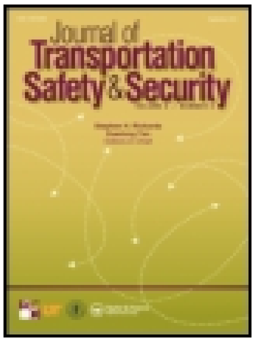


Taylor & Francis
Taylor & Francis Group

Journal of Transportation Safety & Security

ISSN: 1943-9962 (Print) 1943-9970 (Online) Journal homepage: https://www.tandfonline.com/loi/utss20

Traffic sensor data-based assessment of speed feedback signs

Abolfazl Karimpour, Robert Kluger & Yao-Jan Wu

JOURNAL OF TRANSPORTATION SAFETY & SECURITY
https://doi.org/10.1080/19439962.2020.1731038

Traffic sensor data-based assessment of speed feedback signs

Abolfazl Karimpour[a], Robert Kluger[b], and Yao-Jan Wu[a]

[a]Smart Transportation Lab, Department of Civil and Architectural Engineering and Mechanics, University of Arizona, Tucson, Arizona, USA; [b]Department of Civil and Environmental Engineering, J.B. Speed School of Engineering, University of Louisville, Louisville, Kentucky, USA

ABSTRACT
Excessive speed is a significant traffic safety concern on almost all types of roadways. A practical speed management strategy should improve mobility and vehicle progression by reducing nonrecurrent delays and improve public health and traffic safety by reducing the number of speeding-related crashes. Speed feedback signs are an effective speed management strategy. The objective of this article is two-fold: first, quantify the impact of SFS on arterial mobility at the link and intersection levels. Second, to conduct a data-driven safety assessment of arterials with active SFS. A major arterial in Tucson, AZ, with four existing SFS, was selected. Based on the initial results from the collected traffic sensor data, no significant difference was found among all traffic signal performance measures with and without an active SFS. However, statistically significant speed reduction was found at three out of four links after enabling the SFS. In addition, it was found that the impact of SFS on driver's behavior is a function of their approaching speed. The results of the safety assessment of SFS showed that at an arterial with a link speed of 35 mph, the benefit in dollar value per year associated with a reduction in the severe crash could pay as much as $700,000.

KEYWORDS
arterial efficiency; arterial mobility; safety enhancement; speed changing behavior model; speed feedback signs

1. Introduction

Excessive speed is a crucial traffic safety concern on almost all types of roadways. Speeding is the key contributing factor to many crashes (Imprialou, Quddus, Pitfield, & Lord, 2016; Pour-Rouholamin & Zhou, 2016). A study reported by the world health organization (WHO) stated that an increase of 0.6 mph in average speed could increase the risk of an injury crash by 3% and increase the risk of a fatal crash by 4–5%. Overall, drivers with speed higher than the posted speed will have a higher risk of a severe crash (Aarts & Van Schagen, 2006; Rune & Vaa, 2009). Recently, with the emergence of new technologies, ITS solutions, and various data-driven approaches, novel methods to improve mobility, and safety in the

CONTACT Yao-Jan Wu yaojan@email.arizona.edu Smart Transportation Lab, Department of Civil and Architectural Engineering and Mechanics, The University of Arizona 1209 E. Second St. Tucson, AZ 85721.

transportation network are evolving (Rahimi et al., 2019) (Rahimi, Shamshiripour, Shabanpour, Mohammadian & Auld, 2020). Real-time crash prediction (Parsa et al., 2020) (Ariannezhad, Wu & Goftar, 2018), micro-level (Razi-Ardakani, Mahmoudzadeh & Kermanshah, 2018) (Rahimi et al., 2020) and macro-level (Ariannezhad et al., 2020) safety analysis, and hot-spot prediction and analysis (Mansourkhaki et al., 2017) (Mansourkhaki et al., 2017) (Rahimi et al., 2019) (Mousavi, Zhnag, Parr, Pande & Wolson, 2019) are some of the innovative data-driven approaches recently adopted by transportation engineers to enhance roadways mobility and safety. In addition, The evaluation results of various studies showed that law enforcement is an effective speed management strategy. However, law enforcement is usually costly, and human resources are limited (Wegman & Goldenbeld, 2006). Therefore, considerable interest is steadily growing in developing more cost-effective and efficient speed management strategies. Speed feedback sign (SFS) is one practical solution that is usually used to address excessive vehicle speeds. SFSs, sometimes known as dynamic speed display signs (DSDSs), are roadside signs used to show drivers how fast they are driving. SFS typically operates using a radar and a changeable sign and can either be portable or fixed. SFSs are usually characterized into two categories (Jeihani, Ardeshiri, & Naeeni, 2012): (1) warn the drivers exceeding the posted speed limit by displaying "SLOW DOWN" or similar warning message (Garber & Srinivasan, 1998; McAvoy & Stocker Center, 2011), and (2) as a passive information device to show the speed limit and passing vehicles' speeds (Ullman & Rose, 2004).

SFSs are generally installed in work zones, school zones, and other areas with a high risk of crashes. The effectiveness of SFS depends on the location of deployment (e.g., work zones, school zones), and the change in impact over time. That is, the speed reduction due to the installation of SFS might be different in school zones compared to work zones. In addition, average speed reduction is relatively more immediately after installation compared to weeks after installation (Chitturi & Benekohal, 2006; Jeihani et al., 2012; McAvoy & Stocker Center, 2011; Pesti & McCoy, 2001; Strawderman, Huang, & Garrison, 2013; Ullman & Rose, 2005; Wrapson, Harré, & Murrell, 2006).

For work zones, Pesti and McCoy (2001) studied three SFSs along a 2.7-mile segment between two work zones on I-80 and collected speed data for five weeks. The mean, 85th percentile and standard deviation of vehicle speeds were used as the measures of effectiveness. Pesti and McCoy found that SFSs are effective in reducing average speed and the proportion of drivers exceeding the speed limit during the study period (Pesti & McCoy, 2001). Similar studies on a high-speed work zone showed that SFS could reduce the speed in the work zone by about 5 mph (Carlson, Fontaine, Hawkins, Murphy, & Brown, 2000).

Ullman and Rose (2005) installed several SFSs in three types of locations: a school zone, a horizontal curve, and a speed transition zone ahead of a school zone. The results from their study showed that SFS could reduce the speed by 9 mph in school zones and by less than 5 mph in other locations (Ullman & Rose, 2005). The short-term and long-term effects of SFS in the school zone were also assessed in a study in South Korea. Two school zones were selected, and two SFSs were installed. The short-term results showed that the speed of vehicles was reduced by 17.5% throughout the day. However, long-term results showed that the speed was reduced by only 12.5% throughout the day at the SFS locations (Lee, Lee, Choi, & Oh, 2006).

The effectiveness of SFS in reducing speed on urban roads and within a transition area (i.e., the segment between two consecutive speed limits) was also assessed in many studies. Wrapson et al. (2006) installed an SFS on a congested two-lane road in Waitakere City, New Zealand. The results demonstrated a statistically significant reduction in the proportion of drivers exceeding the speed limit by 6 mph (Wrapson et al., 2006). Another study assessed the impact of installing SFS on single-lane urban roads in London. This study was conducted at ten sites in London for three weeks. Overall, the average vehicle speeds for all sites were reduced by 1.4 mph. In addition, a statistically significant increase in speed limit compliance was achieved (Walter & Broughton, 2011). The impact of SFS in the transition areas were also assessed in a study by Cruzado and Donnell (2009) and (Sandberg, Schoenecker, Sebastian & Soler, 2006). In this study, twelve sites were selected such that each had a different speed limit transition. An SFS was active for a one week to two weeks period at each site. The results showed that the average vehicle speed was reduced by 6 mph, and the proportion of vehicles exceeding the speed limit was also reduced. However, the observed reduction disappeared after removing the signs. Reverting to previous speeds after sign removal indicates the signs were effective at the study sites within the scope of the study (Cruzado & Donnell, 2009).

Effectiveness of SFS in the reduction of average speed and proportion of vehicles exceeding the speed limit has been studied in some of the most recent studies. Karimpour, Kluger, Liu, and Wu (2020) evaluated the effectiveness of three different speed management strategies, namely: (1) speed feedback sign (SFS), (2) periodic law enforcement (E), (3) SFS supported by periodic law enforcement (SFS + E), in reducing the average speed and speed violations in Tucson, Arizona. The results of this study revealed that supporting SFS with periodic law enforcement is the most effective strategy. Also, Karimpour et al. showed that supporting speed feedback with periodic law enforcement can eliminate the halo effect caused by fixed-point speed management strategies (Karimpour et al., 2020). Zineddin et al. (2016) installed SFS on 20 high-crash curve sites on rural two-lane roadways sites. The results of this study showed that for almost all the sites, average and 85th percentile of speed was decreased by up to 11 mph and 3 mph, respectively. Also, a significant reduction in the number of vehicles traveling over the speed limits was observed (Zineddin, Hallmark, & Hawkins, 2016) . In a similar study, Hallmark et al. (2015) evaluated the effectiveness of SFS on both average speed and crash reduction at 22 sites in several states. Data were collected 1, 12, and 24 months after installation of the signs. The average speed reduction was 1.82 mph, 2.57 mph, and 1.97 mph on average for all the sites, for 1, 12, and 24 months after signs installation. Moreover, the authors suggested SFS's crash modification factor of 0.9–0.95 (Hallmark, Hawkins, & Smadi, 2015). In another study, Ardeshiri and Jeihani (2014) evaluated the positive impact of installing SFS on driver's behavior at three corridors with different speed limits (25 mph, 35 mph, and 45 mph. Speed data was collected at upstream of, adjacent to, and downstream of the signs for a short-time and long-time after installing the signs. Based on three methods, conventional *t*-test, regression models and Bayesian methods, it was found that speed limit compliance was increased by 5% and average speed was reduced in more than 40% of the cases (Ardeshiri & Jeihani, 2014). Furthermore, the impact of different types of SFS in reducing speed and improving traffic safety was evaluated in a study in Germany. Three types of SFS, (i) SFS with driver's actual speed; (ii) SFS with driver's actual speed that highlights whether the car driver complied with or exceeded the speed limit; and (iii) a verbal SFS with the word "Thank You" when the car driver kept the speed limit and the word SLOW when the driver exceeded the speed limit. The results showed that all three types were effective in reducing average speed, 85th percentile of speed, and the percentage of vehicles exceeding the speed limit (Gehlert, Schulze, & Schlag, 2012). Table 1 summarizes all the studies conducted on the effectiveness of SFS from 2000 to 2020.

As shown by previous studies, the positive impact of deploying SFSs in reducing speed and increasing speed limit compliance in work zones, school zones, and transition areas has been widely studied. However, most studies focused on either mobility (efficiency) or the safety impacts instead of providing a comprehensive approach to evaluating the impacts of SFS on both mobility and safety. When it comes to mobility evaluation, previous studies focused more on the arterial level instead of breaking the evaluation into the link (the segment between two intersections) and the intersection levels. The evaluation process tends to be influenced by the upstream and downstream intersections, so the vehicles running on the link would still dynamically change their speeds. Investigating SFS

Table 1. Previous studies on the effectiveness of SFS.

Authors	Year	Roadway type	Impact (comments)
Carlson et al.	2000	Work zone	• Reduction in the average speed • Increase in the speed limit compliance
Pesti and McCoy	2001	Work zone	• Reduction in average speed • Increase in the speed limit compliance
Ullman and Rose	2005	School zone; horizontal curve; speed transition zone	• Average speed reduced by nine mph in the school zone • Average speed reduced by less than five mph in other locations
Lee et al.	2006	School zone	• Short-term effect: average speed reduced by 17.5% • Long-term effect: average speed reduced by 12.5%
Wrapson et al.	2006	Two-lane urban road	• Average speed reduced by six mph
Sandberg et al.	2006	Transition zones	• Average speed reduced by six to eight mph • Increase in the speed limit compliance
Cruzado and Donnell	2009	Transition areas	• Average speed reduced by six mph • Increase in the speed limit compliance
Walter and Broughton	2011	Single-lane urban roads	• Average speed reduced by 1.4 mph
Gehlert et al.	2012	Two-lane local main street	• Reduction in the average speed • Reduction in the 85th percentile of speed • Increase in the speed limit compliance
Ardeshiri and Jeihani	2014	Three corridors with different speed limits	• Speed limit compliance was increased by 5 % Average speed was reduced in more than 40% of the cases
Hallmark et al.	2015	Nationwide study	• Average speed reduction was 1.82 mph, 2.57 mph, and 1.97 mph on average for all the sites
Zineddin et al.	2016	Two-lane rural curves	• On average, most sites had a reduction in the average speed by almost 11 mph
Karimpour et al.	2020	Nine sites in major arterials- supported SFS with periodic law enforcement	• Supporting SFS with periodic law enforcement is more effective in reducing average speed and the percentage of vehicles exceeding the speed limit than SFS only, compared to SFS-only • Supporting speed feedback with periodic law enforcement can eliminate the halo effect

impact at both link and intersections levels provide more comprehensive insight. Furthermore, the majority of the studies used historical crash data to investigate the SFS impact on safety. Collecting such data takes time and effort. A comprehensive approach to evaluating safety and mobility would be critical to advance the studies of SFS. Therefore, the objectives of this study were are three-fold: (1) evaluating the impact of SFS at the intersection and the link levels to identify the impacts of SFS on mobility, (2) developing driver's speed change behavior models to relate the driver speed before and after disabling the SFS, and (3) developing a method revised from previous research to estimate the safety benefit of SFS without collection of crash data.

2. Observational study design

Ina Rd, a major signalized arterial in Tucson, Arizona, with a speed limit of 45 mph, was selected as the study corridor. Ina Rd is a multimodal arterial that moves traffic east-west with access to Interstate 10. Four segments shown in Figure 1 were used as study sites. SFS was installed in advance of each intersection, and MioVision TrafficLink (MioVision Team, 2019) unit was installed at each intersection, providing real-time performance metrics through an online platform. This corridor was selected because of the existing SFSs installed by PCDOT along the corridor between signalized intersections and the due to the presence of advanced traffic data collection systems. The corridor operates on a coordinated plan during peak hours, and the signals operate independently in the off-peak hours.

Table 2 lists the four study segments, including the segment length, speed limit, upstream and downstream intersection, and the distance of each SFS to the downstream intersection.

The SFSs used in this study were fixed black and white rectangular signs with "YOUR SPEED" text above the display. When excessive speed is detected (10 mph over speed limit), the "SLOW DOWN" message is displayed; otherwise, the vehicle speed is displayed. The signs were paired with speed limit signs for driver reference (Figure 2).

The data collection period was four weeks (May 28–June 25, 2018), and the existing signs were disabled for two weeks (June 11th–June 25th) during the data collection. To evaluate the arterial operations, five performance measures were collected at each intersection using MioVision's TrafficLink

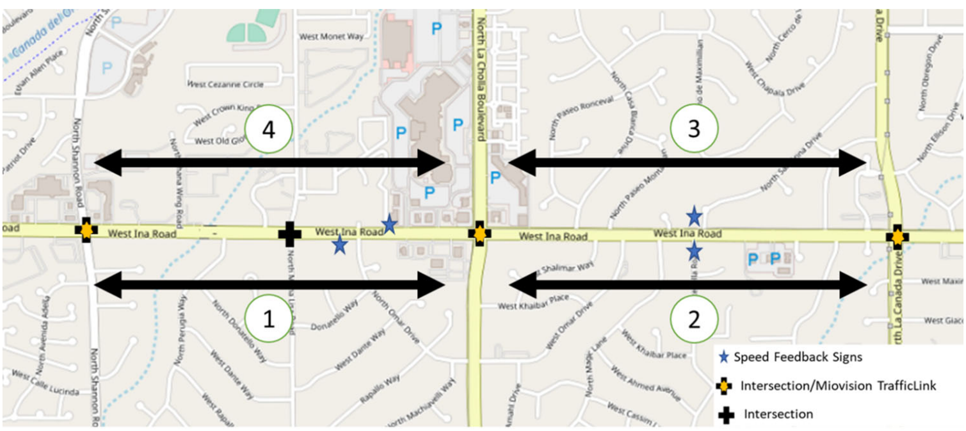


Figure 1. Study corridor.

Table 2. Description of study segments.

Segment ID	Direction	County	Upstream intersection	Downstream intersection	Segment length (miles)	SFS distance to downstream (miles)	Speed limit (mph)
1	Eastbound	Pima	N Shannon Rd	N La Cholla Blvd.	0.98	0.24	45
2	Eastbound	Pima	N La Cholla Blvd	N La Canada Dr.	1.02	0.4	45
3	Westbound	Pima	N La Canada Dr	N La Cholla Blvd.	1.02	0.47	45
4	Westbound	Pima	N La Cholla Blvd	N Shannon Rd.	0.98	0.38	45

Figure 2. Speed feedback sign used in this study.

platform (MioVision Team, 2019), including volume, percent arrival on red, intersection delay, split failures, and link speed. Percent of arrival on red, split failure, and intersection delay were collected using high-resolution controller event-based data, and the link speed was estimated using Wi-Fi sensors. The definition of each performance measure is:

1. Volume: Number of vehicles arriving at an intersection, aggregated every 15-min by each approach.
2. Percent arrival on red: This measure shows the percentage of vehicles that arrived at the intersection when the signal was red.
3. Intersection delay: Total amount of time that all vehicles spend in the intersection queue while waiting to pass the intersection.
4. Split failure: The occurrence of left-over demand for a specific approach at an intersection. It indicates at least one vehicle from the queue was not served during the cycle.
5. Link speed: The average vehicles operating speed on each roadway links.

The first four measures were collected at the intersection level. The last measure, link speed, was collected at a link level. A link is the roadway segment between two intersections.

3. Preliminary results

Using the performance measures collected from Miovision sensors, the potential impact of SFS on arterial safety and mobility was evaluated. The evaluation was conducted at the link and intersection levels. Highway Capacity Manual (HCM) recommends using control delay and queue length for evaluating the intersection performance measure and travel time and travel speed as the corridor performance measure (Urbanik et al., 2015). In addition, many studies suggested using arrivals on green/red and split failure for evaluating corridor and intersection performance (Day, Li, Sturdevant, & Bullock, 2018; Day et al., 2016; Remias, Day, Waddell, Kirsch, & Trepanier, 2018). For instance, Day et al. (2018) evaluated the improvement of signalized intersection performance after retiming and coordinating the intersections on SR 77, Indiana using the arrival on red and arrival on green measures. Similarly, in this study, percent of arrival on red, intersection delay, and split failure were used as the intersection level measures, and link speed was used as the corridor level measure.

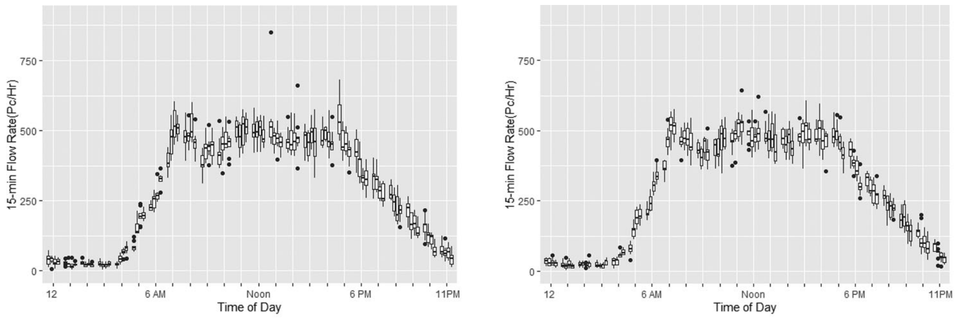
Before conducting the before and after comparison of the measures, aggregated traffic flow from major and minor streets was used to capture the possible fluctuation of traffic flow during the study period. Figure 3 illustrates the average hourly traffic flow for the study segments during the study periods.

Based on Figure 3, for a given time of day before and after disabling SFS, only a little variation in traffic flow was observed. Similar traffic flow peaks for all the segments suggest that traffic flow was not affected by disabling the SFS.

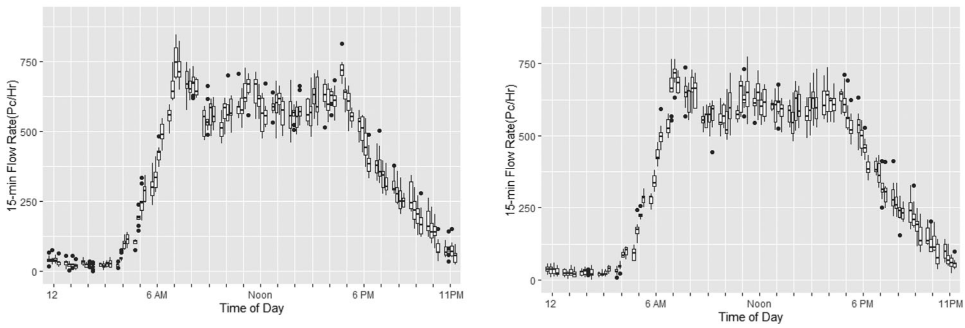
In the next section, the mobility impact of SFS on intersection and corridor will be evaluated. In addition, to evaluate the impact of SFS on driver behavior, the driver's speed change behavior models will be developed.

4. Mobility impact at intersections

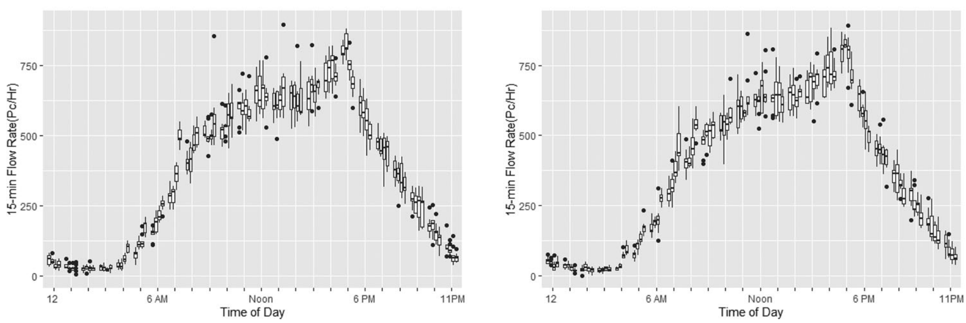
The mobility impact of SFS was evaluated at intersection and corridor levels. To evaluate the impact of SFS at an intersection level, several signal performance measures were used, and a before-after study framework was designed as in Table 3. *AR*, *SF*, and *De* are the segment percent arrival on red, split failure, and intersection delay, respectively. In Table 3, the null hypothesis (H_0) states that the population means (e.g., arrival on red) are equal between the related segments before and after disabling the SFS, and the alternative hypothesis (H_a) states that the population means (e.g., mean travel time) are not equal between the related segments before and after disabling the SFS (i.e., for at least one segment the population means before and after disabling the SFS is different). Table 3 illustrates the hypotheses



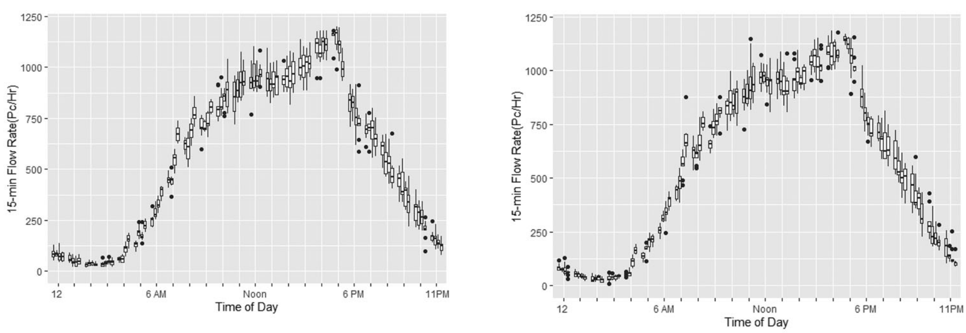
Segment 1: Eastbound from N Shannon Rd. to N La Cholla Blvd.



Segment 2: Eastbound from N La Cholla Blvd. to N La Canada Dr.



Segment 3: Westbound from N La Canada Dr. to N La Cholla Blvd.



Segment 4: Westbound from N La Cholla Blvd. to N Shannon Rd.

Figure 3. Traffic flow dispersion before and after disabling SFS.

Table 3. Hypothesis test.

Hypothesis tests	Other statistics to be tested
$H_0: \mu_{AR}^{S1}ON = \mu_{AR}^{S1}OFF\ \&\ \mu_{AR}^{S2}ON = \mu_{AR}^{S2}OFF\ \&\ \mu_{AR}^{S3}ON = \mu_{AR}^{S3}OFF\ \&\ \mu_{AR}^{S4}ON = \mu_{AR}^{S4}OFF$	Variance (σ^2)
$H_a: \mu_{AR}^{S1}ON \neq \mu_{AR}^{S1}OFF\ OR\ \mu_{AR}^{S2}ON \neq \mu_{AR}^{S2}OFF\ OR\ \mu_{AR}^{S3}ON \neq \mu_{AR}^{S3}OFFOR\ \mu_{AR}^{S4}ON \neq\ \mu_{AR}^{S4}OFF$	
$H_0: \mu_{SF}^{S1}ON = \mu_{SF}^{S1}OFF\ \&\ \mu_{SF}^{S2}ON = \mu_{SF}^{S2}OFF\ \&\ \mu_{SF}^{S3}ON = \mu_{SF}^{S3}OFF\ \&\ \mu_{SF}^{S4}ON = \mu_{SF}^{S4}OFF$	Variance (σ^2)
$H_a: \mu_{SF}^{S1}ON \neq \mu_{SF}^{S1}OFF\ OR\ \mu_{SF}^{S2}ON \neq \mu_{SF}^{S2}OFF\ OR\ \mu_{SF}^{S3}ON \neq \mu_{SF}^{S3}OFF\ OR\ \mu_{SF}^{S4}ON \neq \mu_{SF}^{S4}OFF$	
$H_0: \mu_{De}^{S1}ON = \mu_{De}^{S1}OFF\ \&\ \mu_{De}^{S2}ON = \mu_{De}^{S2}OFF\ \&\ \mu_{De}^{S3}ON = \mu_{De}^{S3}OFF\ \&\ \mu_{De}^{S4}ON = \mu_{De}^{S4}OFF$	Variance (σ^2)
$H_a: \mu_{De}^{S1}ON \neq \mu_{De}^{S1}OFF\ OR\ \mu_{De}^{S2}ON \neq \mu_{De}^{S2}OFF\ OR\ \mu_{De}^{S3}ON \neq \mu_{De}^{S3}OFF\ OR\ \mu_{De}^{S4}ON \neq \mu_{De}^{S4}OFF$	

developed for the Mean (μ) value of each measure. Similar hypotheses were also developed for the variance of each measure (σ^2).

It is worthwhile to mention that the logical operator used for the alternative hypotheses is "OR", meaning that the null hypothesis could be rejected if at least one mean (or other respective parameters) is different in related segments for before and after condition.

To develop the hypothesis in Table 3, parametric or non-parametric statistical tests that examine the differences between the selected performance measures (e.g., mean delay, the variance of delay) before and after disabling the SFS should be used. Generally, tests with repeated measures are the best approach to find the difference between a treatment (in this case, SFS or No SFS) across multiple attempts (in this case, different segments) (Gueorguieva and Krystal, 2004). However, before using parametric tests with repeated measures, such as ANOVA with repeated measures, two assumptions of population normality and homogenously of variance among treatments need to be tested (Vincent & Weir, 1999). In this study, these assumptions were tested using Kolmogorov–Smirnov (K-S) tests, and the results showed that none of the measures in this study conformed to a normal distribution. Therefore, an appropriate alternative non-parametric test was selected

Compared to more traditional parametric tests, non-parametric tests have fewer assumptions regarding the underlying distribution of the population. Moreover, the assumption of the equal variance of the populations can be ignored by using ranks in non-parametric approaches. Since the Friedman test (Friedman, 1937) does not assume a particular distribution (i.e., normal) for the data, and is a standard test to compare treatments across blocks (Zimmerman & Zumbo, 1993), it is a suitable non-parametric test for our study. In the Friedman test, the null hypothesis states that responses from different treatments have the same or similar distributions (Pereira, Afonso, & Medeiros, 2015; Sidney, 1956).

To develop the Friedman test statistic, the measures (e.g., delay) are formatted into a matrix with N rows and K columns (Benavoli, Corani, & Mangili, 2016); K denotes the treatments and N denotes the number of blocks for each treatment. Assume we have a matrix in the form of $\{x_{i,j}\}_{N,K}$:

$$x_{i,j} = \begin{bmatrix} x_{1,1} & x_{1,2} & x_{1,3} & \cdots \\ x_{2,1} & x_{2,2} & x_{2,3} & \cdots \\ x_{3,1} & x_{2,3} & \ddots & \cdots \\ \vdots & \vdots & \vdots & x_{N,K} \end{bmatrix}$$

where the columns represent each treatment (i.e., before and after disabling the SFS), and the rows represent each block (for our study, the measures are collected from four segments). Now, denote r_{ij} as a new matrix of $\{r_{i,j}\}_{N,K}$, where r_{ij} is the rank of $x_{i,j}$ within each attempt, the test statistic T for the Friedman test is defined by Equation 1 (Sidney, 1956):

$$T = \frac{N\sum_{j=1}^{K}(\bar{r}_{.j}-\bar{r})^2}{\frac{1}{N(K-1)}\sum_{i=1}^{N}\sum_{j=1}^{K}(r_{ij}-\bar{r})^2} \tag{1}$$

where:

$$\bar{r}_{.j} = \frac{1}{N}\sum_{i=1}^{N} r_{ij} \tag{2}$$

$$\bar{r} = \frac{1}{NK}\sum_{i=1}^{N}\sum_{j=1}^{K} r_{ij} \tag{3}$$

where N is the number of blocks, K is the number of treatments, and T is the test statistic. As N approaches infinity, T will follow a chi-square distribution with $K-1$ degrees of freedom. A study conducted by Zimmerman and Zumbo (1993) showed that the Friedman test pattern is essentially the same, whether using two treatments, three treatments, or many treatments.

In our study, $K=2$ and is the number of treatments (before and after disabling the SFS), and the number of blocks, $N=4$, is the number of segments. Based on a study done by Pereira et al. (2015) for a small value of K and N, the exact critical values should be directly used from available tables (Pereira et al., 2015).

To include the time factor in our analysis, the hypothesis tests in Table 3 were implemented for morning-peak, afternoon-peak, and off-peak hours during the weekdays. To evaluate the impact of SFS on percent arrivals on red, the hypotheses were developed based on two statistics: mean and variance of percent arrivals on red. The hypotheses will be used to test whether there is any difference between the parameters associated with the percent arrivals on red before and after disabling the SFS. For instance, the hypothesis for mean percent arrivals on red was as below:

Table 4. Hypothesis tests for percent arrivals on red.

	Friedman test	Period	Chi-square (χ^2)	*P*-value	Decision[a]
Mean	H_0 : $\mu_{AR}^{Si}ON = \mu_{AR}^{Si}OFF$ H_a= for at least one segment,	AM-peak	6	0.11	✗
	the mean percent arrival on red before	PM-peak	6	0.11	✗
	and after disabling the SFS is different	Off-peak	6	0.11	✗
Variance	H_0 : $\sigma^{2Si}_{AR}ON = \sigma^{2Si}_{AR}OFF$ H_a= for at least one segment,	AM-peak	6	0.11	✗
	the variance of percent arrival on red before	PM-peak	5.4	0.14	✗
	and after disabling the SFS is different	Off-peak	6	0.11	✗

[a]Fail to reject (✗), reject (✓); AR: percent of arrival on red.

$$
\begin{aligned}
H_0 &: \mu_{AR}^{S1}ON = \mu_{AR}^{S1}OFF \ \& \ \mu_{AR}^{S2}ON = \mu_{AR}^{S2}OFF \ \& \ \mu_{AR}^{S3}ON \\
&= \mu_{AR}^{S3}OFF \ \& \ \mu_{AR}^{S4}ON = \mu_{AR}^{S4}OFF \\
H_a &: \mu_{AR}^{S1}ON \neq \mu_{AR}^{S1}OFF \ OR \ \mu_{AR}^{S2}ON \neq \mu_{AR}^{S2}OFF \ OR \ \mu_{AR}^{S3}ON \ / \\
&= \mu_{AR}^{S3}OFF \ OR \ \mu_{AR}^{S4}ON \neq \mu_{AR}^{S4}OFF
\end{aligned}
$$

The null hypothesis (H_0) states that the mean percent arrivals are equal between the related segments before and after disabling the SFS, and the alternative hypothesis (H_a) states that at least one of the mean percent arrivals are not equal between the related segments before and after disabling the SFS. Similar null and alternative hypotheses were also developed for the variance of percent arrivals on red. Table 4 illustrates the summary result of the hypotheses and the corresponding p-values for each test.

Results from Table 4 indicate that, at a significance level of $\alpha = 0.05$, there is not sufficient evidence to reject the null hypothesis. In other words, based on these results, the operation of SFS does not have a statistically significant impact on the percent arrivals on red. To visualize the results from Table 4, the density plot for the percent arrivals on red for the morning peak-hours during the study period is illustrated in Figure 4. The gray dashed-lines show the conditions when the SFS was active, and the black solid lines show the conditions when the SFS was off. The distribution of the percent arrivals on red, before and after disabling the SFS have similar peaks for each of the segments.

The summary of hypotheses for intersection delay and split failure are provided in Table 5. The intersection delay and split failure were collected for all the movements. Therefore, the results were separated for through and left-turn movements.

The results from Table 5 indicate that, at a significance level of 0.05, there is not sufficient evidence to reject the null hypothesis. In other words, based on these results, the existence of SFS does not have a statistically significant impact on either the split failure or intersection delay.

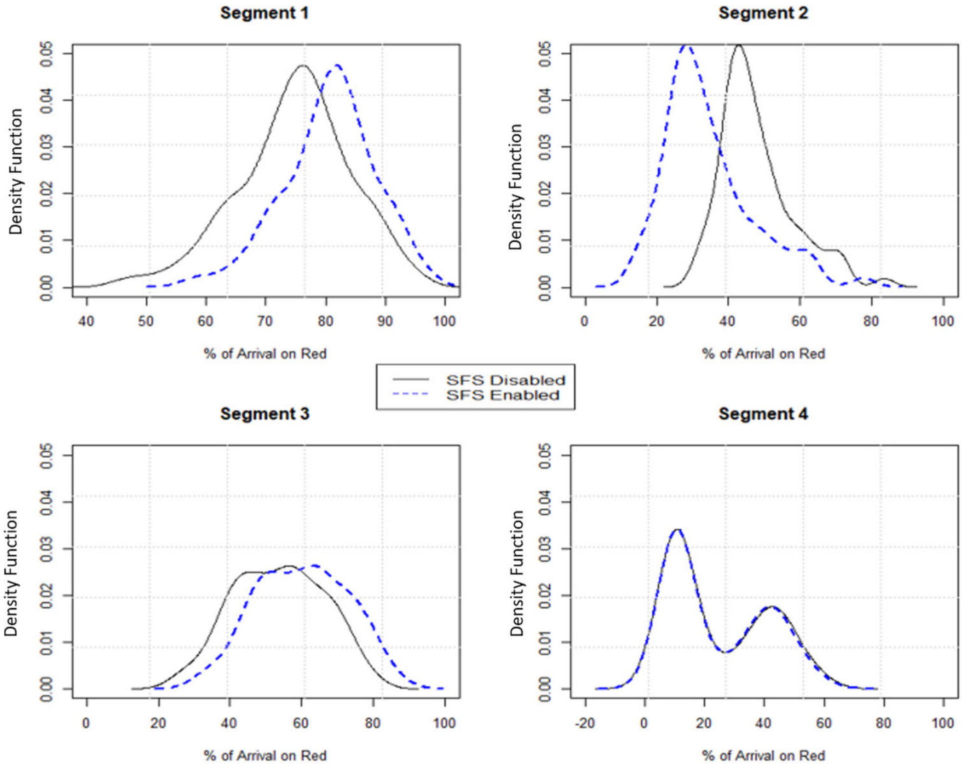


Figure 4. Density plot for arrival on red; morning peak hours.

Table 5. Hypothesis tests for split failure and intersection delay.

	Friedman test	Movement	Period	Chi-square (χ^2)	*P*-Value	Decision[a]
Split failure						
Mean	$H_0 : \mu_{SF}^{Si}ON = \mu_{SF}^{Si}OFF$ H_a= for at least one segment, the mean split failure before and after disabling the SFS is different	Through	AM-peak	5.4	0.14	✗
			pm-peak	6	0.11	✗
			Off-peak	6	0.11	✗
		Left	AM-peak	6	0.11	✗
			PM-peak	6	0.11	✗
			Off-peak	6	0.11	✗
Variance	$H_0 : \sigma^{2Si}_{SF}ON = \sigma^{2Si}_{SF}OFF$ H_a= for at least one segment, the variance of split failure before and after disabling the SFS is different	Through	AM-peak	5.4	0.14	✗
			PM-peak	6	0.11	✗
			Off-peak	5.4	0.14	✗
		Left	AM-peak	6	0.11	✗
			PM-peak	6	0.11	✗
			Off-peak	6	0.11	✗
Delay						
Mean	$H_0 : \mu_{De}^{Si}ON = \mu_{De}^{Si}OFF$ H_a= for at least one segment, the mean delay before and after disabling the SFS is different	Through	AM-peak	6	0.11	✗
			PM-peak	6	0.11	✗
			Off-peak	6	0.11	✗
		Left	AM-peak	6	0.11	✗
			PM-peak	6	0.11	✗
			Off-peak	6	0.11	✗
Variance	$H_0 : \sigma^{2Si}_{De}ON = \sigma^{2Si}_{De}OFF$ H_a= for at least one segment, the variance of delay before and after disabling the SFS is different	Through	AM-peak	5.4	0.14	✗
			PM-peak	5.4	0.14	✗
			Off-peak	6	0.11	✗
		Left	AM-peak	6	0.11	✗
			PM-peak	6	0.11	✗
			Off-peak	6	0.11	✗

[a]Fail to reject (✗), reject (✓); SF: intersection split failure; De: intersection delay.

Overall, based on the results from the statistical tests, with 95% confidence, we were not able to point out any significant effect caused by SFS on the signal performance measures, and consequently, the arterial mobility at the intersection level. However, further inspection is required to point out if enabling the SFS will affect the arterial mobility at the link level.

5. Mobility impact on arterial links

To evaluate the potential impact of SFS on arterial links, the performance measure used was the link speed. Statistical comparisons between link speed before and after disabling the SFS were performed as appropriate. Tables 6 and 7 demonstrate the average link speed and 85th percentile of link speed, respectively, during the times were SFS were enabled and disabled.

Tables 6 and 7 show a statistically significant increase at the level of $p = 0.05$ in the link speed and 85th percentile of link speed after disabling the SFS. Overall, after disabling the SFS link speed increased at three out of four sites during the weekday and two out of four sites during the weekend. It is worthwhile to mention that, intuitively, the extent of the impact of SFS on driver operating speed is varied, and it is expected to be a function of their running speed. That is, drivers with a higher running speed tend to reduce their speed at a higher rate after observing their speed on the SFS display.

Speed variability is another factor that could directly impact arterial mobility and signal performance (Kockelman & Ma, 2007; Wang, Zhou, Quddus, & Fan, 2018). Therefore, it is also essential to evaluate the

Table 6. Link speed and 85th percentile link speed-weekday.

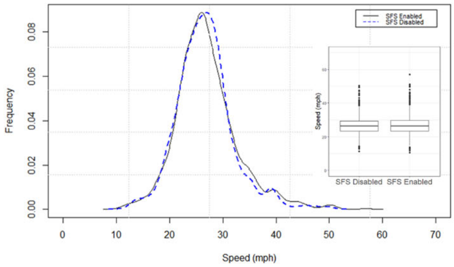
Weekday									
		Link speed (mph)				85th percentile link speed (mph)[b]			
Site	Sample Size	Disabled	Enabled	*P*-value	Decision[a]	Disabled	Enabled	*P*-value	Decision[a]
1	970	28.2	27.3	<0.05	✓	32.9	29.1	<0.05	✓
2	970	34.2	33.1	<0.05	✓	38.1	37.2	0.01	✓
3	970	35.8	34.2	<0.05	✓	38.7	37.8	<0.05	✓
4	970	34.9	34.4	0.6250	✗	40.2	39.5	0.09	✗

[a]Fail to reject (✗), reject (✓).
[b]To compare the 85th percentile of link speed permutation test is used.

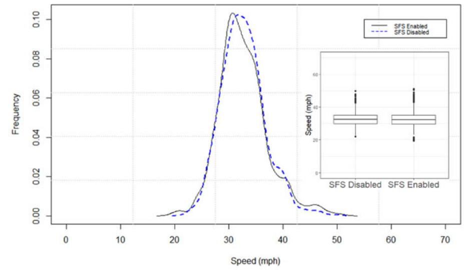
Table 7. Link speed and 85th percentile link speed-weekend.

Weekend									
		Link speed (mph)				85th percentile link speed (mph)[b]			
Site	Sample size	Disabled	Enabled	*P*-value	Decision	Disabled	Enabled	*P*-value	Decision[a]
1	388	30.7	28.6	<0.05	✓	34.1	31.5	<0.05	✓
2	388	35.1	33.2	<0.05	✓	38.2	37.1	0.02	✓
3	388	35.6	35	0.11	✗	39.1	38.5	0.75	✗
4	388	37	36	0.14	✗	41.1	40	0.31	✗

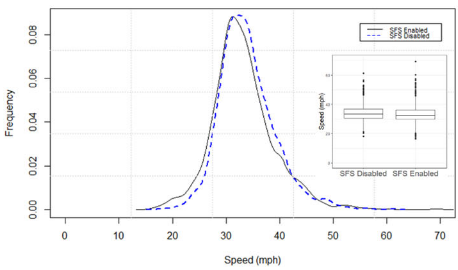
[a]Fail to reject (✗), reject (✓).
[b]To compare the 85th percentile of link speed permutation test is used.



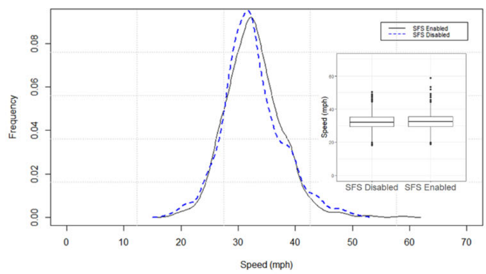
Segment 1: from N Shannon Rd to N La Cholla Blvd.
($SD_{SFS-enabled}$ = 5.9 mph; $SD_{SFS-disabled}$ =5.3 mph)



Segment 2: from N La Cholla Blvd. to N La Canada Dr.
($SD_{SFS-enabled}$ = 4.5 mph; $SD_{SFS-disabled}$ = 4.01 mph



Segment 3: from N La Canada Dr. to N La Cholla Blvd.
($SD_{SFS-enabled}$ = 5.8 mph; $SD_{SFS-disabled}$ =5.2 mph)



Segment 4: from N La Cholla Blvd. to N Shannon Rd.
($SD_{SFS-enabled}$ = 4.9 mph; $SD_{SFS-disabled}$ = 5.1 mph)

Figure 5. Speed density distribution and speed box plot.

potential impact of SFS on link speed variation. Figure 5 illustrates the probability density plot and box plot of the link speed at each segment before and after disabling the SFS. The standard deviations of the speed distribution before and after disabling the SFS are shown in the parenthesis.

For all the segments (except segment 4), link speed before and after disabling the SFS has a similar peak. However, the mean value has been shifted and increased after disabling the SFS. In addition, for all the segments (except segment 4), the speed variation decreased by disabling the SFS. Based on the results of the statistical test for equality of the variance, the difference of link speed variances before and after disabling the SFS was statistically significant for all the segments at level of $p = 0.05$, except segment 4 (p-value= 0.08).

5.1. Impact of SFS on vehicle speed dispersion

Speeding is a general issue in traffic studies and is usually a contributing factor to both crash severity and frequency. In this study, driver speed change behavior models were estimated to understand drivers' behavior while approaching SFS. These behavior models relate the link speed before and after disabling the SFS. To develop the driver speed change behavior model, linear mixed models (LMM) were formulated between the link speed before and after disabling the SFS.

LMM models are an extension of simple linear models that allow the users to include both fixed and random effects into the modeling procedure (Fox, 2015). The mixed models are usually used when modeling the data from multiple levels (in our case, the data are collected from multiple sites). In addition to the fixed-effect terms in a simple linear model, the mixed model incorporates several random-effect terms. The random-effect terms made the mixed models appropriate for modeling the data that are collected hierarchically. In theory, the linear mixed models are formulated in Equation 4 (West, Welch, & Galecki, 2014):

$$y = X\beta + Zc + \epsilon \tag{4}$$

where y is the vector of outcomes, X is the design matrix of fixed-effect terms, β is the vector of fixed-effect coefficients. Z is the matrix of random-effect terms, c is the vector of random-effect terms and ϵ is the vector of residuals.

The design matrix of fixed-effect terms (X) is consist of two columns: intercept and $y_{t,j}^{off}$; where $y_{t,j}^{off}$ is the link speed at the time of t for the jth site, when the SFS is disabled. The vector of outcomes (Y) consists of one column, $y_{t,j}^{on}$; where $y_{t,j}^{on}$ is the link speed at time t for the j^{th} site, when the SFS is enabled. β_0, β_1 are the coefficients of the fixed-effect terms. In the design matrix of random-effect terms (Z), each column represents one site and each row represents one observation. If the observation belongs to the site in that column, $z_{t,j} = 1$ otherwise, $z_{t,j} = 0$. Equation 4 can be reformulated as bellow:

$$\begin{aligned} \begin{bmatrix} y_{1,1}^{on} \\ y_{1,2}^{on} \\ \vdots \\ y_{4,N}^{on} \end{bmatrix}_{N\times 1} &= \begin{bmatrix} \text{Intercept} & y_{1,1}^{off} \\ 1 & y_{1,2}^{off} \\ \vdots & \vdots \\ 1 & y_{4,N}^{off} \end{bmatrix}_{N\times 2} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix}_{2\times 1} \\ &+ \begin{bmatrix} z_{1,1} & z_{2,1} & z_{3,1} & z_{4,1} \\ z_{1,2} & z_{2,2} & z_{3,2} & z_{4,2} \\ \vdots & \vdots & \vdots & \vdots \\ z_{1,N} & z_{2,N} & z_{3,N} & z_{4,N} \end{bmatrix}_{N\times 4} \begin{bmatrix} c_1 \\ c_2 \\ c_3 \\ c_4 \end{bmatrix}_{4\times 1} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_N \end{bmatrix}_{1\times N} \end{aligned} \tag{5}$$

where c_1 to c_4 are the random effects and ϵ_i is the vector of residual error.

Table 8. Results of fitted linear mixed models.

LMM	# of observation	AIC	Log likelihood	Coefficient	Estimate	*P*-value	Function
Weekday	3880	20812	−10402	β'_0	22.55	1.16	$y^{on} = 22.55 + 0.3y^{off}$
				β'_1	0.3	0.01	
Weekend	1552	8228.2	−4060.1	β'_0	23.79	1.02	$y^{on} = 23.79 + 0.31y^{off}$
				β'_1	0.31	0.02	

y^{on} = speed when SFS is enabled, y^{off} = speed when SFS is disabled

In this study, N is the total number of link speed observations collected during the four weeks (May 28–June 25, 2018) of the study period. The total number of random-effect terms is equal to the number of study sites (j = 4), which accounts for variations unique to each segment. The notation of the model can be reformulated into a system of equations as:

$$y_{t,j}^{on} = \beta'_0 + \beta_1 y_{t,j}^{off} + \epsilon \tag{6a}$$

$$\beta'_0 = c_i + \beta_0 \tag{6b}$$

$$\beta'_1 = \beta_1 \tag{6c}$$

The coefficients in Equation 6a (β'_0 and β'_1) can be represented as the combination of the fixed-effect terms (β_0 *and* β_1) and random-effect terms (c_i). For this study, the random-effect terms are only included in the intercept. Substituting the (6b) and (6c) equations into (6a) equation, the final mixed model will be developed as:

$$y_{t,j}^{on} = \beta_1 y_{t,j}^{off} + (c_i + \beta_0) + \varepsilon \tag{7}$$

To develop the final model (Equation 7), maximum likelihood estimation is used to estimate the regression coefficients. The random-effect terms (c_i) are usually assumed to follow normal distributions with a mean of zero and variance of G; G is the covariance matrix of random effects. Table 8 summarizes the results of fitting mixed models on the observation.

The models developed in Table 8 relate the link speed when the SFS is enabled (y) to the link speed when SFS is disabled (x). Based on Equation 6a, in the mixed models, the random-effect terms are complemented to the coefficients of the fixed-effect terms. The p-value for the estimated coefficients shows both variables are significant to the mixed model. To demonstrate the effectiveness of the speed feedback sign based on the value of the link speed, a visualization relating the effectiveness versus different link speed is illustrated in Figure 6. A negative value for the effectiveness shows enabling the SFS will make the drivers increase their speed (increase in link speed) after observing their speed. While a positive value for effectiveness shows enabling the SFS will make the drivers decrease their speed (reduction in link speed) after observing their speed. The models developed in Table 8 are used to find the effectiveness values.

The following findings could be observed from the models developed in Table 8 and the SFS effectiveness plot in Figure 6:

1. Analyzing the speed change behavior model and the SFS effectiveness plot for the weekday shows for link speeds equal or lower than 32 mph, the drivers might speed up after they are informed of their speed by the SFS. However, with link speeds equal or more than 32 mph, the drivers might slow down after they informed of their speed by the SFS. Therefore, the link speed of 32 mph could be assumed as the breakpoint at which the SFS drivers behave differently while noticing the SFS.

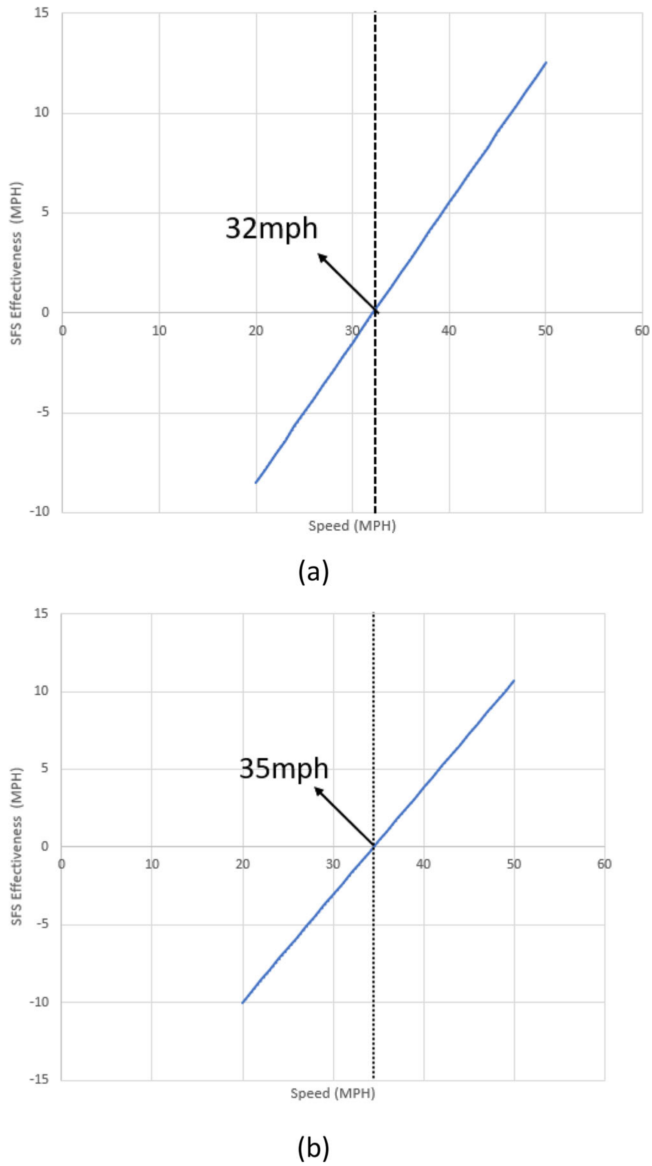


Figure 6. Effectiveness of SFS: (A) weekday, (B) weekend.

2. Similar results could be concluded by analyzing the model and the SFS effectiveness of the weekend. For link speeds equal or lower than 35 mph, the drivers might speed up after they are informed of their speed by the SFS. However, with link speeds equal or more than 35 mph, the drivers might slow down after they are informed of their speed by the SFS.
3. For both models (weekend and weekday), the speed reduction rate is higher for the drivers operating at higher speeds compared to drivers operating at a lower speed.

Further investigation on the relationship between the link-level mobility and safety will shed more light on the potential impact of SFS on arterial safety. The next section will provide further details on the relationship between speed and crash frequency and severity.

6. Connecting mobility to safety

Measuring the safety impact of SFS requires a massive amount of crash data (Hallmark, Qiu, Hawkins, & Smadi, 2015). However, this type of historical crash data is not always available or sufficient for transportation agencies to conduct robust safety studies. One way to evaluate the potential improvement of an arterial after installing SFS is to extrapolate mobility measures into the safety ones. The advantage of using mobility information to estimate safety benefit is that no historical crash data is required.

The relationship between mobility and safety could be explored in the kinetic energy equation. The kinetic energy equation shows that higher speeds will lead to higher kinetic energy ($E \sim v^2$; E: kinetic energy and v: speed), and consequently leading to more severe crashes. Nilsson (1982) showed that the expected number of injury crashes due to the change in the average speed could be estimated using Equation 8 (Nilsson, 1982).

$$N_2 = N_1 \left(\frac{S_2}{S_1} \right)^2 \tag{8}$$

where N_1 and N_2 are the total number of severe crashes before and after the change in the average speed, and S_1 and S_2 are the former and new average speed. A similar formulation was also reported by Kockelman, Bottom, Kweon, Ma, and Wang (2006) and Malyshkina and Mannering (2008).

In this study, to estimate the benefit in dollar value associated with the reduction in severe crashes (average economic cost per one severe injury crash is approximately \$1.0 million (Blincoe, Miller, Zaloshnja, & Lawrence, 2015)), crash count for our study corridor was obtained from the Pima Association of Governments (PAG). Based on the information

Table 9. Quantification of safety benefit.

	Link speed ($SFS_{disabled}$), mph	Link speed ($SFS_{enabled}$), mph	Percentage of severe crash reduction (%)	Benefit in dollar value per year associated with a reduction in the severe crash for the study corridor
Weekday	45	36	36	\$1,008,000
	40	34.5	25.6	\$737,280
	35	33	11.1	\$319,680
Weekend	45	37.7	29.8	\$357,600
	40	36.2	18.1	\$217,200
	35	34.6	8.5	\$102,000

provided by PAG, the total number of four severe crashes occurred before implementing the SFS in 2015. Using the model developed in Table 8, the link speed before and after disabling the SFS was estimated. Then, based on Equation 8 the percentage of severe crashes reduction was estimated. Table 9 shows the percentage of severe crash reduction due to the implementation of SFS, and the benefit in dollars associated with this reduction.

7. Conclusion

To evaluate the potential impact of SFSs on arterial mobility and safety, an observational before-after study was conducted on an arterial road in Tucson, AZ. The arterial mobility was evaluated at intersection and link levels. In addition, the effect of SFS on the dispersion of operating speed was also investigated by developing a speed change behavior model. Last, the safety benefit of an active SFS was quantified at the link speed level using the proposed driver speed change model.

To evaluate the arterial mobility at the intersection level, three performance measures, including percent of arrival on red, intersection delay and split failures were used. The results showed that at no statistically significant differences in either mean or variance of the respective measures before and after disabling the SFS. To evaluate the arterial mobility at the link level, link speed was selected as the performance measure. Statistical comparisons between link speed before and after disabling the SFS were performed as appropriate. The results showed that at three out of four sites, the reduction in the link speed was significant during the times the SFS was enabled. In addition, it was found that the impact of SFS on driver's behavior is a function of their approaching speed. Drivers within specific speed bins behave differently after they were informed of their speed by the SFS. Finally, the benefit in dollar value per year associated with a reduction in severe crashes on the study arterial with active SFS showed promising safety enhancement.

Overall, the outcome of this research showed that the sensor data-based assessment could also be used as a useful and practical approach for evaluating other speed management strategies. In addition, the developed driver's speed change behavior models could be easily applied to other arterials and locations as long as the models are well-calibrated.

Even though the study showed promising results, it could be further improved in future work. One potential future work would be increasing the number of samples by expanding the coverage of the traffic sensors and extending the data collection period. Larger sample sizes are always helpful in making the data-driven decisions more statistically robust. Another possible future work would be verifying the safety benefit using years of crash data collected after implementing SFS. Future studies should focus more on the impact of other speed management strategies on corridor mobility. Signal retiming and green waves could improve progression on coordinated arterials in addition to reducing average speed, 85th percentage speed, and the percentage of vehicles exceeding the speed limit

Acknowledgments

The authors would like to thank Tim Scott for data collection, Tobin Bennett-Gold and Seth Chalmers for professional advice. Special thanks to Justin King for facilitating data collection from the MioVision cloud-based platform.

Funding

The authors would like to thank the Pima County Department of Transportation (PCDOT) for funding and data support.

ORCID

Abolfazl Karimpour http://orcid.org/0000-0002-8707-6408
Robert Kluger http://orcid.org/0000-0002-2511-3410
Yao-Jan Wu http://orcid.org/0000-0002-0456-7915

References

Aarts, L., & Van Schagen, I. (2006). Driving speed and the risk of road crashes: A review. *Accident Analysis & Prevention*, *38*, 215–224. doi:10.1016/j.aap.2005.07.004

Ardeshiri, A., & Jeihani, M. (2014). A speed limit compliance model for dynamic speed display sign. *Journal of Safety Research*, *51*, 33–40. doi:10.1016/j.jsr.2014.08.001

Ariannezhad, A., Wu, Y.J. and Goftar, V.N. (2018). Real-Time Crash Prediction Using Data Mining Techniques. 97th Annual Meeting of the Transportation Research Board, Washington DC.

Ariannezhad, A., Karimpour, A., & Wu, Y.-J. (2020). Incorporating Mode Choices into Safety Analysis at the Macroscopic Level. *Journal of Transportation Engineering, Part A: Systems*, *146*(4), 04020022. doi:10.1061/JTEPBS.0000337.

Benavoli, A., Corani, G., & Mangili, F. (2016). Should we really use post-hoc tests based on mean-ranks?. *The Journal of Machine Learning Research*, *17*, 152–161.

Blincoe, L., Miller, T. R., Zaloshnja, E., & Lawrence, B. A. (2015). The economic and societal impact of motor vehicle crashes, 2010 (Revised). *Annals of Emergency Medicine*, *66*(2), 194–196.

Carlson, P. J., Fontaine, M., Hawkins, H., Murphy, K., & Brown, D. (2000). *Evaluation of speed trailers at high-speed temporary work zones*. 79th Annual Meeting of the Transportation Research Board, Washington, DC.

Chitturi, M. V., & Benekohal, R. F. (2006). Effect of speed feedback device on speeds in interstate highway work zones. In *Applications of Advanced Technology in Transportation* (pp. 629–634).

Cruzado, I., & Donnell, E. (2009). Evaluating effectiveness of dynamic speed display signs in transition zones of two-lane, rural highways in Pennsylvania. *Transportation Research Record: Journal of the Transportation Research Board*, *2122*(1), 1–8. doi:10.3141/2122-01

Day, C. M., Bullock, D. M., Li, H., Lavrenz, S. M., Smith, W. B., & Sturdevant, J. R. (2016). Integrating traffic signal performance measures into agency business processes. Purdue University, West Lafayette, Ind.

Day, C. M., Li, H., Sturdevant, J. R., & Bullock, D. M. (2018). Data-driven ranking of coordinated traffic signal systems for maintenance and retiming. *Transportation Research Record: Journal of the Transportation Research Board*, *2672*(18), 167–178. doi:10.1177/0361198118794042

Fox, J. (2015). *Applied regression analysis and generalized linear models*. Printed in United States of America: SAGE Publications.

Friedman, M. (1937). The use of ranks to avoid the assumption of normality implicit in the analysis of variance. *Journal of the American Statistical Association*, *32*(200), 675–701. doi:10.1080/01621459.1937.10503522

Garber, N., & Srinivasan, S. (1998). Influence of exposure duration on the effectiveness of changeable-message signs in controlling vehicle speeds at work zones. *Transportation Research Record: Journal of the Transportation Research Board*, *1650*(1), 62–70. doi:10.3141/1650-08

Gehlert, T., Schulze, C., & Schlag, B. (2012). Evaluation of different types of dynamic speed display signs. *Transportation Research Part F: Traffic Psychology and Behaviour*, *15*(6), 667–675. doi:10.1016/j.trf.2012.07.004

Gueorguieva, R., & Krystal, J. H. (2004). Move Over ANOVA. *Archives of General Psychiatry*, *61*(3), 310. doi:10.1001/archpsyc.61.3.310.

Hallmark, S., Hawkins, N., & Smadi, O. (2015). *Evaluation of dynamic speed feedback signs on curves: A national demonstration project*. United States: Federal Highway Administration.

Hallmark, S. L., Qiu, Y., Hawkins, N., & Smadi, O. (2015). Crash modification factors for dynamic speed feedback signs on rural curves. *Journal of Transportation Technologies*, *5*(1), 9–23. doi:10.4236/jtts.2015.51002

Imprialou, M.-I M., Quddus, M., Pitfield, D. E., & Lord, D. (2016). Re-visiting crash–speed relationships: A new perspective in crash modelling. *Accident Analysis & Prevention*, *86*, 173–185. doi:10.1016/j.aap.2015.10.001

Jeihani, M., Ardeshiri, A., & Naeeni, A. (2012). *Evaluating the effectiveness of dynamic speed display signs* (National Transportation Center Research Report).

Karimpour, A., Kluger, R., Liu, C., & Wu, Y.-J. (2020). *Periodic law enforcement enhances the effectiveness of speed feedback sign. Transportation Research Record: Journal of the Transportation Research Board.(In press).*

Kockelman, K., Bottom, J., Kweon, Y., Ma, J., & Wang, X. (2006). *Safety impacts and other implications of raised speed limits on high-speed roads*. Washington, DC, USA: Transportation Research Board.

Kockelman, K. M., & Ma, J. (2007). Freeway speeds and speed variations preceding crashes, within and across lanes. *Journal of the Transportation Research Forum*, *46*, 43–61. doi:10.5399/osu/jtrf.46.1.976

Lee, C., Lee, S., Choi, B., & Oh, Y. (2006). Effectiveness of speed-monitoring displays in speed reduction in school zones. *Transportation Research Record: Journal of the Transportation Research Board*, *1973*(1), 27–35. doi:10.1177/0361198106197300104

Malyshkina, N. V., & Mannering, F. (2008). Effect of increases in speed limits on severities of injuries in accidents. *Transportation Research Record: Journal of the Transportation Research Board*, *2083*(1), 122–127. doi:10.3141/2083-14

Mansourkhaki, A., Karimpour, A., & Yazdi, H. S. (2017). Introducing prior knowledge for a hybrid accident prediction model. *KSCE Journal of Civil Engineering*, *21*(5), 1912–1918. doi:10.1007/s12205-016-0495-4.

Mansourkhaki, A., Karimpour, A., & Sadoghi Yazdi, H. (2017). Non-stationary concept of accident prediction. *Proceedings of the Institution of Civil Engineers- Transport*, *170*(3), 140–151. doi:10.1680/jtran.15.00053.

McAvoy, D. S., & Stocker Center. (2011). *Work zone speed reduction utilizing dynamic speed signs*. (Working paper, report: 01353750). University of Ohio.

MioVision Team. (2019). *MioVision's TrafficLink platform* [Online]. Retrieved from https://miovision.com/trafficlink/

Mousavi, S. M., Zhang, Z., Parr, S. A., Pande, A. & Wolshon, B. (2019). Identifying High Crash Risk Highway Segments Using Jerk-Cluster Analysis. International Conference on Transportation and Development 2019. 112–123.

Nilsson, G., 1982. Effects of speed limits on traffic accidents in Sweden. VTI särtryck, ISSN 1102-626X; 68.

Parsa, A. B., Movahedi, A., Taghipour, H., Derrible, S., & Mohammadian, A. (2020). Toward safer highways, application of XGBoost and SHAP for real-time accident detection and feature analysis. *Accident Analysis & Prevention*, *136*, 105405. doi:10.1016/j.aap.2019.105405.

Pereira, D. G., Afonso, A., & Medeiros, F. M. (2015). Overview of Friedman's test and post-hoc analysis. *Communications in Statistics—Simulation and Computation*, *44*(10), 2636–2653. doi:10.1080/03610918.2014.931971

Pesti, G., & McCoy, P. (2001). Long-term effectiveness of speed monitoring displays in work zones on rural interstate highways. *Transportation Research Record: Journal of the Transportation Research Board*, *1754*(1), 21–30. doi:10.3141/1754-03

Pour-Rouholamin, M., & Zhou, H. (2016). Investigating the risk factors associated with pedestrian injury severity in Illinois. *Journal of Safety Research*, *57*, 9–17. doi:10.1016/j.jsr.2016.03.004

Rahimi, E., Shamshiripour, A., Shabanpour, R., Mohammadian, A., Auld, J. (2020). Analysis of Transit Users' Response Behavior in Case of Unplanned Service Disruptions. Transportation Research Record: *Journal of the Transportation Research Board*. (In press).

Rahimi, A., Azimi, G., Asgari, H., & Jin, X. (2019). Clustering Approach toward Large Truck Crash Analysis. *Transportation Research Record: Journal of the Transportation Research Board*, *2673*(8), 73–85. doi:10.1177/0361198119839347.

Rahimi, E., Shamshiripour, A., Samimi, A., & Mohammadian, A. . (2020). Investigating the injury severity of single-vehicle truck crashes in a developing country. *Accident Analysis & Prevention*, *137*, 105444 doi:10.1016/j.aap.2020.105444.

Rahimi, E., Shamshiripour, A., Shabanpour, R., Mohammadian, A., & Auld, J. (2019). Analysis of transit users' waiting tolerance in response to unplanned service disruptions.

Transportation Research Part D: Transport and Environment, *77*, 639–653. doi:10.1016/j.trd.2019.10.011.

Razi-Ardakani, H., Mahmoudzadeh, A. and Kermanshah, M. (2018). A Nested Logit analysis of the influence of distraction on types of vehicle crashes. *European Transport Research Review*, *10*(2), p.44. doi:10.1186/s12544-018-0316-6.

Remias, S. M., Day, C. M., Waddell, J. M., Kirsch, J. N., & Trepanier, T. (2018). Evaluating the performance of coordinated signal timing: Comparison of common data types with automated vehicle location data. *Transportation Research Record: Journal of the Transportation Research Board*, *2672*(18), 128–142. doi:10.1177/0361198118794546

Rune, E., & Vaa, T. (2009). *The handbook of road safety measures*. Emerald Group Publishing Limited, pp. 759-857. doi:10.1108/9781848552517-012.

Sandberg, W., Schoenecker, T., Sebastian, K. and Soler, D., (2006). Long-term effectiveness of dynamic speed monitoring displays (DISMAYED) for speed management at speed limit transitions. In 2006 ITE Annual Meeting and Exhibit Compendium of Technical PapersInstitute of Transportation Engineers (ITE).

Sidney, S. (1957). Nonparametric statistics for the behavioral sciences. *The Journal of Nervous and Mental Disease*, *125*(3), p.497.

Strawderman, L., Huang, Y., & Garrison, T. (2013). The effect of design and placement of work-zone warning signs on driver speed compliance: A simulator-based study. *IIE Transactions on Occupational Ergonomics and Human Factors*, *1*(1), 66–75. doi:10.1080/21577323.2012.714839

Ullman, G. L., & Rose, E. R. (2004). *Effectiveness of dynamic speed display signs (DSDS) in permanent applications*. Texas Transportation Institute, Texas A&M University System. Report 0-4475-S.

Ullman, G. L., & Rose, E. R. (2005). Evaluation of dynamic speed display signs. *Transportation Research Record: Journal of the Transportation Research Board*, *1918*(1), 92–97. doi:10.1177/0361198105191800112

Urbanik, T., Tanaka, A., Lozner, B., Lindstrom, E., Lee, K., Quayle, S., … Gettman, D. (2015). *Signal timing manual*. Washington, DC: Transportation Research Board.

Vincent, W. J., & Weir, J. P. (1999). *Statistics in kinesiology*. Champaign, IL: Human Kinetics.

Walter, L., & Broughton, J. (2011). Effectiveness of speed indicator devices: An observational study in South London. *Accident Analysis & Prevention*, *43*, 1355–1358. doi:10.1016/j.aap.2011.02.008

Wang, X., Zhou, Q., Quddus, M., & Fan, T. (2018). Speed, speed variation and crash relationships for urban arterials. *Accident Analysis & Prevention*, *113*, 236–243. doi:10.1016/j.aap.2018.01.032

Wegman, F., & Goldenbeld, C. (2006). *Speed management: Enforcement and new technologies* (No.5). *Institute for Road Safety Research, SWOV: Leidschendam, The Netherlands.*

West, B. T., Welch, K. B., & Galecki, A. T. (2014). *Linear mixed models: A practical guide using statistical software*. Chapman and Hall/CRC. Taylor & Francis Group, Boca Raton, Fl, USA.

Wrapson, W., Harré, N., & Murrell, P. (2006). Reductions in driver speed using posted feedback of speeding information: Social comparison or implied surveillance? *Accident; Analysis and Prevention*, *38*(6), 1119–1126. doi:10.1016/j.aap.2006.04.021

Zimmerman, D. W., & Zumbo, B. D. (1993). Relative power of the Wilcoxon test, the Friedman test, and repeated-measures ANOVA on ranks. *The Journal of Experimental Education*, *62*(1), 75–86. doi:10.1080/00220973.1993.9943832

Zineddin, A., Hallmark, S., Smadi, O. and Hawkins, N. (2016). Spotlighting Speed Feedback Signs. *Public Roads*, *79*(5).