journey Speed Estimation Model

According to the Iowa model proposed by Zhang (1999), the link-journey speed is based on two types of speeds. The model is defined as

$$\hat{S}_J(t) = \gamma \hat{S}_{v/c}(t) + (1-\gamma)\hat{S}_L(t) \tag{7}$$

where $\hat{S}_J(t)$ = estimated link-journey speed for time interval t, $\hat{S}_L(t)$ estimates the link-journey speed on the basis of the loop detector outputs; $\hat{S}_{v/c}(t)$ estimates the link-journey speed on the basis

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Table 1. Results

				Individual g-factor for each link								Universal g-factor ($g = 2.2$)							
				Model coefficients (using Dataset 2)		Before correction (using Dataset 3)			After correction (using Dataset 3)			Model coefficients (using Dataset 1)		Before correction (using Dataset 3)			After correction (using Dataset 3)		
Route	Link ID	g-factor[a] using Dataset 1	g-factor[a] using Dataset 2	a	b	MAE	ME	RSME	MAE	ME	RSME	a	b	MAE	ME	RSME	MAE	ME	RSME
Route 1	1-1	2.02	2.01	1.62	0.16	1.56	−0.24	1.96	0.88	−0.41	1.18	1.45	0.11	1.88	−1.31	2.24	1.68	1.12	2.11
(8th	1-2	2.35	2.29	1.46	0.11	2.34	−2.28	2.57	0.81	−0.17	1.08	1.39	0.10	1.43	−1.13	1.69	1.26	1.11	1.58
Street WB)	1-3	2.03	1.95	0.94	0.14	5.43	5.43	5.76	0.38	−0.16	0.53	0.94	0.12	4.46	4.46	4.81	0.91	0.65	1.08
	1-4	2.45	2.35	1.16	0.11	2.48	2.40	3.03	0.89	0.06	1.14	1.04	0.09	4.22	4.22	4.70	0.96	0.45	1.28
	1-5	2.31	2.32	0.95	0.10	5.32	5.32	5.79	1.08	−0.07	1.32	0.81	0.06	6.16	6.16	6.60	1.57	1.07	1.99
	1-6	2.37	2.30	1.20	0.11	4.49	4.49	4.83	1.12	0.57	1.35	1.26	0.10	6.06	6.06	6.33	2.66	2.66	2.93
	1-7	2.25	2.32	1.29	0.14	3.41	3.01	4.02	1.06	−0.36	1.42	1.32	0.12	3.71	3.37	4.32	2.74	2.48	3.07
	Average	2.25	2.22			3.58	2.59	3.99	0.89	−0.08	1.14			3.99	3.12	4.38	1.68	1.36	2.00
Route 2	2-1	2.27	2.38	1.41	0.09	1.73	1.73	1.92	0.29	0.18	0.39	1.34	0.09	2.65	2.65	2.79	0.52	0.49	0.61
(8th	2-2	2.39	2.37	0.74	0.00	6.34	6.34	6.40	0.65	−0.02	0.78	0.84	0.06	8.44	8.44	8.48	0.76	0.50	0.92
Street EB)	2-3	2.16	2.23	1.11	0.14	2.85	2.85	3.28	0.59	0.02	0.70	1.06	0.12	2.63	2.63	3.07	0.95	0.64	1.19
	2-4	2.43	2.32	1.23	0.11	1.73	1.66	1.96	0.47	−0.03	0.64	1.19	0.10	3.36	3.36	3.57	1.21	1.16	1.32
	2-5	2.36	2.30	0.76	0.12	7.05	7.05	7.21	0.41	−0.05	0.50	0.51	0.04	8.04	8.04	8.20	0.53	0.13	0.66
	2-6	2.22	2.24	1.16	0.14	4.04	4.04	4.31	0.39	0.02	0.50	1.02	0.12	4.18	4.18	4.44	0.64	0.33	0.78
	2-7	2.39	2.36	1.37	0.10	2.26	−2.06	2.60	1.29	−0.07	1.57	1.35	0.09	1.43	−0.57	1.69	1.77	1.58	2.23
	2-8	2.32	2.35	1.10	0.08	3.57	3.57	3.79	0.89	−0.15	1.12	1.35	0.10	4.94	4.94	5.11	1.59	1.41	1.93
	2-9	2.12	2.14	1.42	−316.81	5.58	−5.58	5.78	1.75	−0.32	2.15	2.46	0.18	5.94	−5.94	6.12	3.79	3.66	4.24
	Average	2.29	2.30			3.91	2.18	4.14	0.75	−0.05	0.93			4.62	3.08	4.83	1.31	1.10	1.54
Route 3	3-1	2.42	2.39	0.93	0.00	1.84	1.74	2.46	1.48	0.45	1.94	1.10	0.07	3.58	3.58	3.93	2.04	1.87	2.76
(112th SB)	3-2	2.17	2.17	1.12	0.15	2.73	2.59	3.32	0.93	−0.07	1.10	1.06	0.12	2.61	2.46	3.21	1.19	0.58	1.49
	3-3	2.35	2.38	1.47	0.12	1.40	−0.32	1.66	0.99	0.32	1.20	1.36	0.09	1.59	0.93	1.96	2.42	2.42	2.76
	3-4	2.37	2.35	0.98	0.11	4.56	4.55	4.90	0.74	−0.18	0.89	0.90	0.09	5.71	5.71	6.05	1.09	0.85	1.34
	3-5	2.39	2.37	1.35	0.10	1.52	1.43	2.10	1.19	−0.07	1.58	1.09	0.07	3.62	3.62	3.94	1.11	0.72	1.67
	3-6	2.25	2.23	1.06	0.12	4.93	4.93	5.16	0.81	0.21	0.99	0.90	0.09	5.33	5.33	5.55	0.89	0.48	1.06
	Average	2.33	2.31			2.83	2.48	3.26	1.02	0.11	1.28			3.74	3.61	4.11	1.46	1.15	1.85
Route 4	4-1	2.39	2.37	1.23	0.08	1.45	1.29	1.84	1.20	−0.29	1.39	1.15	0.07	3.49	3.49	3.73	1.12	0.62	1.47
(112th NB)	4-2	2.34	2.35	0.78	0.09	9.20	9.20	9.45	0.65	0.00	0.80	0.76	0.08	10.40	10.40	10.66	1.19	1.07	1.38
	4-3	2.32	2.35	1.53	0.12	1.84	0.06	2.24	1.33	−0.36	1.67	1.45	0.10	2.13	1.10	2.61	3.08	2.98	3.45
	4-4	2.27	2.32	0.99	0.13	5.54	5.54	5.95	0.71	−0.07	0.89	1.03	0.11	6.00	6.00	6.41	1.90	1.88	2.18
	4-5	2.35	2.34	1.26	0.09	1.71	1.38	2.28	1.31	0.42	1.82	1.20	0.09	2.92	2.85	3.40	1.30	0.54	1.85
	4-6	2.28	2.19	1.30	0.19	2.36	2.30	2.84	0.72	−0.01	1.21	1.02	0.12	2.67	2.62	3.14	1.03	0.66	1.27
	Average	2.32	2.32			3.68	3.29	4.10	0.99	−0.05	1.29			4.60	4.41	4.99	1.60	1.29	1.94
All-route average		2.30	2.29			3.50	2.64	3.87	0.91	−0.02	1.16			4.24	3.55	4.58	1.51	1.23	1.83
Before—after improvement									73.97%	99.38%	70.01%						64.31%	65.47%	59.99%

[a]Note that the data collection point in VISSIM is regarded as a point detector without any loop length. All of the g-factors have been adjusted by assuming the detector length is 6 ft.

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of v/c ratio; and $0 \le \gamma \le 1$ = weight factor depending on traffic congestion levels ($\gamma = 1$ for heavy traffic and $\gamma = 0$ for light traffic). $\hat{S}_{v/c}$ is defined as

$$\hat{S}_{v/c}(t) = S_F(t) - \alpha \exp\left(\beta \frac{v}{c}\right) \tag{8}$$

where S_F (free-flow speed), α, and β are model parameters that require calibration, and $\hat{S'}_L$ is given by

$$\hat{S}_L(t) = 0.379 \frac{q(t)}{o(t)} \tag{9}$$

where the constant 0.379 is the reciprocal of its $g = 2.63$, assuming the effective vehicle length = 20 ft. To verify the results, the g-factors calibrated by Dataset 2 are applied to show the best result possible. For all links on Route 4, $\hat{S}_L$ is estimated using Eq. (3) with calibrated g-factors. Fig. 3(a) shows the relationship between the ground truth link speed S_J and estimated loop speed $\hat{S}_L$ for 112th Avenue (SB). To better visualize the data, the data are aggregated every 10 cycles. As shown, $\hat{S}_L$ tends to be overestimated when the ground truth link speed is high for each individual link. Compared with the speed estimation result in Zhang (1999) as shown in Fig. 3(b), each link shows the trend of overestimation. This shows that the speed-conversion procedure results in a similar outcome. All of the links in this research are nonhomogenous because the signal timing and street layout are more complicated than previous research disscused in the literature review. Additionally, the links in this research are relatively shorter.

To deal with the overestimation errors and other associated errors, the writers propose a simplified speed-estimation model using a nonlinear modeling approach (Ritz and Streibig, 2008) without the signal timing plan information. As observed in Fig. 4(a), the loop speeds estimated by accurately calibrated g-factors are not able to represent the entire link speed. The speed needs to be corrected on the basis of the characteristics of each link.

The proposed, simplified link-speed estimation model is based on Zhang's approach. Eqs. (8) and (9) can be substituted into Eq. (7). The estimated link-journey speed $\hat{S}_J(t)$ model can be rearranged as

$$\hat{S}_J(t) = \underbrace{\gamma(S_F) + (1-\gamma)\hat{S}_L(t)}_{a\hat{S}_L(t)} - \underbrace{\gamma\alpha \exp\left(\beta \frac{v}{c}\right)}_{\kappa \exp(b\hat{S}_L(t))} \tag{10}$$

The first two terms, free-flow speed and estimated loop speed in Eq. (10), can be simplified as $\hat{S}_L(t)$ multiplied by the coefficient. The second term can be simplified as $\kappa \exp(b\hat{S}_L)$, assuming that the effect of v/c ratio can be captured by $\hat{S}_L$. This is reasonable on the basis of observations of situations in which traffic volume is high and the ground truth link speed S_J is also high; most speed reductions may originate from resistances along the entire link instead of delays caused by signal control. In this case, the speed measured from the advance loop is less likely to capture such delay.

In this study, it was found that the effect of κ can be normally captured by b. That is, κ in Eq. (10) could be removed without affecting the results. Hence, the speed-estimation model is further simplified and formulated as

$$\hat{S}_J(t) = a\hat{S}_L(t) - \exp(b\hat{S}_L(t)) + 1 \tag{11}$$

where a and b are coefficients that require calibration. The constant value, 1, allows the calibrated model to pass through the origin (0,0). In brief, the first term is to capture the effect of cruise speed and congestion, and the second term is used to reduce the effect of overestimation. The overestimation effect primarily results from the fact that the advance detector can only capture the speed changes when the vehicles are approaching the intersection. When the measured speed is higher, it indicates that vehicles may suffer more from the intersection signal delay than the resistances between vehicles and link infrastructure. In this case, the volume on each link is usually relatively lower. This is why the v/c ratio can be replaced with $\hat{S}_L$. In fact, $\hat{S}_L(t)$ cannot capture all of the effects caused by different v/c ratios because the proposed model is designed to potentially estimate the link-journey speed for most signal-control scenarios, especially for the coordinated semi-actuated control cases in this research. The introduced errors will be discussed in the Model Evaluation section.

Evaulation

Measure of Accuracy

In this section, the robustness and transferability of the proposed approach will be evaluated. Three measures of accuracy, mean error (ME), mean absolute error (MAE), and root square mean error (RSME), are used in this study and defined as follows (Washington et al. 2003):

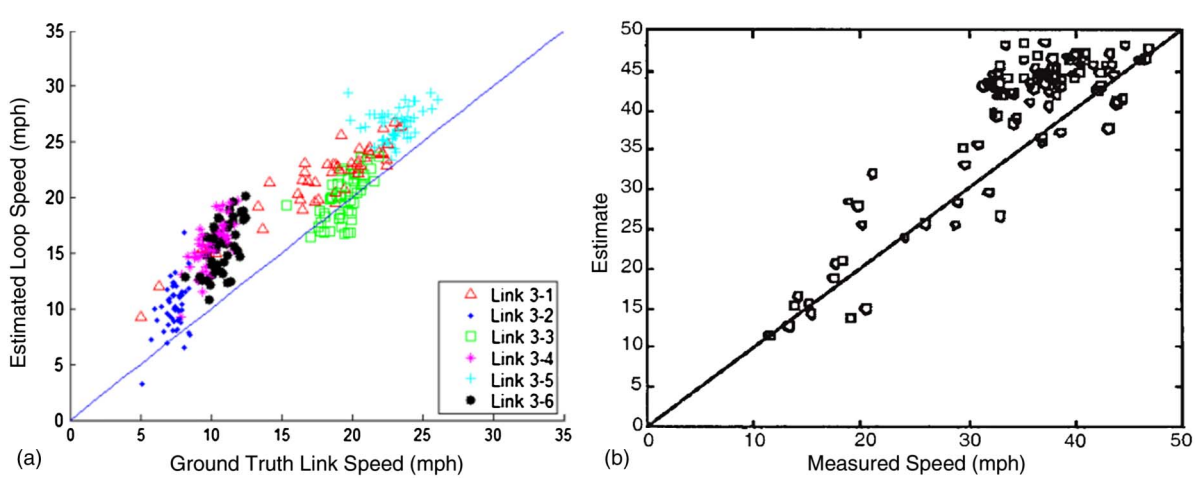

Fig. 3. Relationship between estimated loop speed $\hat{S}_L$ and measured speed (ground truth link speed S_J: (a) speed conversion results for 112th SB using Dataset 2 (aggregated every 10 cycles); (b) Zhang's results (1999)

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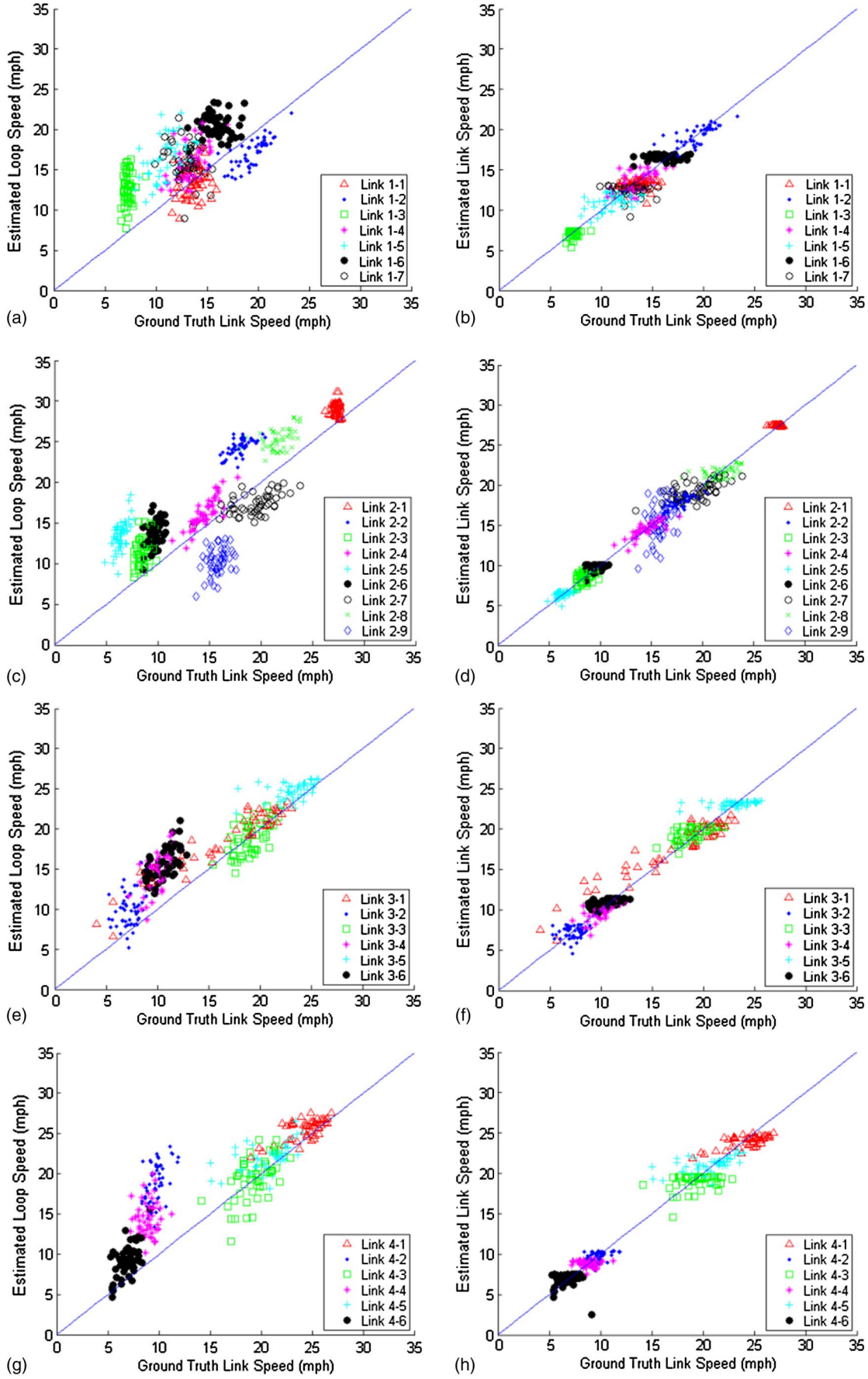

Fig. 4. Scenario 1 comparisons between estimated link speed $\hat{S}_L$, estimated link speed $\hat{S}_J$, and ground truth link speed S_J: (a) 8th Street WB (before); (b) 8th Street WB (after); (c) 8th Street EB (before); (d) 8th Street EB (after); (e) 112th Avenue SB (before); (f) 112th Avenue SB (after); (g) 112th Avenue NB (before); and (h) 112th Avenue NB (after)

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$$\mathrm{ME} = \frac{\sum_{t=1}^{n} (F(t) - G(t))}{n} \tag{12}$$

$$\mathrm{MAE} = \frac{\sum_{t=1}^{n} |(F(t) - G(t)|}{n} \tag{13}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{n} (F(t) - G(t))^2}{n}} \tag{14}$$

where $G(t)$ = ground truth link speed at time interval t; $F(t)$ = estimated (corrected) link speed at time interval t; and n = total number of samples for verification. Estimation error is defined by the difference between $G(t)$ and $F(t)$.

ME shows the effectiveness of mitigating system errors. This measure shows how accurately the model can estimate despite its precision. In terms of arterial performance, the link-speed estimation is usually averaged over a specific route or link over a period of time. In this case, random errors tend to be canceled out. Moreover, ME can show the directions of errors, including underestimation and overestimation. Unlike ME, MAE considers both random and system errors and shows how close the estimated link speeds are to the ground truth. RMSE is an appropriate measure of precision. RMSE measures the average magnitude of the error but penalizes large errors. The MAE and RMSE can be used jointly to determine the variation of the errors. The improvement percentage of the before and after study is calculated as

$$\text{Improvement} = \frac{B - A}{B} \times 100\% \tag{15}$$

where B = the before statistic and A is the after statistic.

Experimental Design

Two scenarios are designed for model verification. The first scenario is more ideal than the second one. In this case, the potential model users can decide how much effort is required to calibrate the model to the satisfactory level.

Scenario 1:

- Dataset 1 was used for g-factor calibration (Column 1 in Table 1). $\hat{S}_L(t)$ is calculated on the basis of the calibrated g-factor for each individual link.
- The link-speed estimation model was calibrated using Dataset 2 (500 cycles).

Scenario 2:

- A universal g-factor ($g = 2.2$) was calculated by randomly choosing one link from each route (Link 1-5, 2-5, 3-6, 4-4) is used for calculating $\hat{S}_L$.
- The link-speed estimation model is calibrated by using Dataset 1 (50 cycles). Cycle-by-cycle data are used to increase the sample size.

All of the calibrated models are applied to Dataset 3. To better visualize the results, the data are aggregated every 10 cycles (1,400 s). The evaluation results are shown in Table 1. Figs. 4 and 5 illustrate the visualization results of Scenarios 1 and 2, respectively. The left and right columns of Figs. 4 and 5 are the results before and after link-speed estimation, respectively. Visually, the proposed approach provides satisfactory results for estimating the link-journey speed. The quantitative analysis is elaborated in the next section.

Discussion

Effect of g-Factor

As expected, a universal g-factor ($g = 2.2$) results in relatively high MAE, ME, and RSME for every study route. As shown in Table 1, switching from using a specific g-factor for each link (Scenario 1) to using a universal g-factor (Scenario 2) increases MAE, ME, and RSME by 21.14% (from 3.5 to 4.24 mph), 34.83% (from 2.64 to 3.55 mph), and 18.17% (from 4.10 to 4.58 mph), respectively. This is not surprising because a better calibration can be achieved if site-specific data is used for the calibration at each location. The differences can be identified by visually comparing Figs. (4a, c, e, and f) with Figs. (5a, c, e, and f), respectively.

Model Evaluation

The proposed link-speed estimation model can be alternatively regarded as a link-speed correction model because the model considers only one parameter, $\hat{S}_L(t)$, and improves the results of $\hat{S}_L(t)$. After applying the proposed link-speed estimation model in Scenario 1, the MAE, ME, and RSME of all study routes decrease an average of 73.97% (from 3.5 to 0.91mph), 99.38% (from 2.64 to −0.02 mph), and 70.01% (from 3.87 to 1.16 mph), respectively. For all of the links, MEs are reduced to the range of [−0.47, 0.57].

The results are very encouraging. In Scenario 2, even though $\hat{S}_L(t)$ estimation is slightly worse because of a universal g-factor and the link-speed estimation model is calibrated using Dataset 1, a smaller dataset, the MAE, ME, and RSME of all routes improve an average of 64.31% (from 4.24 to 1.51 mph), 65.47% (from 3.55 to 1.23 mph), and 59.99% (from 4.58 to 1.83 mph), respectively. This result indicates that the accuracy of link-speed estimation can be significantly improved with relatively minor calibration efforts.

In both scenarios, the effectiveness of link-speed estimation can be observed in every link. For example, Link 4-2 has a dramatic improvement in the MAE (from 9.20 to 0.65 mph in Scenario 1 and from 10.40 to 1.19 mph in Scenario 2), ME (from 9.20 to 0 mph in Scenario 1 and from 10.40 to 1.07 mph in Scenario 2), and RSME (from 9.45 to 0.80 mph in Scenario 1 and from 10.66 to 1.38 mph in Scenario 2), respectively. This result shows the proposed model can effectively reduce the variation of the errors. The same effectiveness can be observed in Links 2-2 and 2-5. The higher the error, the more effective the improvement will be.

Model Limitation

The proposed model assumes the link-journey speed would be overestimated and the effect will increase as the measured loop speed increases. This assumption constrains the effectiveness of improvement for those underestimated link-journey speeds. The drawback of this constraint can be clearly found in Link 2-9. This link is a fairly challenging section because this section begins with two through lanes and ends with three through lanes and two left-turn lanes at the intersection approach. Additionally, this section includes two on-ramps and one off-ramp. All of these spatial factors are likely to result in inaccurate loop-speed estimation. Nevertheless, the speed-estimation model can still capture the underestimation effect by adopting a higher coefficient ($a = 1.42$). However, the coefficient ($b = -316.81$) in the speed-reduction term fails to capture the exponential speed-reduction effect. Even though Link 2-9 still has the highest RSME (2.15 mph) among all links after link-speed estimation, this result is still satisfactory for most applications. However, Link 2-9 performs less effectively in

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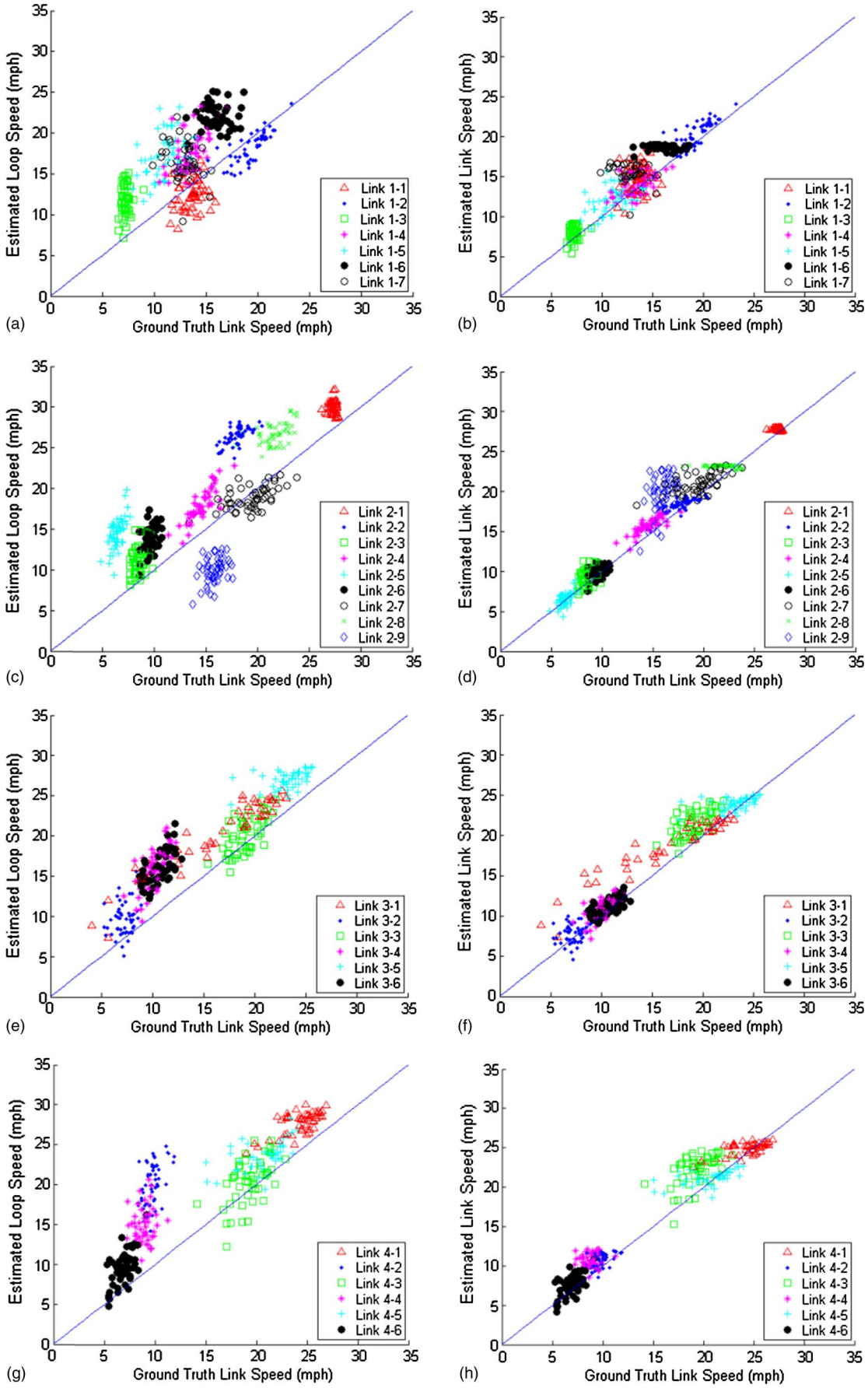

Fig. 5. Scenario 2 comparisons between estimated link speed $\hat{S}_L$, estimated link speed $\hat{S}_J$, and ground truth link speed S_J: (a) 8th Street WB (before); (b) 8th Street WB (after); (c) 8th Street EB (before); (d) 8th Street EB (after); (e) 112th Avenue SB (before); (f) 112th Avenue SB (after); (g) 112th Avenue NB (before); and (h) 112th Avenue NB (after)

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Scenario 2 with only minor improvement in MAE (from 5.94 to 3.79 mph), ME (−5.94 to 3.66 mph), and RSME (from 6.12 to 4.24 mph). One can observe that the coefficient ($a = 2.46$) for the link-speed estimation model is obviously overestimated and overcorrects the speeds. The same situation can be observed in Link 1-7. This might be because Link 1-7 begins with two through lanes and ends with two left-turn lanes, two through lanes, and one right-turn lane. Hence, only minor speed improvement is made in Scenario 2 according to MAE (from 3.71 to 2.74 mph), ME (3.37 to 2.48 mph), and RSME (from 4.32 to 3.07 mph). Both examples show the drawbacks of using a small sample size when calibrating the speed-estimation model for a roadway section with a complex geometric design. The corresponding results for Links 2-9 and 1-7 in Scenario 1 demonstrate the effectiveness of improvement by increasing the sample size.

Conclusions and Recommendations

Travel speed ties directly to travel time and hence is an important measure for quantifying arterial performance. However, accurately estimating the urban link travel speed is difficult because of traffic fluctuations and stop-and-go conditions caused by signal control. This research proposes a two-step approach to effectively estimate the link-journey speeds using merely advance loop detector outputs. The first step is to estimate the spot speed for the advance loop detector using the g-factor approach. A robust regression technique can then be used to calibrate the g-factor for loop-speed estimation. The second step is to estimate the link speed using the simplified speed-estimation model proposed in this research without any knowledge of signal timing plans. Traffic operations in the central business district (CBD) of the City of Bellevue, Washington, are simulated using the VISSIM traffic simulation model. The results show that only 50 cycles worth of data are needed to calibrate the g-factor in loop-speed estimation and the same datasets can be used to calibrate the proposed link-speed estimation model. The results are encouraging and satisfactory. The results also show that the accuracy of speed estimation may be further increased when more data are applied for calibration.

The proposed approach demonstrates its capability of handling system errors but it still has difficulties in minimizing some random errors. Hence, the approach is suitable to assist the arterial performance measurement over a relatively long time period, e.g., hourly. A thorough investigation is needed to reduce random errors when applying this approach to real-time cycle-by-cycle application. Even though the model is designed to accommodate most scenarios, only congestion conditions were considered and tested in this research. More extensive studies are needed to test and improve the proposed approach for various scenarios, such as different signal control schemes and congestion levels.

Acknowlegments

The writers would like to thank the City of Bellevue for providing arterial data and the VISSIM model. Specifically, the writers would like to thank Dong Hu, Mike Whiteaker, Fred Liang, and Poch Mark in the City of Bellevue for their assistance. Special thanks to Jonathan Corey for English assistance.

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