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Evaluating the Effectiveness of Dynamic Speed Display Signs

Mansoureh Jeihani, Ph.D.
Anam Ardeshiri
Amir Naeeni
Department of Transportation and Urban Infrastructure Studies

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16. Abstract
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EXECUTIVE SUMMARY

This study investigates the impact of dynamic speed display signs (DSDSs) on driversô speed-related behavior. A survey questionnaire regarding attitudes and reactions to a DSDS on different road classes was distributed to Maryland drivers of different ages and socioeconomic backgrounds. In addition, the research team collected vehicle speed data upstream and downstream of the DSDS location on different corridors. The data was collected with a portable Trax Flex High Speed Counter, which records vehiclesô length, speed, and number of axels as they pass over the deviceôs tubes on the road. The speed data was collected on three road segments with different speed limits: 25 mph, 35, mph, and 45 mph. Conventional statistical analysis, Bayesian network, and planned behavior theory were applied to assess the DSDSôs effectiveness with reducing speed. To investigate the short-term and long-term effects of the DSDS, the research team collected the data in different periods (few days to few months) after the installation. Furthermore, the effective distance for the DSDS was investigated. Two different sizes of the DSDS were used to find the impact of size on driversô compliance.

INTRODUCTION

Different studies have described the effect of vehicle speed reduction on accident rates. Finch et al. (1994) and OôCinneide and Murphy (1994) demonstrated that lower speeds and decreased speed variance resulted in less traffic accidents.

Variable message signs (VMSs), also called dynamic message signs (DMSs) or changeable message signs (CMSs), have been used successfully for informational and advisory purposes. The signs show different messages to inform and advise drivers about traffic conditions, road works, speed, hazards, and etc. Radar attachment improved the dynamic feature of VMSs, as the radar allowed the signs to detect the speed of each passing vehicle (Garber and Patel, 1995). Radar-controlled VMSs are referred to as dynamic speed display sign (DSDSs). When a vehicle passes a DSDS, the device displays and compares the vehicleôs speed to the roadôs speed limit as a reminder to the driver. On the other hand, variable speed sign (VSS) refers to a device that shows different speed limits at different times or locations (e.g., severe weather conditions or a work zone). VSSs are sometimes called variable speed limits (VSLs). The terms VSS, VSL, DSDS, and VMS are sometimes used interchangeably, but the devices are not the same. Figures 1-3 present each.

The few studies about the effectiveness of DSDSs on speed reduction and traffic safety reached varying conclusions. In addition, the signsô effectiveness, in terms of maintaining a speed reduction for a period and distance away from the sign has not been fully investigated. The Transportation Research Boardôs committee on transportation safety management (ANB10) has requested that researchers evaluate the effect of DSDSs on speed reduction before further implementation of the technology (TRB research needs statements, 2010).

In this research, the authors utilized conventional statistical analysis and a Bayesian network to assess DSDS effectiveness with reducing speed. In order to calibrate the model and study the effectiveness of the device, the authors used a survey questionnaire to collect data about driversô attitudes and reactions to the DSDS, and collected upstream and downstream vehicle speed data before and after installation of the DSDS on different corridors. The short-term and long-term effects of the DSDS were investigated by collecting the data in different periods (few days to few months) after the installation.

Figure 1: VSS (VSL) Unit

Figure 2: DSDS Unit

Figure 3: VMS Unit

LITERATURE REVIEW

As stated earlier, few studies have assessed the effectiveness of DSDSs. While some researchers used DSDSs to warn speed violators to reduce their speed via messages such as ñEXCESSIVE SPEEDò and ñSLOW DOWNò (Garber and Srinivasan, 1998; McAvoy, 2011), others utilized DSDSs as passive informational devices (Rose and Ullman, 2003; Bloch, 1998). In the latter case, the DSDS simply showed the speed limit and the speed of the passing vehicle.

DSDSs have been applied mostly in work zones, and several researchers (Garber and Patel, 1994; McCoy et al., 1995; and McAvoy, 2011) have investigated their effectiveness. DSDSs have also been used in school zones, residential areas, sharp horizontal curves, and high-speed signalized intersections (Rose and Ullman, 2003; Bloch, 1998; Walter and Broughton, 2011). The signsô effectiveness has been investigated for the short-term (McAvoy, 2011) and the long-term (Rose and Ullman, 2003; Bloch, 1998). Studies of long-term effects repeated the data collection a few months after the DSDS installation.

Some researchers used hand-held lidar guns (Rose and Ullman, 2003), while others used tubes and automatic traffic counters (Garber and Patel, 1994) or radar (Bloch, 1998) to collect and compare pre- and post-DSDS speed data. The speed data was recorded either for all vehicles or for selected vehicles. The collection period was a few hours per day or 24 hours, a few days to a few weeks, weekdays only (Warner and Broughton, 2011), or the whole week. Some researchers utilized non-real traffic data, such as a driving simulator (McAvoy, 2011) or survey questionnaires, to investigate driversô compliance with the speed limit (Elliot and Armitage, 2006).

Many researchers employed conventional statistical models, such as linear regression, F-test, t-test, and analysis of variance (ANOVA), to analyze post-DSDS speed changes (Rose and Ullman, 2003; Garber and Srinivasan, 1998; Bloch, 1998; McAvoy, 2011; Walter and Broughton, 2011).

Rose and Ullman (2003) found that a DSDS significantly reduced vehicle speeds in a school zone. The pre-DSDS average speed in the school zone was about 10 mph higher than the posted speed limit. The average speed decreased more than 9 mph after the DSDS installation. The speed reduction continued four months after the DSDS installation. However, the DSDS effect was much lower for sharp horizontal curves and high-speed signalized intersection approaches. In those areas, average speeds returned to pre-DSDS levels after four months.

Bloch (1998) compared the effectiveness of DSDS and photo radar. The study focused on three roads in Riverside, California. The study concluded that both devices effectively reduced speed by 4-5 mph and reduced the number of vehicles travelling 10 mph or more over the speed limit. Supplementing the DSDS with police enforcement significantly increased the signôs effectiveness, but only for the short term. The unenforced DSDS was the most cost-effective method.

McAvoy (2011) employed a driving simulator and an eye-tracking device to assess the effectiveness of DSDS and VSL in reducing work-zone speed. Thirty-nine students, who were between 16 and 25 years old, participated in the study. The study stated that a ñSLOW DOWN 45ò message lowered work-zone speed by about 18 mph more than a VSL with a speed limit of 45 mph did. However, the message ñSLOW DOWNò lowered speed by only 2 mph more than the VSL did.

Garber and Patel (1995) studied DSDS effectiveness in a 55 mph work zone. The signs displayed messages to vehicles traveling over 59 mph. The study concluded that DSDSs reduced speeds by 10 mph or more. Of the four messages tested, the most effective was ñYOU ARE SPEEDING SLOW DOWN.ò

Buddemeyer et al. (2010) utilized a speed sensor on a corridor and found that for every one mph reduction in the speed limit on a VSL, drivers reduced their speeds 0.47 to 0.75 mph. Rama and Schirokoff (1999) utilized loop detectors to record vehicles speed. The study used a VSL to vary the speed limit for specific traffic and environmental conditions. The study showed that a weather-related decrease in the speed limit reduced the mean speed and speed variation of free-flow traffic.

Table 1 shows the results of a before-and-after study of DSDSs. Poulter and McKenna (2005) focused on five 30 mph roads in London. Speed data was collected for four weeks: one week before the devices were installed, two weeks while they were in operation, and one week after they were removed. The effectiveness of the DSDS decreased over time and its effect decreased dramatically after removal.

Walter and Knowles (2008) used a similar approach on 10 sites in London. The study found that speed decreased 1.4 mph for the first two weeks the DSDS was in operation; however, the study reported no explicit conclusion for the third week of operation. The speed reduction continued 650 feet downstream of the DSDS, but not beyond that. The speed changes during the fifth week were not statistically significant at the 5 percent level of significance. Because speeds returned to initial levels after the DSDS removal, the researchers proposed a DSDS rotation program to maintain and improve safety gains.

Table 1: Effectiveness of a DSDS on Average Speed over Time in Two Studies

Chronological week	Poulter & McKenna (2005)		Walter and Knowles (2008)	
	DSDS in operation	Change in speed compared to the 1st week	DSDS in operation	Change in speed compared to the 1st week
1	No	–	No	–
2	Yes	-1.3	Yes	-1.5
3	Yes	-1.2	Yes	-1.5
4	No	-0.2	Yes	–
5	–	–	No	0.0
6	–	–	No	0.1

Walter and Broughton (2011) investigated DSDS effectiveness in free-flow traffic conditions across 10 sites in London. All of the sites were 30 mph segments on a two-way, single carriageway with no restrictions on vehiclesô free-flow speed. The researchers used headway criterion to remove the speed data for the congested periods (i.e., the morning and evening peaks) to ensure that other vehicles did not affect driversô speed choice. Headways under two seconds and speeds less than 20 mph were eliminated from analysis. The researchers expanded the evaluation to determine DSDS effectiveness on vehiclesô speed in three different scenarios: while the DSDS was in operation, after the DSDS was removed, and downstream of the operational DSDS.

Walter and Broughton (2011) applied an ANOVA contrast over the mean speeds to test DSDS effectiveness. Table 2 shows the number of sites for different time-distance configurations. The studyôs baseline was the average speed of vehicles passing 0.12 miles upstream of the possible DSDS location. For the whole period the DSDS was in operation, the study reported an average reduction of 1.4 mph; however, the average speed 0.12 miles (200 m) downstream of the DSDS decreased by 0.2 mph and increased by 0.6 mph at 0.25 miles (400m) downstream. Observing that the mean speed remained unchanged in the first week and increased 0.1 mph the second week after the DSDS removal, the study concluded that a DSDS had no continuing effect. Although a DSDS was viewed as a temporary strategy, collision reduction was estimated based on the average speed reduction in the study.

Table 2: Configuration of Time-Distance Invariants in the Walter and Broughton (2011) Study

Week	Time period regarding DSDS installation	Number of study sites in each time-distance combination			
		200m upstream of DSDS	At DSDS	200m downstream of DSDS	400m downstream of DSDS
1	Before	10 (baseline)	10	10	6
2	During1	10	10	10	6
3	During2	7	7	7	6
4	During3	3	3	3	3
5	After1	10	10	10	6
6	After2	10	10	10	6

Ullman and Rose (2005) suggested that DSDSs could be permanent and effective tools for speed reduction if ñappropriate site conditions apply,ò although the study did not collect speed data after DSDSs were removed. Speed data from two periodsð the week immediately after installation and four months after installationð were collected and compared to the pre-DSDS installation speeds at an upstream control point. Results showed that a DSDS reduced speed in school zones more than it did in other areas. To evaluate the effective distance of a DSDS, the study used linear regression with regard to individual speed. Speed at the DSDS location was modeled by the speed at a control point approximately 2,000 to 3,000 feet upstream. The authors

found that a DSDS had a more substantial effect on drivers at higher speeds (e.g., more than 65 mph).
Cruzado and Donnell (2009) found that DSDSs were effective self-enforcement tools while in place; however, the effect disappeared when DSDSs were removed. The experiment involved 12 transitional zones in Pennsylvania. Speed data was collected during weekdays and non-peak daytime periods in two locations: adjacent to the DSDS and 0.5 miles upstream. The data was collected before DSDS installation, during the DSDSøs first week of operation, and one week after DSDS removal. Comparison of the mean and 85th percentile speeds indicated that drivers understood the role of DSDS. Drivers reduced their speeds as they approached the signs, but increased their speeds after they passed. The authors conducted two linear regression models: one used pre-installation speeds to predict the speed reduction during DSDS operation, and the other used DSDS-operation speeds to predict speed reduction after DSDS removal. Modeling was based on the aggregated speed data for the 12 sites.

Drivers' Behavior

Driver behavior is of primary importance in traffic safety. Human characteristics influence driver behavior and choice. Most studies of driver behavior use age, gender, education, and driving background as variables due to their availability. Speed choice is used as an indicator of the driverøs attitudes and characteristics. Although regression analysis of driversô demographic information allows researchers to make conclusions, regression models are not capable of explaining the reasons for a driverøs speed choice (Elliot et al., 2003). Therefore, there has been a gap in the literature to explain the reasons for driversô speed choice.

Psychological behavioral theories, on the other hand, attempt to identify invariants to address this gap. One of the best-developed approaches is the theory of planned behavior (TPB), which was first introduced by Ajzen (1985). Many researchers have used this theory to scrutinize driversô attitude towards speed choice and to enhance traffic safety models. TPB postulates that intention determines human behavior. An individualøs attitude, subjective norms, and perceived behavioral control are independent components of intention. Elliot et al. (2003) used a TPB questionnaire to evaluate how demographics affect driversô speed. Five hundred ninety-eight drivers were interviewed twice over three months. The study found a strong synthesis between TPB variables and driversô demographics (particularly, age and gender).

To investigate driversô speed choice, Warner and Aberg (2008) gave a TPB questionnaire to 162 drivers. The driversô responses allowed the study to develop a predictive model for speed limit violations. Drivers with a higher intention to exceed the speed limit paid less attention to speed signs or more easily disregarded them than those with no intention to exceed the speed limit. Driversô intention to comply with the speed limit was shown to vary by cultural qualifications. Drivers from a region with lower accident rates had a more positive attitude and greater intention towards speed compliance than drivers from a region with higher accident rates (Warner et al., 2009).

METHODOLOGY

The research team distributed a survey questionnaire among Baltimore residents in order to understand driversô compliance with and attitudes toward DSDSs. The research team also collected vehiclesô speed data on three different road segments before and after (one day to three months after) installation a DSDS. The research team also collected speed data upstream and downstream of the DSDS location.

Conventional statistical analysis, Categorical Regression (CATREG), and Bayesian network (BN) were utilized to assess a DSDSôs effectiveness with reducing speed. Besides the effective time (short term and long term), the effective distance for the DSDS was investigated. Two different sizes of the DSDS were used to find the impact of DSDS size on driversô compliance.

Categorical Regression Analysis

Categorical regression (CATREG) extends conventional multiple regression to accommodate categorical (nominal and ordinal) variables. CATREG transforms categorical variables into interval variables and then applies multiple regression analysis. Since many of the variables in this study were categorical variables, the research team applied CATREG to the aggregated data to find the important factors affecting speed compliance pre- and post-DSDS installation. The CATREG results were also used to form the Bayesian Network.

Bayesian Network

The Bayesian network (BN) has been recently applied in various studies that involve with uncertainty and complexity. BN has been used in classification, clustering, forecasting, and decision-making purposes. Xie et al. (2007) used a Bayesian neural network (BNN) to predict motor vehicle crashes. The study compared BNN to two powerful models of back-propagation, neural network and negative binomial regression modeling. In most cases, BNN produced more realistic predictions and generalization than the other two models did. Jin et al. (2010) presented a BN model to estimate speed from single-loop detector data. The study validated the estimated speeds with observed data and tested the results of conventional methods. De Ona et al. (2011) classified traffic accidents by injury severity and then identified significant factors associated with fatalities and injuries. De Ona et al. concluded that BN was a useful tool for injury severity analysis.

A BN is a powerful, directed graphical model. A BN is comprised of nodes and links that illustrate random variables, relationships between variables, and conditional probability distributions for the states of each variable. BN software packages provide an intuitive visualization of interactions among different variables. They also show the result of changes to a variable on other variables, especially on a target variable. The current study used Netica (2011) software package to develop the BN model.

BNs are derived from the Bayes rule on posterior simulation. The Bayes rule is defined by the conditional probability of a specific event given another event. It can be used to predict a future event given a past event (Koski and Noble, 2009). The BNôs learning algorithm employs a training dataset, called a case file, which is derived from the observed data. Each case fileôs record is associated with an actual event. The final learned BN can be used for policy scenario analysis and case file tests.

In most applications of pattern classification, machine learning incorporates a sample dataset to learn the modelôs spatial structure and conditional probability tables. Statistical parameters are necessary tools to predict a future outcome based on past information and posterior distribution. The BN structure in this study was performed using the research teamôs prior knowledge and literature. The linkage between variables was established using the statistical modelsô results. Network topology is very important in BN construction, since the network arrangement should imply a realistic cause-and-effect relationship between variables. Parameter learning, which determines each nodeôs conditional probability tables given the data and the structure of the network, is usually based on the application of minimax criterion to minimum error-rate classification (Duda et al., 2001).

BN is usually initiated based on the cause-and-effect relationship of effective variables (Ulengin et al., 2007). A cause-and-effect map is a visual representation of the system. Because this map illustrates results, it can provide a better understanding of the problem than conventional analysis tools do. A graph, which includes causal relationships among variables, forms the BN structure. In the graph, nodes represent the variables and links represent relationship between variables.

Causal relations among the nodes in this study were identified using traditional econometric techniques and expert judgment. According to past studies, combining BN with traditional statistical models produces a pure BN with a precise estimate. For instance, Xu et al. (2005) performed a study to estimate delay propagation in aviation systems and demonstrated that the integration of expert judgment with statistical methods improved BN prediction accuracy. The artificial neural network (ANN) has been shown to capture properly the causal relationships between non-linear and multi-collinear variables (Ulengin et al., 2007). The research team utilized CATREG in order to construct the initial BN. Correlations among explanatory variables and the effect of each variable on the final node (dependent variable) are important factors in constructing a BN. This initial topology was then complemented by the authorsô judgment. In BN, two nodes can be connected either directly or indirectly via one or more mediator nodes. The correlation coefficients of categorical regression analysis determine the directness or indirectness of the relationships between any two BN nodes.

RESULTS

Survey Questionnaire

The research team distributed the questionnaire among students in Morgan State Universityôs Department of Transportation and Urban Infrastructure Studies. In order to have an unbiased sample, each student was given three questionnaires: one to be answered by themselves and the other two to be answered by a friend or family member outside the school. Eighty-eight questionnaires were returned to the research team: 34 respondents were female and 54 were male. The socioeconomic information of the sample is summarized in Figures 4-7. Ninety-five percent of the respondents were familiar with DSDSs. Most drove near the signs regularly: 43 percent encountered a DSDS 3-5 times a week, and 30 percent encountered a DSDS a few times a month.

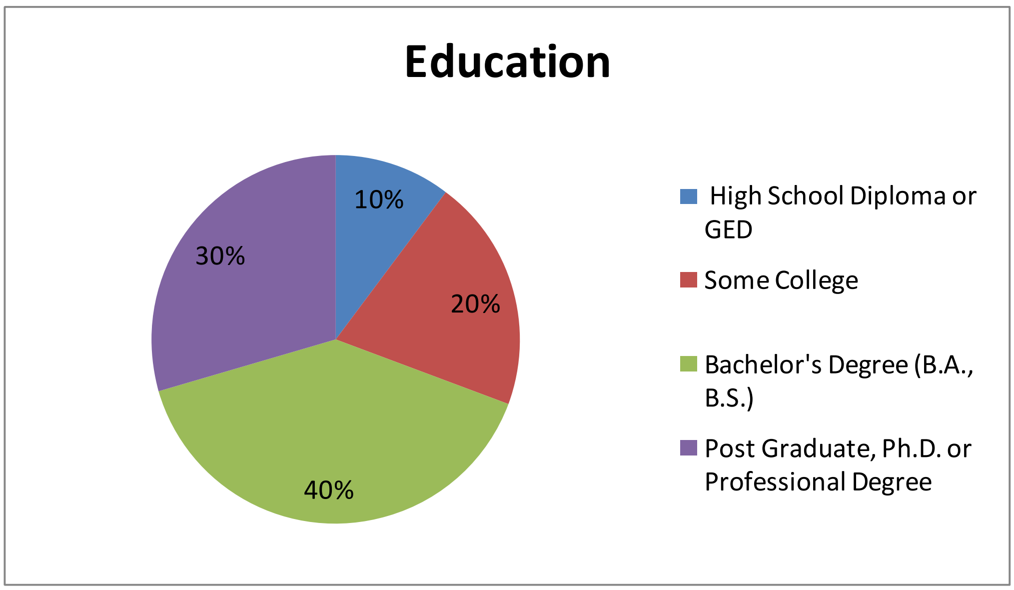

Figure 4: Respondents' Education Level

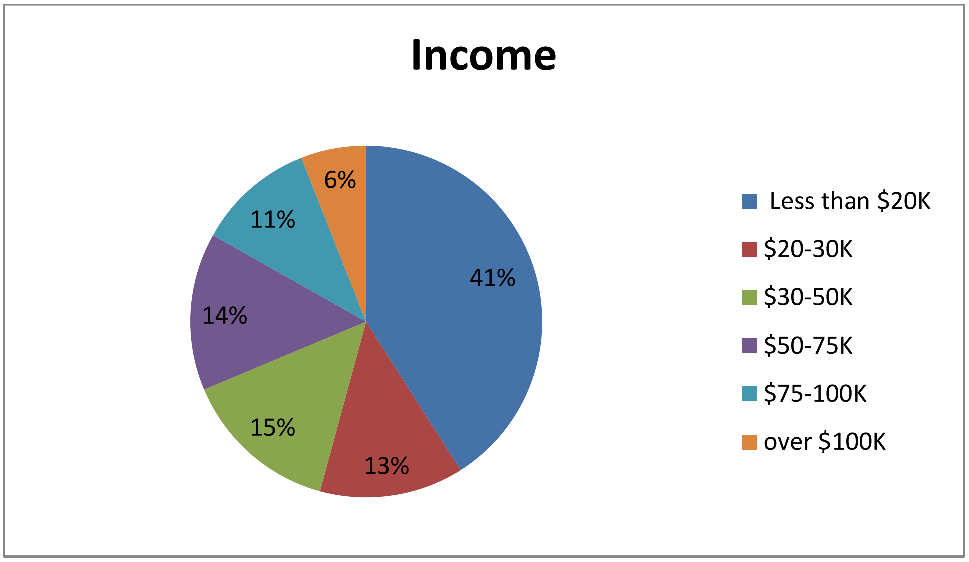

Figure 5: Respondents' Income

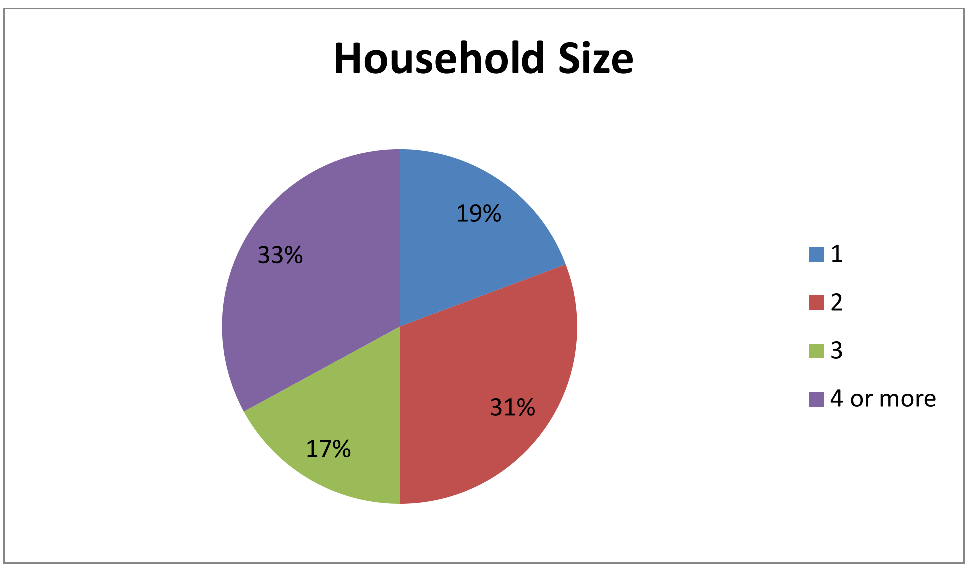

Figure 6: Number of People in Respondents' Households

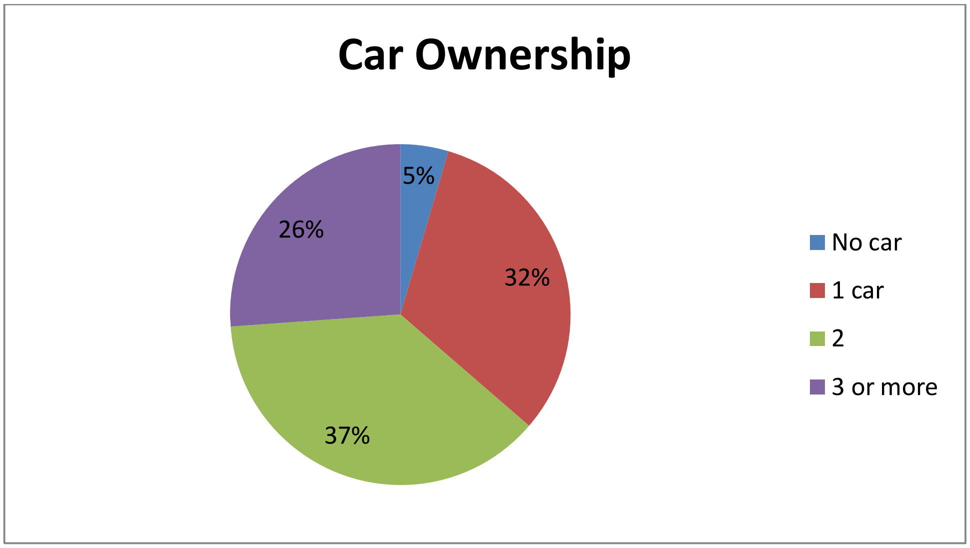

Figure 7: Number of Cars in the Respondents' Households

The respondents were asked how much they reduced their speed when they saw a DSDS on 25, 35, and 45 mph roads. As presented in Figure 8, most of the respondents stated that they reduced their speed to the speed limit (SL) for each road class. However, the highest percentage did not change speed on the 45 mph road class (15.3 percent), and the highest percentage of reduction to the speed limit belonged to the 25 mph road class (70.1 percent).

When asked why they sped, 59 percent of respondents stated that they did not realize they were speeding and the DSDS informed them of their speeding, 14 percent stated that the speed limit was too low, 14 percent forgot the speed limit, and 13 percent stated that they liked to drive at a high speed whenever possible. Sixty-three percent of the respondents reduced their speed after passing a DSDS because they were afraid of receiving a speeding ticket, while 37 percent did not intend to exceed the speed limit and the DSDS was a good reminder. Forty-eight percent stated that they would increase their speed if a DSDS showed that they were driving below the speed limit.

Figure 9 shows that 55 percent of the respondents believed that DSDSs increase safety, and 25 percent believed that the devices improve safety and traffic flow. Eighteen percent believed that DSDSs improve neither.

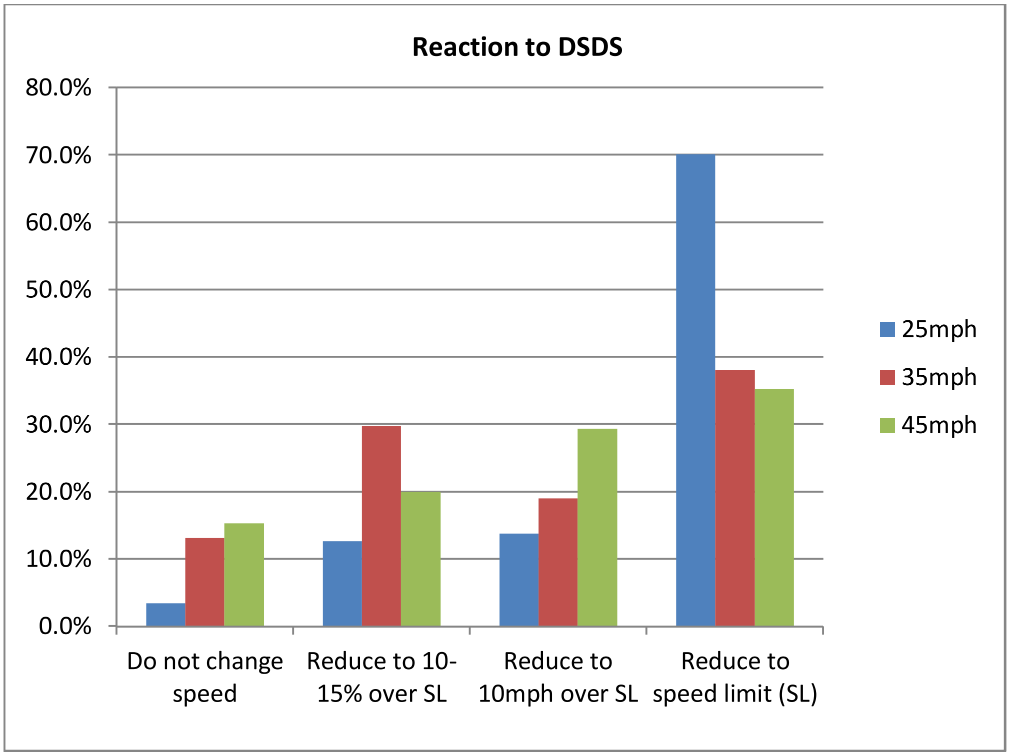

Figure 8: Respondents' Reactions to a DSDS by Road Class

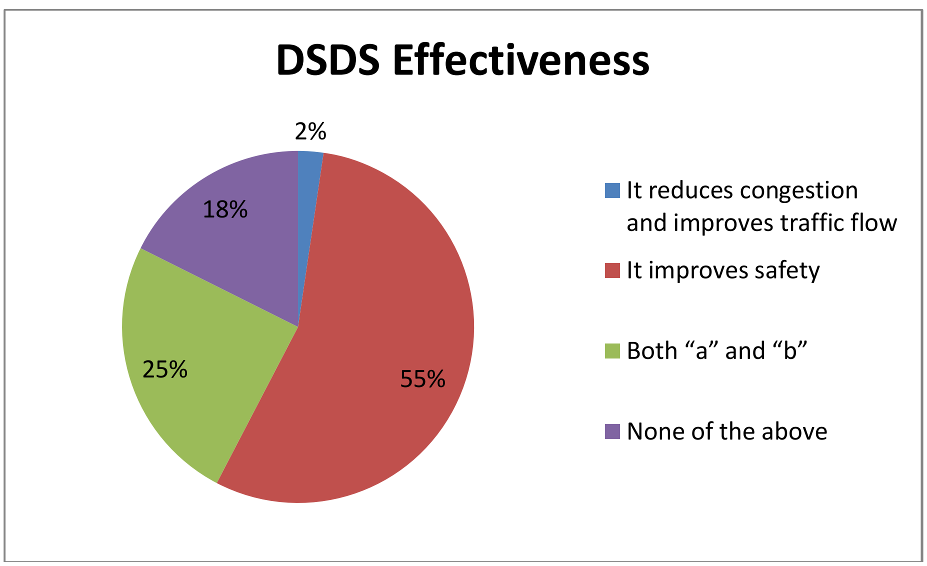

Figure 9: Respondents' Attitudes about DSDS Effectiveness

Fifty-two percent of the respondents categorized themselves as non-aggressive drivers, 6 percent as aggressive, and 42 percent sometimes aggressive (Figure 10).

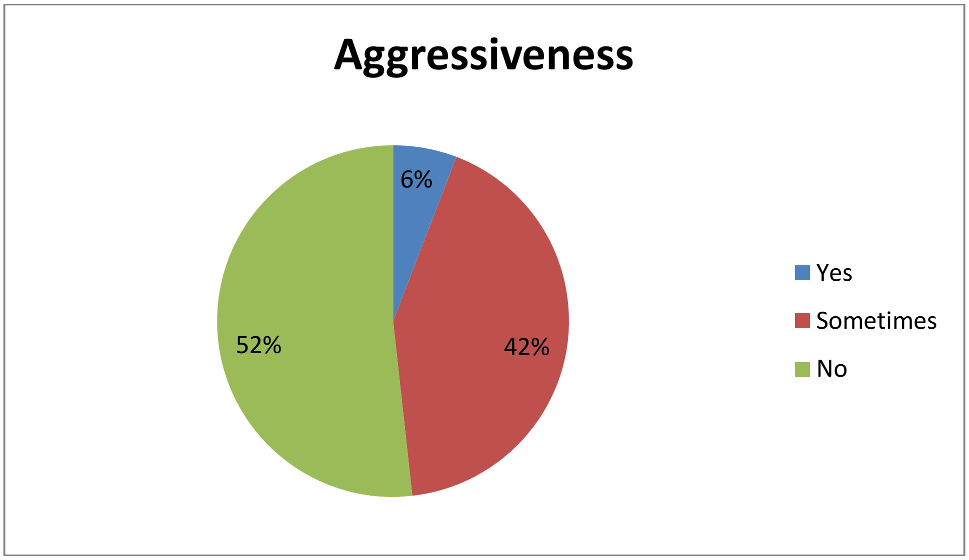

Figure 10: Respondents' Aggressiveness

Speed Data Collection

The research team collected data using a digital traffic recorder. The deviceð JTF-HS-16M-4RT-S, Trax Flex High Speed Counter with locks and chainð tallies vehicles in both high- and low-speed situations. The counter includes a digital box and tubes. The deviceôs tubes calculate the speed, number of axels, and length of each vehicle. The tubes are taped to the road surface. When a car passes the tubes, the counter senses the tire pressure and the speed is calculated based on the time that it takes the front and rear tires to pass the tubes. A digital box records the information. The results of each situation were validated with manual counts.

The research team chose three corridors with different speed limits: 45 mph, 35 mph, and 25 mph. The research team installed a DSDS and two counters on each corridor. One counter was upstream of the DSDS and the other was downstream. There were no merge or diverge points between the two counters in order to have the same flow. The selected corridors are as follows.

Perring Parkway Corridor

The first corridor was northbound Perring Parkway between Echodale Avenue and McClean Boulevard (Figure 11). The three-lane corridor is 1.4 miles long, with an unposted speed limit of 45 mph.

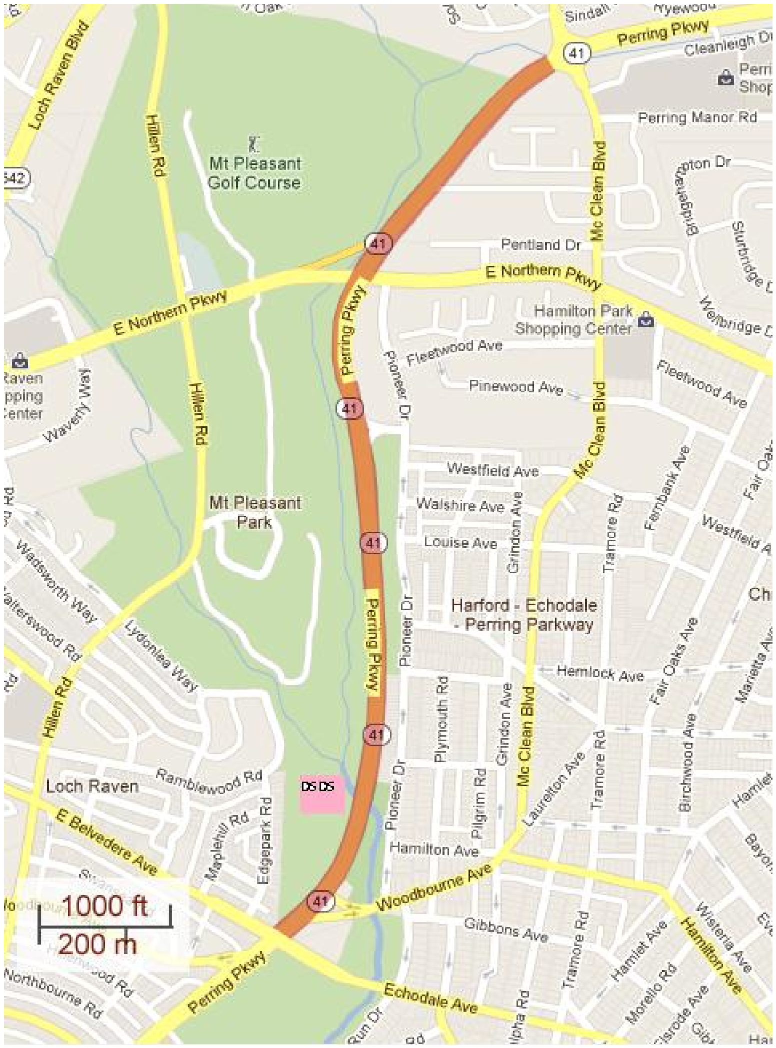

Figure 11: Perring Parkway Study Area

Fenwick Avenue Corridor

The second study area was southbound Fenwick Avenue between Hartsdale and Winford roads. The one-lane road is 0.2 miles long and is located within a 25 mph school zone. The speed limit was not posted.

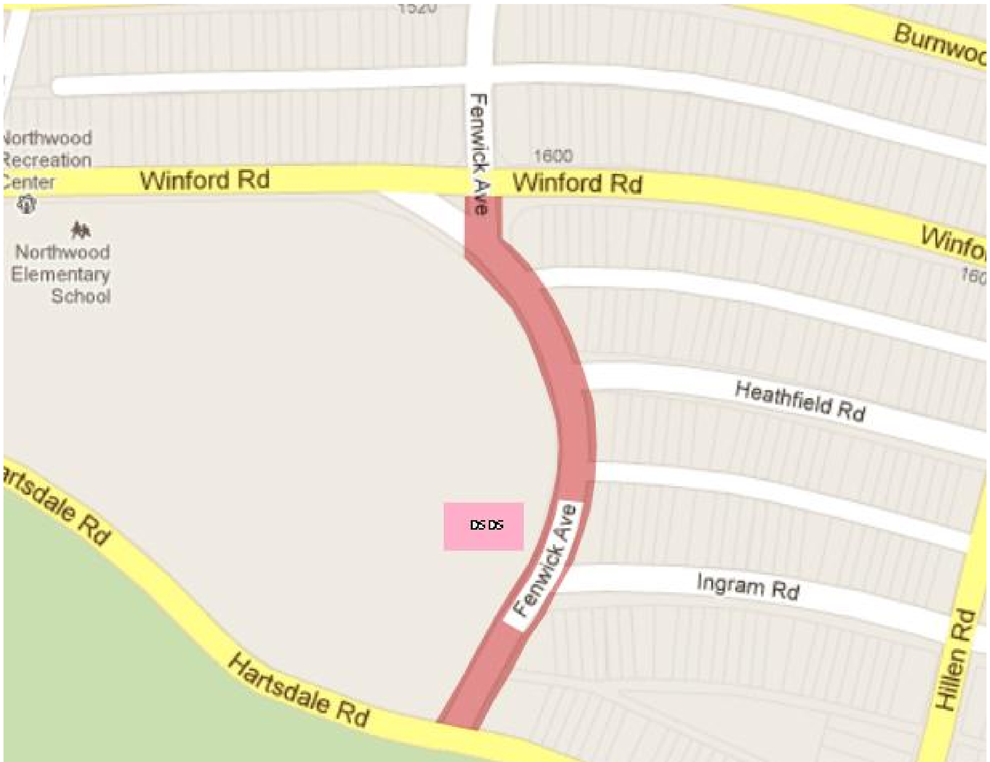

Figure 12: Fenwick Avenue Study Area

Hillen Road Corridor

The third study area was Hillen Road between Roundhill Road and E. 33rd Street. The corridor is 0.6 miles long and its speed limit is 35 mph (Figure 13). It includes three lanes, with one lane used for parking after the morning peak period. The City of Baltimore had received complaints from residents about speeding on the corridor.

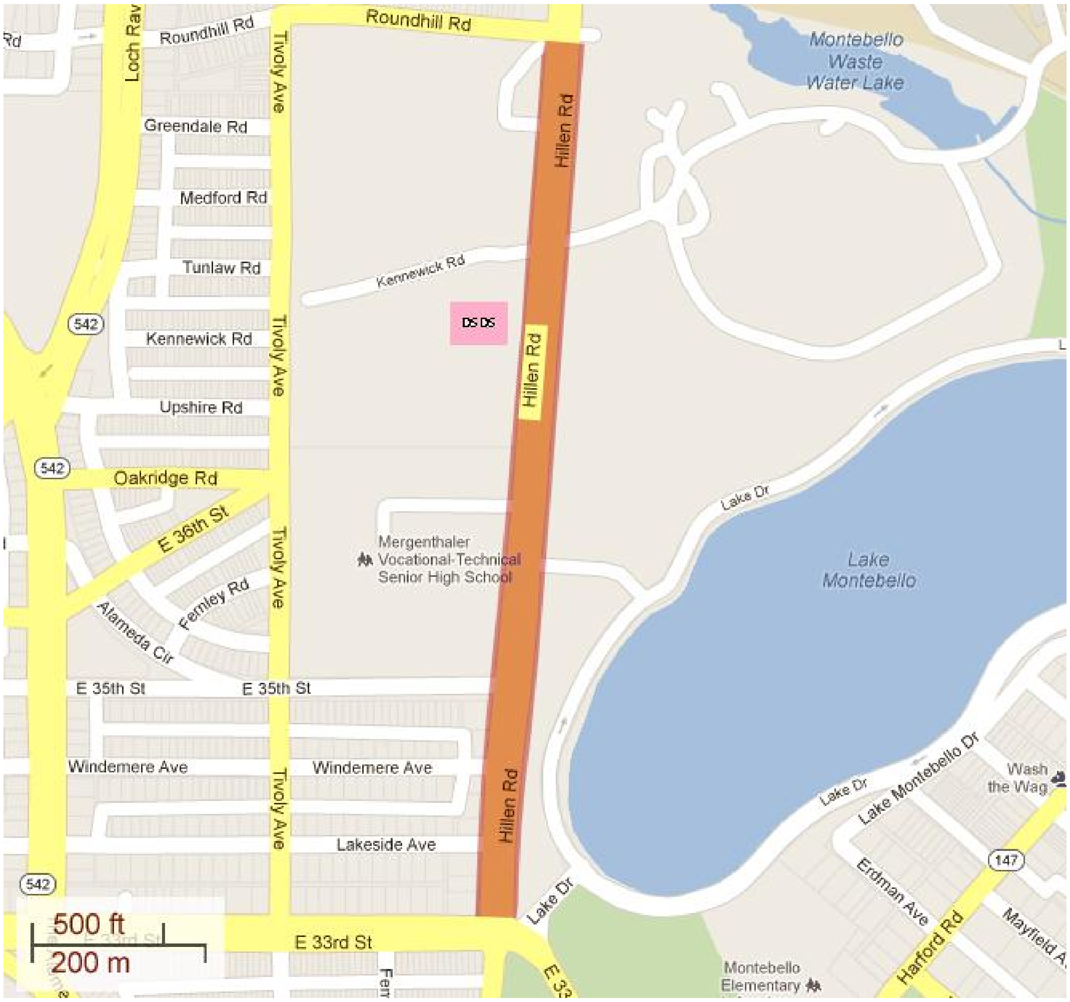

Figure 13: Hillen Road Study Area

The research team installed counters on Perring Parkway on October 18, 2010, and on Fenwick Road on October 22, 2010. The researchers collected the traffic data for one week. Then, Baltimore City installed a speed limit sign on both roads. Starting on November 9, the research team collected traffic data upstream and downstream of the speed limit signs for a week. On December 4, a DSDS device was installed next to each corridorøs speed limit sign, and the traffic data was collected for one week.

Unlike the other sites, Hillen Road already had a speed limit sign. The City of Baltimore installed the DSDS before the research team had a chance to install the counters. Consequently, the Hillen Road data collection began on October 29, after the DSDS installation. The data was collected for a week and only on Hillen Roadøs left lane because its right lane is used as street parking.

Two sizes of the DSDS were utilized. A large (1.5 feet by 3 feet) DSDS was installed on Perring Parkwayøs median, next to the left lane that carries higher speed vehicles. The large sign ensured that speeding drivers could see it. A small (15 inches by 8 inches) DSDS was installed on Fenwick Avenue and Hillen Road.

The Perring Parkway site was selected to test the duration and effective distance of the DSDS. The site is a relatively long stretch without any entrances or exits. After the DSDS had been operating for three months, two counters were reinstalled upstream and downstream of the DSDS to see if the device was still effective. In addition, on December 4, six counters were installed on the segment to find the effective distance for the DSDS. If the DSDS is effective and drivers reduce their speed, they most probably will increase their speed at a certain distance. The distance at which the reduced speed is held, is called the effective distance.

Data Cleaning

The research team cleaned the data for a reliable analysis. To ensure that ambient conditions did not influence the vehiclesô speed, the team eliminated low speeds from the dataset. The research team determined low speeds to be less than 10 mph for the 25 mph road, less than 15 mph for the 35 mph road, and less than 20 mph for the 45 mph road. Gaps were also eliminated for the same reason. Very high speeds (e.g., higher than 75 mph) were removed to exclude authorized high-speed vehicles such as police cars. Furthermore, records with a headway less than or equal to one second were removed to increase the dataôs accuracy.

Weather conditions, high car volume, and unknown people damaged or disconnected some tubes. As a result, the research team eliminated data for some days from the study due to unreliability, and repeated the data collection up to three times. Although the traffic counterôs vendor recommended that a device with more than 10 percent of its data missing should be declined from analysis, the research team eliminated data with more than five percent of its values missing. Sites with more than five percent missing values were subject to recounting.

Descriptive Analysis

Figures 14-16 show the diurnal distribution of traffic for seven consecutive days at the three sites. Figures 17-19 present the daily volume distribution for several consecutive days. Peak periods for each day were found by looking at the individual daily trend. Although all three sites had the same traffic pattern, peak periods were different at each site. There was no apparent peak period for weekends, which is quite plausible.

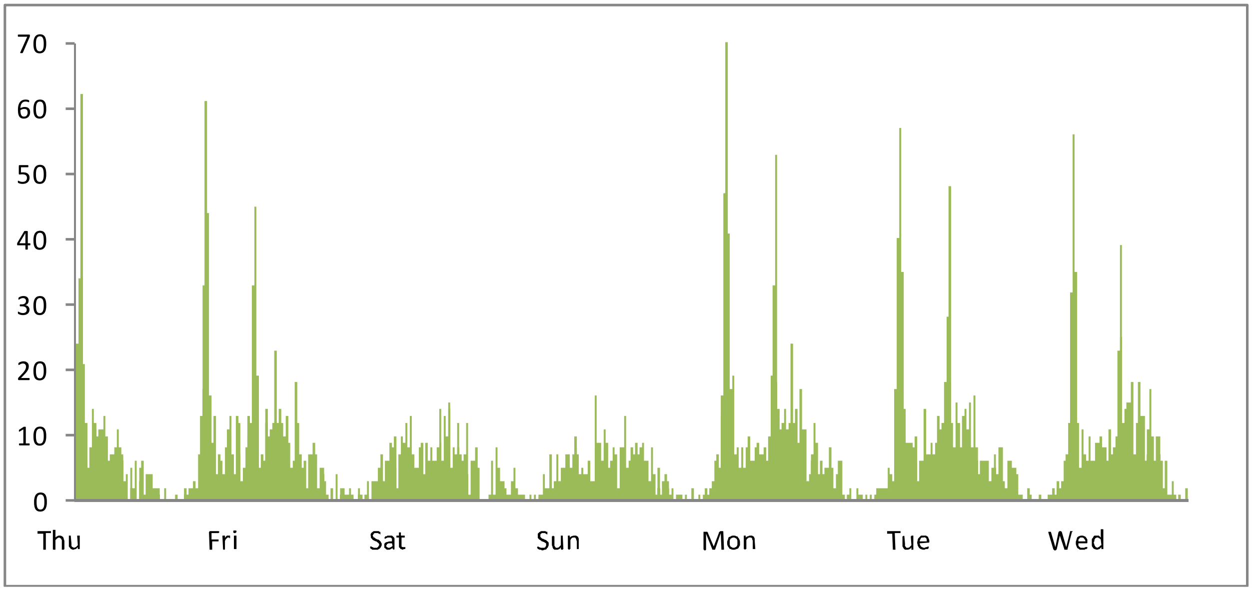

Figure 14: Diurnal Distribution of Fenwick Avenue over Seven Consecutive Days (veh/ln/15min)

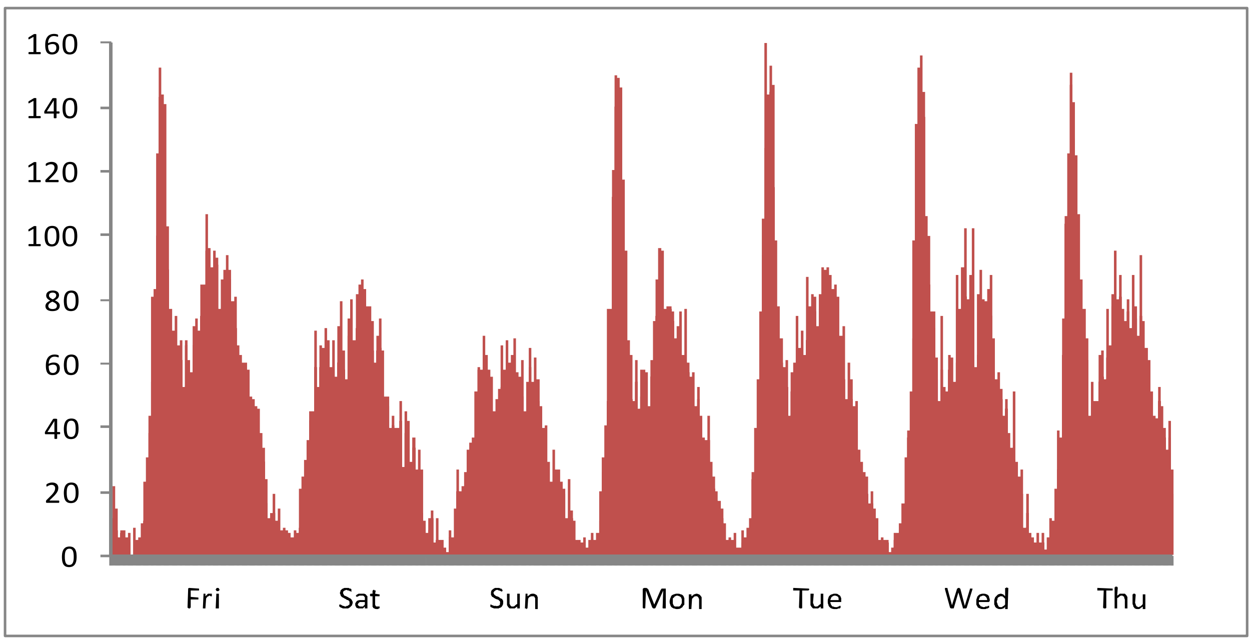

Figure 15: Diurnal Distribution of Hillen Road over Seven Consecutive Days (veh/ln/15min)

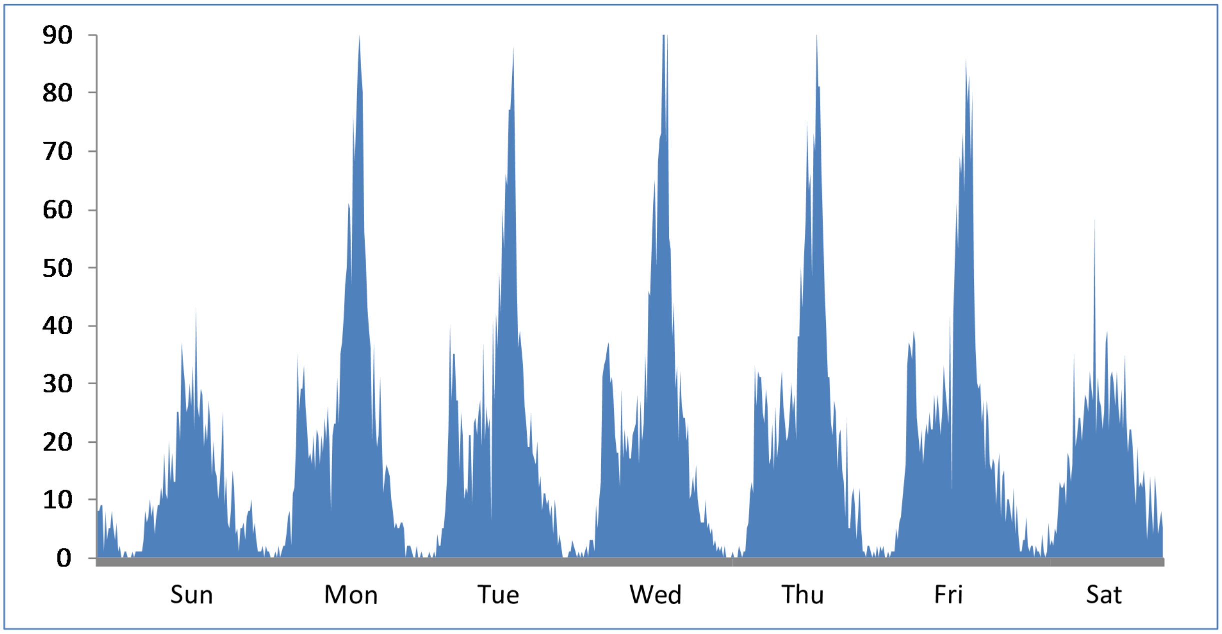

Figure 16: Diurnal Distribution of Perring Parkway over Seven Consecutive Days (veh/ln/15min)

<u>*Fenwick Avenue*</u>

Figure 17 shows that the weekday morning peak period was 7:15 a.m. to 8:30 a.m. The evening peak usually happened from 2:00 p.m. to 3:00 p.m. The evening peakôs volume was slightly less than the morning peakôs. Weekends did not show any significant peak period because the study area was a school zone and the road was not of much attraction during the weekend. There was no specific distinction between Saturday and Sunday.

<u>*Hillen Road*</u>

Figure 18 shows that the traffic volumes were higher in the morning peak than in the evening peak. The morning peak period was 7:00 a.m. to 9:15 a.m. The weekend volume was substantial, but there was no distinct peak period. Saturday had a higher cumulative volume than Sunday.

<u>*Perring Parkway*</u>

The graphs show that the highest volume happened during the weekdaysô evening peak, which ranged from 3:00 p.m. to 8:00 p.m. This is probably due to commuters. The morning peak period, 7:00 a.m. to 9:15 a.m., was not as solid as the evening peak, neither in value nor in interval. For the weekends, the graphs did not show a sharp peak, which could be due to non-work activities. There were slightly more generated trips on Saturday than on Sunday.

Figure 17: Daily Traffic Distribution of Fenwick Avenue for Six Consecutive Days (veh/ln/15min)

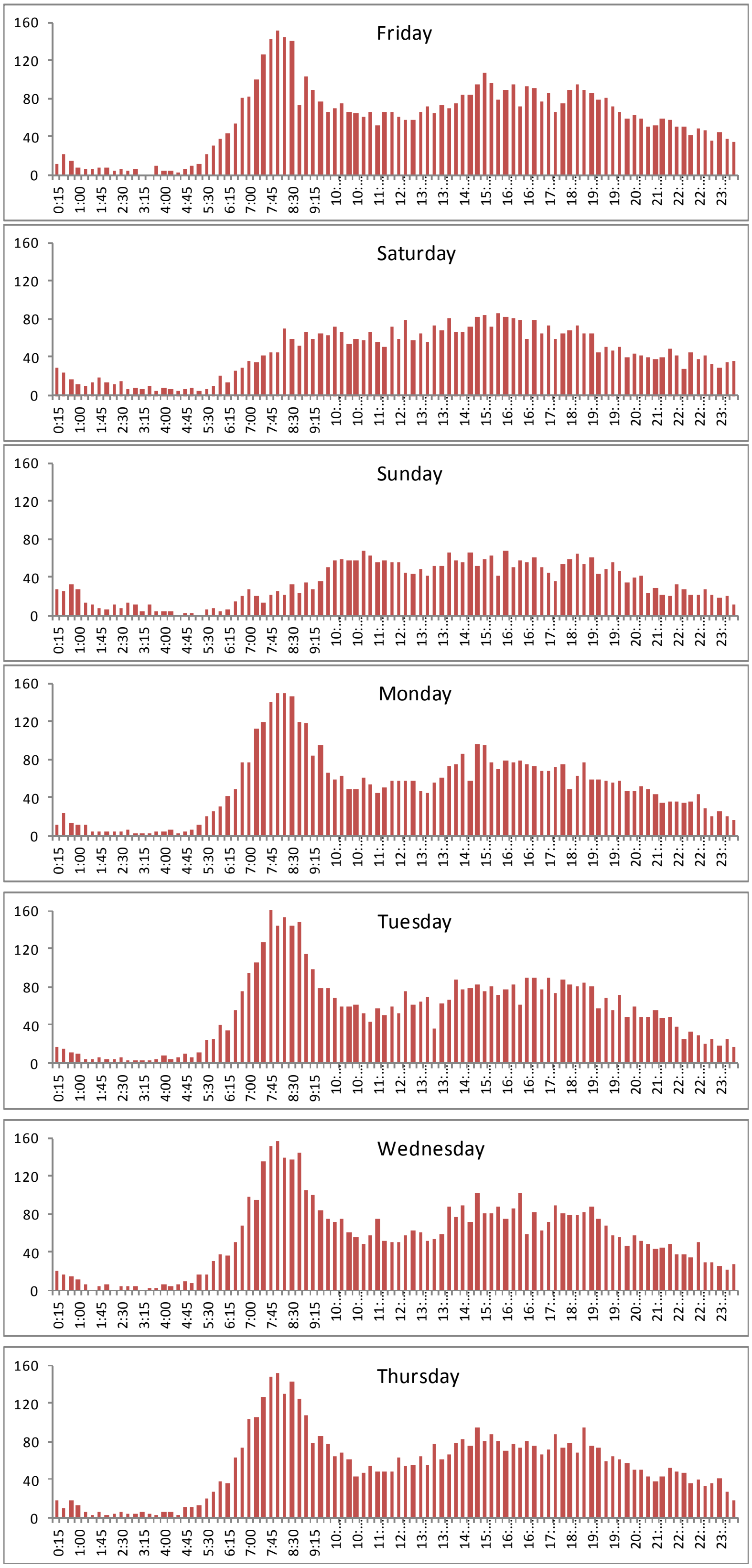

Figure 18: Daily Traffic Distribution of Hillen Road for Seven Consecutive Days (veh/ln/15min)

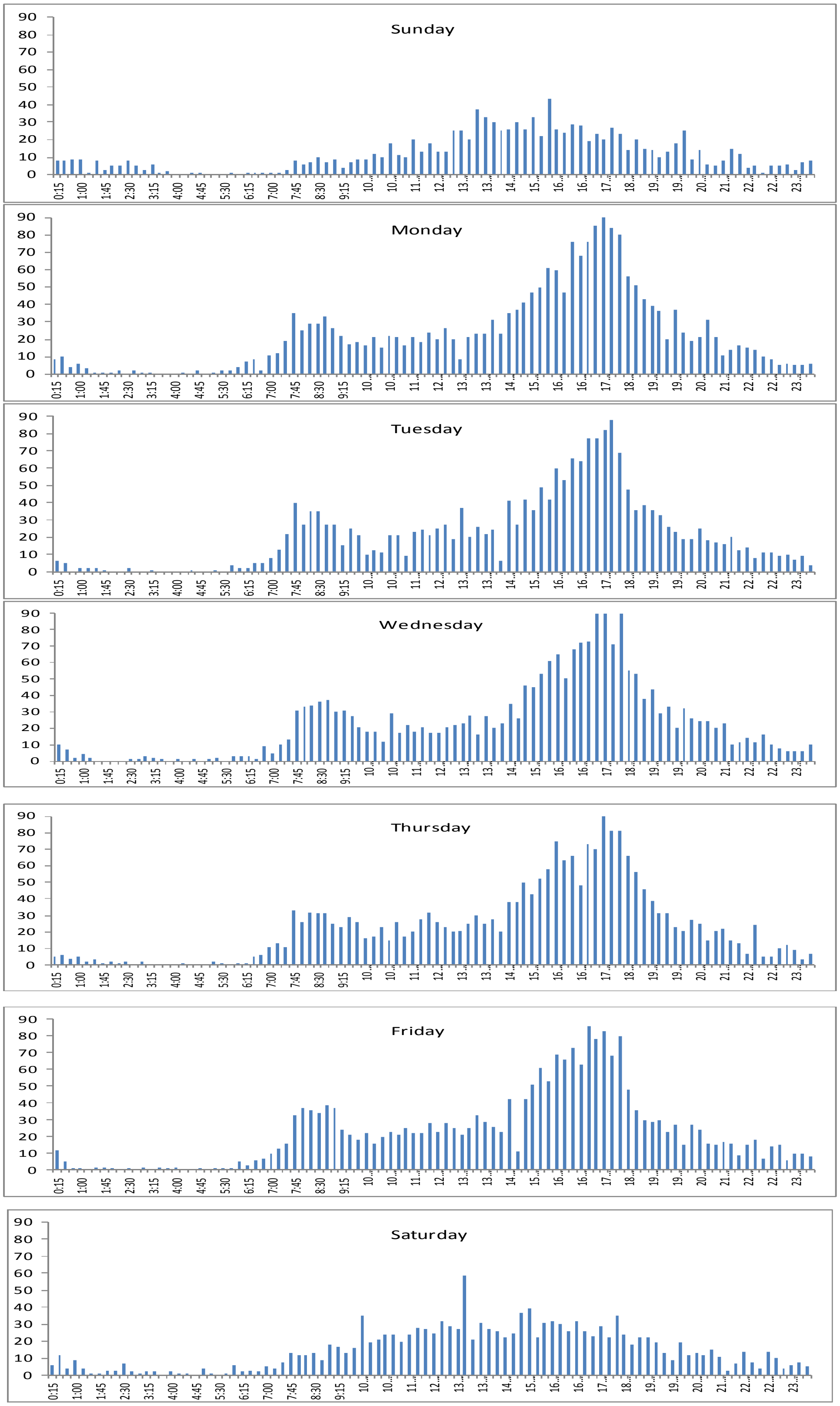

Figure 19: Daily Traffic Distribution of Perring Parkway for Seven Consecutive Days (veh/ln/15min)

Table 3 presents the average speeds before and after installation of a regular speed limit sign (SLS) and DSDS on Perring Parkway. The results indicate that the average speed and 85th percentile upstream speed reduced after the SLS was installed. The speed downstream of the SLS was slightly lower than the speed upstream of the SLS. The research team installed one counter 200 feet upstream of the DSDS and another, which is named Downstream 1, 10 feet downstream of the DSDS. Since Downstream 1 was very close to the DSDS, it was considered adjacent to the DSDS location. In order to find the effective distance of the DSDS, four additional counters were installed 900, 1130, 2390, and 4060 feet downstream of the DSDS. As presented in Table 3, the average speed was higher on Downstream 2, which was 900 feet from the DSDS. This shows that the DSDS affects speed reduction only for a very short distance.

Figure 20 presents the daily speed variation before SLS installation on Perring Parkway. The figures indicate that speeds between 45 mph and 55 mph had the highest frequency.

Table 3: Speed Statistics before and after SLS and DSDS Installation on Perring Parkway (45 mph)

	Upstream		Downstream 1 (Adjacent to the DSDS)		Downstream 2 900 ft		Downstream 3 1130 ft		Downstream 4 2390 ft		Downstream 5 4060ft	
	Avg. Speed	85%	Avg. Speed	85%	Avg. Speed	85%	Avg. Speed	85%	Avg. Speed	85%	Avg. Speed	85%
Before SLS	48.8	56										
After SLS Before DSDS	48.6	54.5	48.4	54								
After DSDS	47.6	56	47.1	54	48.4	53	49.6	55	48.2	55	46.7	52

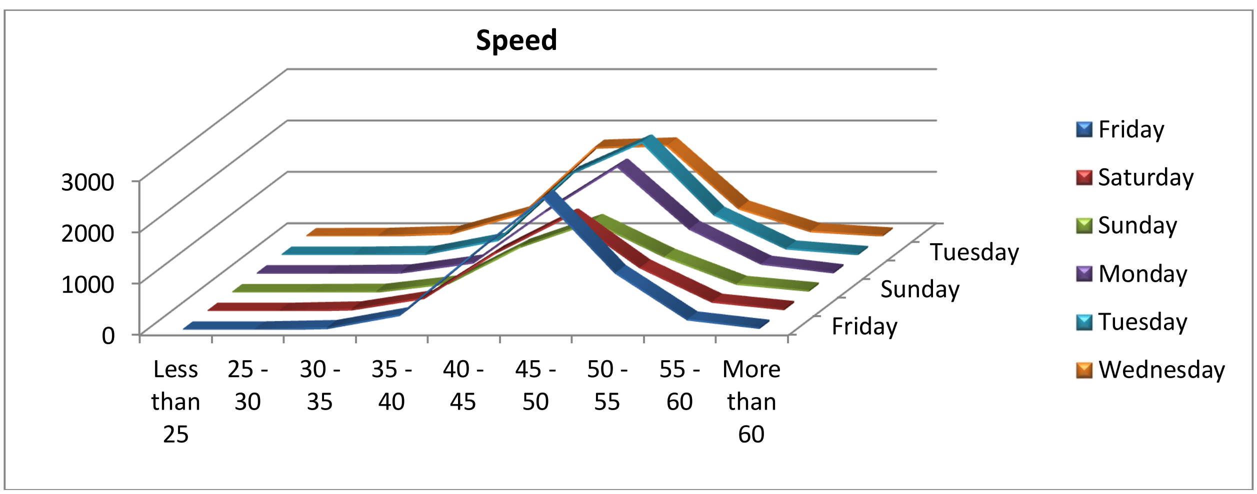

Figure 20: Daily Speed Variation on Perring Parkway

The speed data for the other two sites is summarized in Table 4. The pre-SLS and pre-DSDS data for Fenwick Avenue was excluded because it was not reliable. Speeds on Fenwick Avenue were slightly lower after the DSDS installation. However, of the three corridors, Hillen Road had the highest speed reduction.

Table 4: Speed Statistics after DSDS Installation on Fenwick Avenue and Hillen Road

	Upstream		Downstream (Adjacent)	
	Average Speed	85th Percentile	Average Speed	85th Percentile
Fenwick (25 mph)	21.7	27	21.5	27
Hillen (35 mph)	38.3	43	35.4	38

As stated earlier, after the counters were removed, Perring Parkwayȏs DSDS stayed up and operational for three months. The counters were reinstalled three months after the first installation on Perring Parkway. The counter reinstallation was done to determine the effective time range of the DSDS. Figure 11 presents the speed data upstream and downstream of the DSDS three after months its installation.

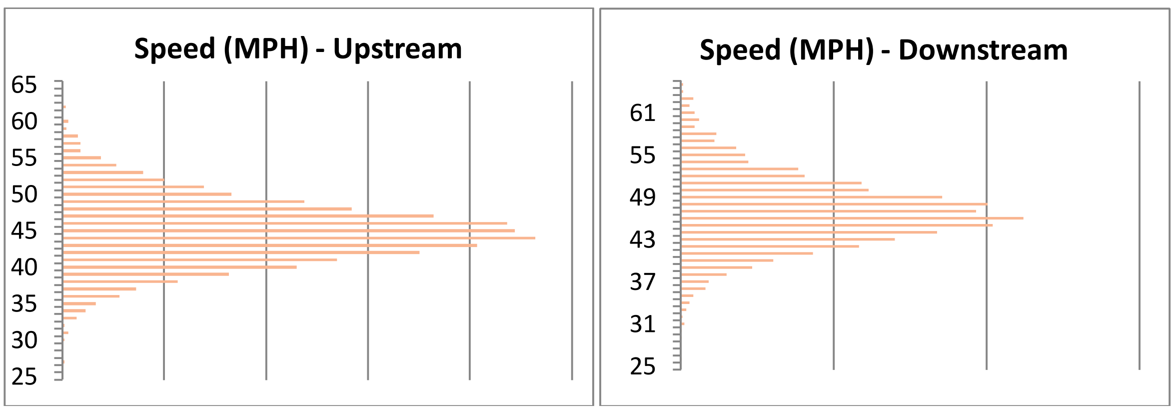

Figure 21: Speed Data Upstream and Downstream of the DSDS on Perring Parkway Three Months after Installation

Conventional Statistical Analysis

The research team performed a conventional statistical analysis of the collected data. Mean speed and variance were calculated for each of the three sitesȏ peak and off-peak periods. Table 5 summarizes the average speeds and sample sizes for each study area. Since roadway geometry affected speed reduction at some downstream locations, the fourth counter downstream of the DSDS was selected as the downstream location because it had a minimal speed variance. Short-term data refers to data collected during the first two weeks of DSDS operation, and long-term data refers to data collected after three months of continuous DSDS operation.

Table 5: Average Mean Speed (mph) and Sample Size of the Three Study Areas

Study Area	Before installation	Short term after installation			Long term after installation	
		Upstream	Adjacent	Downstream	Upstream	Adjacent
Fenwick Ave	–	21.72 4,643	21.50 5,032		–	
Hillen Rd	–	38.31 36,688	35.42 35,306		–	
Perring Pkwy	48.83 111,616*	47.57 22,101	47.10 20,822	48.2 42,631	46.15 28,020	48.4 27,629

*All three lanes

The research team tested whether there was a significant difference in mean speed upstream of and adjacent to the DSDS. Equation 1 shows a typical formulation. The tested hypothesis is $\triangle_1$ is less than zero.

$$\triangle_1 = S_{short\text{-}term}^{(adjacent)} - S_{short\text{-}term}^{(upstream)} \qquad (1)$$

Since sample sizes were large (Table 5) and normal population distribution was assumed, two groups of test data with sample sizes of n_1 and n_2 were drawn from the populations. The distributions were N (ε$_1$, ů$_1$) and N (ε$_2$, ů$_2$). Consequently, the differences between the two speed distributions were as follows.

$$\bar{x}_2 - \bar{x}_1 \sim N\left(\mu_1 - \mu_2, \frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}\right) \qquad (2)$$

$\bar{x}$ is the mean speed, and σ^2 is the populationôs variance. The *t*-test was the most fitted statistical test to address the current hypotheses. There are two models to perform the *t*-test:

(1) The two populations have equal variance (ů$_1^2$ = ů$_2^2$), .i.e., the two datasets are homoscedastic. In this case, the *t* value can be computed as Equation 3 with regard to a pooled estimation of the populationôs variance. The populationôs variance is derived from sample variances. In this equation, s^2, the sampleôs variance, is used to estimate populationôs variance. The *t* value is calculated as follows:

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{n_1 s_1^2 + n_2 s_2^2}{n_1 + n_2 - 2}}\sqrt{\frac{n_1 + n_2}{n_1 n_2}}} \qquad (3)$$

(2) The two populations have unequal variance (ů$_1$ Í ů$_2$), i.e., the two datasets are heteroscedastic. *t* value is calculated as follows:

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{n_1 - 1} + \frac{s_2^2}{n_2 - 1}}} \qquad (4)$$

To determine the equality of variances, an F-test was performed. The F-test compares the value of *f,* which is the ratio of variances (s_1^2/s_2^2), to the critical *f* for the desired significance level considering degrees of freedom. Thus, the null and alternative hypotheses for equality of variances can be stated as Equation 5.

$$H_0{:}\ \sigma_1^2 = \sigma_2^2 \qquad (5)$$
$$H_a{:}\ \sigma_1^2 \neq \sigma_2^2$$

The research questions of this study, which investigate whether there are significant differences between the mean speeds ($\bar{x}$), are summarized in the six propositions in Table 6. Each test was conducted on the appropriate site with the available and relevant speed data. The results of Hypotheses I and V will evaluate the temporary effect of the DSDS on drivers' speed choice. Hypothesis III's results will determine whether a DSDS is effective as a permanent strategy for speed control. The results of Hypotheses II and IV will measure time and distance's effect on DSDS performance.

Table 6: Hypothesis Tests

Hypothesis	Hypothesis Test	Hypothesis of Interest
I	H^{I}_{0}: $\bar{\bar{\square}}_{\text{short-term}}{}^{\text{(adjacent)}} \geq \bar{\bar{\square}}_{\text{short-term}}{}^{\text{(upstream)}}$ H^{I}_{a}: $\bar{\bar{\square}}_{\text{short-term}}{}^{\text{(adjacent)}} < \bar{\bar{\square}}_{\text{short-term}}{}^{\text{(upstream)}}$	A short term after installation, the average speed of vehicles adjacent to the DSDS is less than those upstream.
II	H^{II}_{0}: $\bar{\bar{\square}}_{\text{long-term}}{}^{\text{(adjacent)}} \geq \bar{\bar{\square}}_{\text{long-term}}{}^{\text{(upstream)}}$ H^{II}_{a}: $\bar{\bar{\square}}_{\text{long-term}}{}^{\text{(adjacent)}} < \bar{\bar{\square}}_{\text{long-term}}{}^{\text{(upstream)}}$	A long term after installation, the average speed of vehicles adjacent to the DSDS is less than those upstream.
III	H^{III}_{0}: $\bar{\bar{\square}}_{\text{long-term}}{}^{\text{(upstream)}} \geq \bar{\bar{\square}}_{\text{short-term}}{}^{\text{(upstream)}}$ H^{III}_{a}: $\bar{\bar{\square}}_{\text{long-term}}{}^{\text{(upstream)}} < \bar{\bar{\square}}_{\text{short-term}}{}^{\text{(upstream)}}$	The mean speed upstream of the DSDS increased after three months of continuous DSDS operation.
IV	H^{IV}_{0}: $\bar{\bar{\square}}_{\text{long-term}}{}^{\text{(adjacent)}} \geq \bar{\bar{\square}}_{\text{short-term}}{}^{\text{(adjacent)}}$ H^{IV}_{a}: $\bar{\bar{\square}}_{\text{long-term}}{}^{\text{(adjacent)}} < \bar{\bar{\square}}_{\text{short-term}}{}^{\text{(adjacent)}}$	The mean speed of vehicles adjacent to the DSDS decreased after three months of DSDS operation.
V	H^{V}_{0}: $\bar{\bar{\square}}_{\text{short-term}}{}^{\text{(adjacent)}} \geq \bar{\bar{\square}}_{\text{before}}{}^{\text{(adjacent)}}$ H^{V}_{a}: $\bar{\bar{\square}}_{\text{short-term}}{}^{\text{(adjacent)}} < \bar{\bar{\square}}_{\text{before}}{}^{\text{(adjacent)}}$	The mean speed of vehicles adjacent to the DSDS decreased a short term after DSDS installation.
VI	H^{VI}_{0}: $\bar{\bar{\square}}_{\text{short-term}}{}^{\text{(downstream)}} \geq \bar{\bar{\square}}_{\text{short-term}}{}^{\text{(upstream)}}$ H^{VI}_{a}: $\bar{\bar{\square}}_{\text{short-term}}{}^{\text{(downstream)}} < \bar{\bar{\square}}_{\text{short-term}}{}^{\text{(upstream)}}$	A short term after DSDS installation, the average speed of vehicles downstream of the DSDS is less than those upstream.

Hypothesis Results

Fenwick Road

The researchers tested Hypothesis I to determine whether the mean vehicle speed decreased a short term after DSDS installation. As described earlier in this report, the research team used an F-test to determine inequalities and similarities in the two samplesô variances. Table 7 shows the result. Since the *f* value (1.27) was greater than the critical *f* value at a 5 percent significance level (1.27>1.05), the research team rejected H_0 and concluded that the variances were unequal. Therefore, the research team conducted the t-test suitable for unequal variances. Table 8 shows the result of the t-test. Since the *t* value (1.89) was greater than the critical one-tail *t* value at a 5 percent significance level (1.65), the research team rejected H^{I}_{0} and concluded that the mean speed adjacent to the DSDS was significantly less than the mean speed upstream for a short-term period.

Table 7: F-test Results for Hypothesis I, Fenwick Avenue

Speed (mph)	Upstream	Adjacent
Mean	21.72	21.50
Variance	36.61	28.86
85^{th} percentile	27	27
Observations	4643	5032
df	4642	5031
f	1.268	
f critical one-tail *	1.048	

* For Ŭ= 0.05

Table 8: t-test Results for Hypothesis I, Fenwick Avenue

Speed (mph)	Upstream	Adjacent
Mean	21.72	21.50
Variance	36.61	28.86
Observations	4643	5032
Hypothesized mean difference	0	
df	9308	
t stat.	1.891	
t critical one-tail *	1.645	

* For Ŭ= 0.05

Hillen Road

Table 9 shows the F-test result for Hillen Road. Since the *f* value (2.69) was greater than the critical *f* at a 5 percent significance level (1.02), the research team rejected H_0 and concluded that the variances were unequal. Therefore, the t-test suitable for unequal variances was conducted. Table 10 shows the t-test result. Since the *t* value (93.15) was much greater than the critical one-tail *t* at a 5 percent significance level (1.65), the research team rejected H^I_0 and concluded that the mean speed adjacent to the DSDS was significantly less than the mean speed upstream for a short-term period.

Table 9: F-test Results for Hypothesis I, Hillen Road

Speed (mph)	Upstream	Adjacent
Mean	38.31	35.42
Variance	25.42	9.459
85th percentile	43	38
Observations	36,688	35,306
df	36,687	35,305
f	2.687	
f critical one-tail *	1.017	

* For Ŭ= 0.05

Table 10: t-test Results for Hypothesis I, Hillen Road

Speed (mph)	Upstream	Adjacent
Mean	38.31	35.42
Variance	25.42	9.459
Observations	36,688	35,306
Hypothesized mean difference	0	
df	61,061	
t stat.	93.15	
t critical one-tail *	1.645	

* For Ŭ= 0.05

Perring Parkway

All six hypotheses can be studied with the data from Perring Parkway. Since the other two sitesô distances were shorter, only the effective distance and time were tested on Perring Parkway. Therefore, the rest of this section explains each hypothesisô test results.

Hypothesis I

Table 11 shows the F-test results for Hypothesis I. Since the *f* value (1.51) was greater than the critical *f* at a 5 percent significance level (1.02), H_0 was rejected and the variances were deemed unequal. Therefore, the research team conducted the *t*-test suitable for unequal variances. Table 12 presents the result of the *t*-test. Since the *t* value (6.42) was greater than the critical one-tail *t* at a 5 percent significance level (1.65), the research team concluded that the mean speed adjacent to the DSDS was significantly less than the mean speed upstream for a short-term period.

Table 11: F-test Results for Hypothesis I, Perring Parkway

Speed (mph)	Upstream	Adjacent
Mean	47.57	47.10
Variance	71.07	47.17
85th percentile	56	54
Observations	22,101	20,822
df	22,100	20,821
f	1.507	
f critical one-tail (Ǔ= 0.05)	1.023	

Table 12: t-test Results for Hypothesis I, Perring Parkway

Speed (mph)	Upstream	Adjacent
Mean	47.57	47.10
Variance	71.07	47.17
Observations	22,101	20,822
Hypothesized mean difference	0	
df	42,053	
t stat.	6.417	
t critical one-tail (Ǔ= 0.05)	1.645	

Hypothesis II

The research team tested Hypothesis II to determine whether the DSDS produced a long-term reduction in mean speed. Table 13 shows the F-test result. H_0 could not be rejected since the f value (0.75) was less than the critical f at a 5 percent significance level (0.98). Therefore, the variances were considered equal. Table 14 presents the t-test results. Since t value (-52.4) was less than the critical one-tail t at a 5 percent significance level (1.65), H^{II}_0 could not be rejected. Therefore, the mean speed adjacent to the DSDS was not less than the mean speed upstream for a long-term period, i.e., the DSDS is not an effective long-term tool.

Table 13: F-test Results for Hypothesis II, Perring Parkway

Speed (mph)	Upstream	Adjacent
Mean	46.15	48.36
Variance	21.32	28.40
85^{th} percentile	51	53
Observations	28,020	27,629
df	28,019	27,628
f	0.751	
f critical one-tail (Ŭ= 0.05)	0.980	

Table 14: t-test Results for Hypothesis II, Perring Parkway

Speed (mph)	Upstream	Adjacent
Mean	46.15	48.36
Variance	21.32	28.40
Observations	28,020	27,629
Hypothesized mean difference	0	
df	55,647	
t stat.	-52.38	
t critical one-tail (Ŭ= 0.05)	1.645	

Hypothesis III

The research team tested Hypothesis III to determine whether the mean speed upstream of the DSDS increased after three months of continuous DSDS operation. The F-test results, presented in Table 15, indicated that the variances were unequal. Therefore, the research team conducted a *t*-test for unequal variances. As shown in Table 16, the *t*-test results indicated that the mean speed upstream of the DSDS after three months of operation was more than the mean speed immediately after installation, underlining the long-term effect of the DSDS.

Table 15: F-test Results for Hypothesis III, Perring Parkway

Speed (mph)	Short-Term Upstream	Long-Term Upstream
Mean	47.57	46.15
Variance	71.07	21.32
85th percentile	56	51
Observations	22,101	28,020
df	22,100	28,019
f	3.334	
f critical one-tail (Ŭ= 0.05)	1.021	

Table 16: t-test Results for Hypothesis III, Perring Parkway

Speed (mph)	Short-Term Upstream	Long-Term Upstream
Mean	47.57	46.15
Variance	71.07	21.32
Observations	22,101	28,020
Hypothesized mean difference	0	
df	32,366	
t stat.	22.59	
t critical one-tail (Ŭ= 0.05)	1.645	

Hypothesis IV

The research team tested whether the mean speed of vehicles adjacent to the DSDS decreased after three months of DSDS operation. Based on the F-test results (Table 17), the research team conducted a *t*-test for two samples with unequal variances. The research team concluded that the mean speed adjacent to the DSDS after three months was not less than the mean speed immediately after the DSDS installation.

Table 17: F-test Results for Hypothesis IV, Perring Parkway

Speed (mph)	Short-Term Adjacent	Long-Term Adjacent
Mean	47.10	48.36
Variance	47.17	28.40
85^{th} percentile	54	53
Observations	20,822	27,629
df	20,821	27,628
f	1.661	
f critical one-tail (Ŭ= 0.05)	1.022	

Table 18: t-test Results for Hypothesis IV, Perring Parkway

Speed (mph)	Short-Term Adjacent	Long-Term Adjacent
Mean	47.10	48.36
Variance	47.17	28.40
Observations	20,822	27,629
Hypothesized mean difference	0	
df	38,093	
t stat.	-22.02	
t critical one-tail (Ŭ= 0.05)	1.645	

Hypothesis V

The research team tested whether the mean speed of vehicles adjacent to the DSDS decreased for a short term after DSDS installation. Since the F-test results in Table 19 indicated that the variances were unequal, the research team conducted a *t*-test for two samples with unequal variances. The research team rejected H^V_0. Therefore, the mean speed adjacent to the DSDS a short term after installation was less than the mean speed pre-DSDS installation (Table 20).

Table 19: F-test for Hypothesis V, Perring Parkway

Speed (mph)	Before	Short-Term After
Mean	48.83	47.10
Variance	61.08	47.17
85^{th} percentile	56	54
Observations	111,616	20,822
df	111,615	20,821
f	1.295	
f critical one-tail (Ŭ= 0.05)	1.018	

Table 20: t-test for Hypothesis V, Perring Parkway

Speed (mph)	Before	Short-Term After
Mean	48.83	47.10
Variance	61.08	47.17
Observations	111,616	20,822
Hypothesized mean difference	0	
df	31,750	
t stat.	32.67	
t critical one-tail (Ŭ= 0.05)	1.645	

Hypothesis VI

Finally, the research team tested whether vehiclesô mean speed upstream of the DSDS decreased for a short term after installation. As presented in Table 21, the F-test indicated that the variances were equal. Therefore, the researchers conducted a t-test for two samples with equal variances. The results (Table 22) indicated that a short-term after the installation, the mean speed downstream of the DSDS was not less than the mean speed upstream of the DSDS.

Table 21: F-test for Hypothesis VI, Perring Parkway

Speed (mph)	Upstream	Downstream
Mean	46.15	48.25
Variance	21.32	52.56
85th percentile	51	55
Observations	28020	32631
df	28019	32630
f	0.406	
f critical one-tail (Ǚ= 0.05)	0.981	

Table 22: t-test for Hypothesis VI, Perring Parkway

Speed (mph)	Upstream	Downstream
Mean	46.15	48.25
Variance	21.32	52.56
Observations	28020	32631
Hypothesized mean difference	0	
df	60,649	
t stat.	-41.74	
t critical one-tail (Ǚ= 0.05)	1.645	

Data Aggregation

More than 110,000 pairs of valid speed data (upstream and downstream of a DSDS) were recorded from the three sites for seven days of DSDS operation. Because data was missing in some cases and some cars changed lanes, it was impossible to track individual cars upstream, adjacent to, and downstream of DSDS. The conventional statistical analysis used in the previous section was a complete aggregate analysis, which analyzed the average speeds as a single value. The research team proposed a hybrid analysis to aggregate the data. There are two possible methods for aggregating the speed data.

1- Aggregation based on an equal number of vehicles (n) passing a section in an appropriate time interval. In this approach, different time periods may be used in order to have the same number of vehicles.

2- Aggregation based on equal periods of time (t). In this approach, different number of vehicles may be used in order to have the same time period.

Based on a preliminary analysis, the research team decided to use the first approach. The research team grouped and calculated the mean speed of every 50 consecutive vehicles (n=50).

Fifty vehicles, a small number, are probably in the same time period. In the hybrid approach, a single mean value represents 50 actual records from the original data. After aggregation, the 110,000 pairs of speed data were transformed into 2,210 aggregated values.

The second approach was tested for *t* equal to 15 minutes and 30 minutes. In this case, each record would represent a category and its corresponding volume. This approach is inferior to the first approach because each categoryøs number of cars varies. Consequently, the second approachøs weights required adjustment to attain fair impact of each actual speed in the model. The second approach was not used further in this study.

The research team applied linear regression, CATREG, and BN to the aggregated data in order to supplement the conventional statistical analysis and to answer the research questions.
The research team formed 13 variables from the collected data, 11 of which were categorical. Table 23 describes the variables and categories (states) associated with each variable. The research team classified the variables into five groups. The first three groupsð time & day, road-related (e.g., speed limit and number of lanes), and DSDS-related variablesð were naturally independent variables, while the last two (speed and compliance) were dependent variables. Speed data was not used directly in the analysis; thus, 11 variables were used.

The research team chose the suitable number of states for the BN. When there is a fewer number of states, there is a fewer number of scenarios in the nodesô probability tables. The number of scenarios within any nodeøs probability table is determined by the multiplication of its parentsô number of states by the nodeøs number of states. To ensure that each scenarioøs conditional probability table could be elicited from the data, the number of states in each node was minimized in such a way not to compromise the model fit.

Time and Day

The research team divided the variable Day into weekday and weekend, and divided the variable Time into peak and off-peak. Peak and off-peak were obtained from diurnal distribution of the traffic presented in Figures 14-19.

Road-Related Variables

There were three variables in the road-type group: Speed Limit, School Zone, and Number of Lanes. As mentioned earlier, the speed limits of the three study areas were 25 mph, 35 mph, and 45 mph.

According to the literature, a DSDS highly affects speed compliance in a school zone. In this study, only the 25 mph road (Fenwick Avenue) was located in a school zone. The number of lanes may affect vehicle speed. Two of the sites (Perring Parkway and Hillen Road) had three lanes and one (Fenwick Avenue) had one lane.

Table 23: Variable Description for BN Modeling

Type	Variables	Type	Number of states	States
Time & Day	Day	Discrete	2	weekend / weekday
	Time	Discrete	2	peak / off-peak
Road	Speed Limit	Discrete	3	25 / 35 / 45
	School Zone	Discrete	2	yes / no
	Lane Number	Discrete	2	1 / 3
DSDS	Size	Discrete	2	small / big
	Effective Time	Continuous		1~2 / 3~7 / 8~12 / >12
	Effective Distance	Discrete	2	nearby / far-downstream
Speed	Avg. Speed Upstream	Continuous		_
	Avg. Speed Downstream	Continuous		_
Compliance	Speed Alteration	Discrete	3	decrease / constant / increase
	Compliance Before	Discrete	4	LSL / L1.07SL / L1.15SL / HSL
	Compliance After	Discrete	4	LSL / L1.07SL / L1.15SL / HSL

DSDS-Related Variables

Three DSDS-related variables were used: Size, Effective Time, and Effective Distance. As mentioned earlier, two sizes of DSDS, small (15 inches by 8 inches) and large (1.5 feet by 3 feet), were utilized in the study. Effective Time, a continuous variable, represents the number of days that the DSDS was operational. This variable was discretized into four states: Day 1-2, Day 3-7, Day 8-12, and Day 13+. The effective distance of the DSDS represents the location of the second speed detector: adjacent to the DSDS or downstream of the DSDS.

Speed and Compliance Variables

As stated earlier, speed data upstream and downstream of the DSDS was recorded for each of the three sites. Since the three sitesô aggregated data was combined in a unique dataset to capture the effect of different invariants on the driversô speed limit compliance, the research team formed and utilized three speed-related variables, named compliance variables. The compliance variables were used instead of the absolute speed data. The three compliance variables were Speed Alteration, Compliance Before, and Compliance After.

The research team decided not to treat compliance variables as binary (i.e., compliance and non-compliance) because a vehicle speed slightly above the speed limit can be considered speed limit compliant. In the United States, the policeôs rule of thumb is to issue speeding tickets for speeds 10 to 20 percent above the speed limit. The research team specified four levels of speed compliance:

(i) less than speed limit (LSL)
(ii) more than the speed limit but less than 7 percent above speed limit (L107SL)
(iii) between 7 and 15 percent above the speed limit (L115SL)
(iv) more than 15 percent above the speed limit (H115SL)

The research team evaluated different percentages over the speed limit (such as 5, 7, 10, 15, and 20 percent) and selected values of 7 percent and 15 percent over the speed limit to categorize compliance since the data distribution was uniform.

Speed Alteration and Compliance After can be used as the dependent variables in CATREG and in BNôs final node. Compliance Before affects Compliance After and can be used as an input (independent variable). These three variables were calculated based on the two average speeds of every 50 vehicles traveling upstream and downstream of a DSDS. The frequencies of states for these three variables are presented in Tables 24 and 25.

Table 24: Speed Alteration States

	Decrease	Constant	Increase	Total
No.	831	504	433	1768
%	47.0%	28.5%	24.5%	100

Table 25: States of Compliance before and after DSDS Installation

		LSL	L1.07SL	L1.15SL	HSL	Total
Compliance Before	No.	348	512	740	168	1768
	%	19.7%	29.0%	41.9%	9.5%	100
Compliance After	No.	360	888	463	57	1768
	%	20.4%	50.2%	26.2%	3.2%	100

This study does not deal with the change in average gaps as a performance measure because it is an average quantity and does not show the real and critical gap of individual cars. The effect of DSDS on driversô gap acceptance could be investigated if the complete disaggregate data were available (i.e., *n*=1). For *n*>1, gap may not be useful due to the wide range of gap values.

Linear Regression Model

The research team converted Size, Alteration, Compliance Before, and Compliance After into ordinal variables. Day, Time, and School Zone were converted into binary variables. A linear regression model was then applied to two dependent variables, Compliance After and Speed Alteration, as presented in Tables 26 and 27.

Table 26: Linear Regression Results on Compliance after DSDS Installation

Independent Variable	Coefficient	P-Value
School Zone	-0.610	<0.0001
Speed Limit	0.045	<0.0001
Compliance Before	-0.203	<0.0001
Effective Distance	0.102	0.034
Effective Time	0.002	<0.0001
Constant	-0. 603	<0.0001

R^2=0.324

Table 27: Linear Regression Results on Speed Alteration

Independent Variable	Coefficient	P-Value
Speed Limit	0.026	<0.0001
Compliance Before	-0.587	<0.0001
Effective Distance	0.123	0.001
Effective Time	0.004	<0.0001
Constant	-0.728	<0.0001

R^2=0.657

After DSDS installation, the compliance rate was higher in the school zone than in non-school zones. When the speed limit increases, Compliance After decreases. Interestingly, Compliance Before had a reverse effect on Compliance After. When the distance from the DSDS location increased 10 percent, the Compliance After decreased 0.2 percent. The more time past the DSDS installation date, the less effective the DSDS became.

As stated in Tables 26 and 27, the R^2 value of the second regression model was higher than the first one. Therefore, Speed Alteration can be explained better as a dependent variable than Compliance After in the linear regression model. A school zone designation did not seem to affect speed alteration, probably because drivers were already driving under the speed limit before they observed a DSDS. The rest of the independent variables had a similar effect on Speed Alteration as on Compliance After.

Categorical Regression Model (CATREG)

The research team performed a CATREG model between every two variables to find the correlation between the categorical variables. Then, the research team performed a forward regression to find the model that best explained the relationship between the dependent and independent variables. The developed models were utilized to construct the BN model. As presented in Table 28, the most important factors of Compliance After were School Zone, Size, Effective Distance, Speed Alteration, Effective Time, Day, and Time.

Table 28: CATREG Results

Independent Variable	Importance	Coefficient	P-Value
School Zone	0.604	0.425	<0.0001
Size	0.204	0.206	<0.0001
Effective Distance	0.100	0.258	<0.0001
Speed Alteration	0.061	0.128	<0.0001
Effective Time	0.057	-0.065	0.167
Compliance Before	-0.021	-0.113	<0.0001
Day	-0.007	-0.021	0.006
Time	0.001	0.014	0.615

R^2=0.292

Bayesian Network (BN)

BN Construction

Generally, the network should be as shallow as possible. Redundant links should be eliminated to decrease the network complexity and to avoid over-fitting (Cinar and Kayakutlu, 2010); however, the forecasting capability of the network should not be compromised. In addition, one should avoid creating loops between nodes. The final structure of this studyĝs network is shown in Figure 22. The target node, Compliance After, is green. The research team created a conditional probability table of nodes, wherein each state is presented as a belief bar. To create this format, the research team used Netica software (Netica, 2011), which utilizes the theory of posterior marginal probability to represent the joint probability of an event.

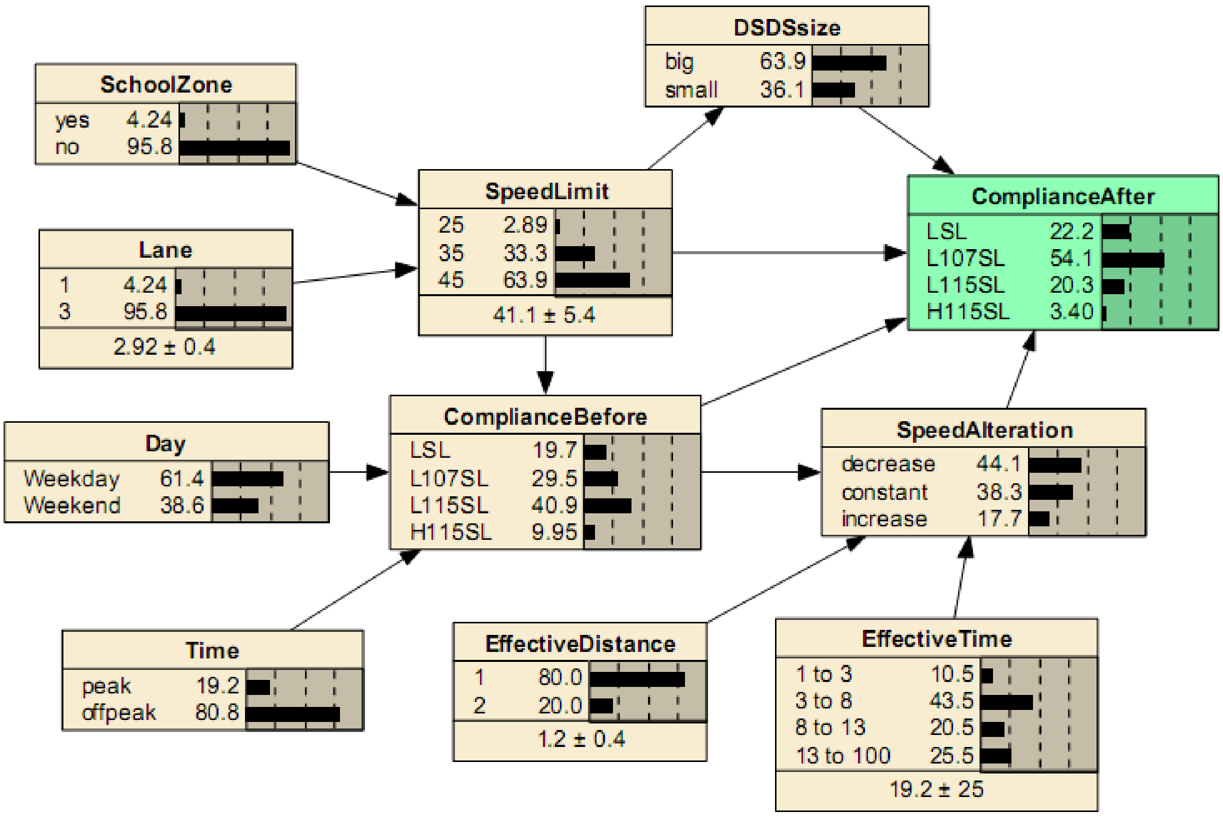

Figure 22: BN Structure

Model Validation

Performance evaluation ensures that a predictive model performs appropriately. Evaluation methods and criteria are critical in the modelôs performance calculations. One of the most predominant methods in this field of study is the division of the dataset into two subsets: one that trains the network and a second smaller set that tests it. Different test-set ratios, ranging from 10 to 25 percent of the data, have been reported in BN-related studies (Xu et al., 2005; Dlamini, 2010). The modelôs error rate and three scoring rules of logarithmic loss, quadratic loss, and spherical payoff for the test set are the most common measures to evaluate the predictive power of the model.

In the current study, 80 percent of the combined data from all three sites was randomly selected for the training set and the remaining 20 percent was used for test set. The learning process was performed only on the first 80 percent to calibrate the BN model. An expectation-maximization algorithm was used in the calibration process. The BN model was calibrated with 1,768 aggregate records and was tested with the other 442 records. The evaluation was a two-step process. First, the BN model was used to predict the probability distribution of the target node (i.e., compliance rate after DSDS). Then, the predicted values were compared to the observed values.

Table 29 presents the BN model’s goodness-of-fit using four criteria. The error rate shows the percentage of false predictions. The three scoring rules (logarithmic loss, quadratic loss, and spherical payoff) are computed based on the actual belief levels of node states. The scoring rules are used to evaluate model efficiency and classification ability, rather than considering only the state with highest probability (Morgan and Henrion, 1990). The logarithmic loss and quadratic loss vary from zero to infinity, with zero as the best fit of model. Spherical payoff varies from zero to one, in which one indicates the best fit. Although these scoring rules display the discrepancy of model outcomes accurately, they are not readily interpretable. Equation 6 shows the formulation of these rules (Netica, 2011). M is the mean function over all cases of test file, P_c is the estimated probability of the true state, and P_j is the estimated probability of j^{th} state when there are n sates for the question node.

$$\begin{aligned} Logarithmic\ loss &= M\left(-\ln P_c\right) \\ Quadratic\ loss &= M\left(1 - 2P_c + \textstyle\sum_{j=1}^{n} P_j^2\right) \\ Spherical\ payoff &= M\left(\frac{P_c}{\sqrt{\sum_{j=1}^{n} P_j^2}}\right) \end{aligned} \quad (6)$$

Table 29 demonstrates a strong correlation between the training and testing parameters, which guarantees that there is no over-fitting problem in the BN learning process. The model assessment results, particularly for the test set, also indicate that the BN model can act as a reliable tool for sensitivity analysis of different components of drivers’ compliance rate.

Table 29: BN Model’s Goodness-of-Fit

Criteria	Train set	Test set
Error Rate	30.94%	33.71%
Logarithmic Loss	0.6561	0.7255
Quadratic Loss	0.4124	0.4551
Spherical Payoff	0.7595	0.7345

Sensitivity Analysis

This study aimed to determine the effectiveness of a DSDS on drivers’ compliance with the speed limit. BN can identify how each node (variable) would change when another node changes. This section describes the sensitivity analysis of speed compliance with respect to other variables’ changes. Sensitivity analysis is a valuable method to study the variation in a statistical model’s output when input changes.

Table 30 summarizes the computed sensitivities for each node in the constructed BN. The variables are based on two factors, mutual information and the percentages. Mutual information, also called entropy reduction, is the anticipated reduction in uncertainty of a random variable due to another random variable. For two random variables of *X* and *Y*, the mutual information of *I*(*X*; *Y*) is a measure of dependency between *X* and *Y.* The mutual information of I is calculated as Equation 7 (Cover and Thomas, 2006). In this equation, *p*(*x, y*) is the joint probability function of *X* and *Y*.

$$I(X;Y) = H(X) - H(X|Y) = \sum_{x,y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)} \qquad (7)$$

Table 30 presents the most effective factors on Compliance After in descending order. As shown, Speed Alteration is the most effective. The top five variables were examined further.

Table 30: Sensitivity of Compliance after DSDS Installation with Respect to Other Variables

Node (Variable)	Mutual info.	Percent
Speed Alteration	0.26828	16.8
Speed Limit	0.15361	9.63
DSDS size	0.09915	6.22
Effective Time	0.06513	4.09
Compliance Before	0.04794	3.01
Lane	0.01109	0.70
School Zone	0.01109	0.70
Effective Distance	0.00423	0.27
Day	0.00012	0.01
Time	0.00010	0.01

Table 31 presents the effect of Table 30ôs five most important variables on the final node, Compliance After. Any change in the probabilities of the independent nodesô states adjusts the belief bars of the target nodeôs state. Hereafter, Base case refers to the results presented in Figure 21. In the Base case, 22.2 percent of sample was LSL downstream of DSDS, and 54.1, 20.3, and 3.4 percent of the sample was L107SL, L115SL, and H115SL, respectively.

Table 31: Compliance After Sensitivity to Other Variables

(Variable) State	LSL % [1]	L107SL % [2]	L115SL % [3]	H115SL % [4]
(Speed Alteration)				
Decrease	38.8	57.0	4.1	0.1
Constant	7.4	65.1	26.5	1.0
Increase	12.6	23.1	47.5	16.8
(Speed Limit)				
25	98.4	0.5	0.5	0.5
35	21.9	72.7	3.4	2.0
45	18.8	46.8	30.1	4.3
(DSDS Size)				
Large	18.8	46.8	30.1	4.3
Small	28.0	66.9	3.2	1.9
(Effective Time)				
1 to 2 days	31.2	55.9	10.5	2.4
3 to 7 days	27.3	58.1	13.2	1.4
8 to 12 days	21.8	53.1	21.6	3.5
More than 12 days	9.9	47.4	35.5	7.2
(Compliance Before DSDS)				
Less than speed limit	29.8	37.3	23.9	9.0
Speed range: 1 ~1.07 of speed limit	20.2	51.7	27.0	1.1
Speed range: 1.07~1.15 of speed limit	20.3	64.5	13.3	1.9
Higher than 1.15 of speed limit	20.5	51.9	22.4	5.2

1: Base percentage: 22.2% 3: Base percentage: 20.3%
2: Base percentage: 54.1% 4: Base percentage: 3.4%

Speed Alteration was divided into three states: decrease, constant, and increase. Table 31 indicates that when all drivers decrease their speed after observing a DSDS, the probability of LSL increases from 22.2 to 38.8 percent, while the probability of L107SL slightly increases from 54.1 to 57 percent. However, the probability of L115SL and H115SL decreases dramatically. If the vehiclesô speeds stay constant, the probability of LSL decreases to 7.4 percent; however, the probability of L107SL and L115Sl increases to 65.1 and 26.5 percent, respectively. If the drivers increase their speed after observing a DSDS, the probability of driving LSL decreases to 12.6 percent, while the probability of driving L107SL drops to 23.1 percent. However, the probability of driving L115SL and H115SL increases.

There were three values for Speed Limit: 25, 35, and 45 mph. When the research team changed the speed limit to 25 mph for all sites, the probability of LSL increased dramatically to 98.4 percent and the probability of L107SL decreased dramatically to 0.5 percent. When all the study sitesô had a speed limit of 35 mph, the probability of LSL slightly decreased to 21.9 percent and the probability of L107SL increased dramatically to 72.7 percent. When all the study sitesô had a speed limit of 45 mph, the probability of LSL decreased to 18.8 percent and the probability of L107SL and L115SL increased dramatically to 46.8 and 30.1 percent. This indicates that speed limit compliance on a 25 mph road is generally higher than on 35 mph and 45 mph roads. The vehicle speeds after DSDS observation are mainly LSL on a 25 mph road, while they are L107SL on a 35 mph road. The speed limit compliance is lower on a 45 mph road than on the other two roads.

When a large DSDS was used for all sites, the probability of LSL for Compliance After decreased to 18.8 percent. This probability also decreased to 46.8 percent for L107SL. When a small DSDS was used for all sites, the probability of LSL and L107SL increased to 28.0 and 66.9 percent, respectively. The research team concluded that the smaller DSDS was more effective. However, the small DSDS was utilized on the roads with lower speed limits. The correlation between Size, Speed Limit, and Number of Lanes was very high.

When the research team used an Effective Time of 1 to 2 days for all cases, the probability of LSL and L107SL increased to 31.2 and 55.9 percent, respectively. When the Effective Time was 3 to 7 days for all cases, the probability of LSLS reduced to 27.3 percent and the probability of L107SL increased to 58.1 percent. However, both percentages were higher than the Base case. When the Effective Time for all cases was more than 12 days, the probability of LSL and L107SL reduced to 9.9 and 47.4 percent, respectively. This indicates that the longer the time after DSDS installation, the lower the effectiveness of the DSDS. As presented in Table 31, the probability of LSL and L107SL reduced while the probability of L115SL and H115SL increased the greater the days after installation.

If all speeds were LSL upstream of a DSDS, the probability of LSL increased to 29.8 percent and the probability of L107S decreased to 37.7 percent. Interestingly, the highest Compliance After happened when the Compliance Before was L115SL. This is probably because drivers traveling 7 to 15 percent higher than the speed limit reduced their speed after passing a DSDS.

DISCUSSION

The research team employed different statistical tools to evaluate the effectiveness of DSDS. The *t*-test indicated that DSDS is effective in the short term only for a short distance. However, the research team utilized other tools because *t*-test is aggregate, only compares average speeds, and cannot do sensitivity analysis.

Since it was impossible to track each individual car, the research team aggregated the upstream and downstream speeds for every 50 cars. To find the important factors affecting speed compliance, the research team applied a linear regression model. The regression results showed that factors affecting speed compliance downstream of a DSDS were school zone, speed limit, speed compliance upstream of DSDS, period after installation, and distance from DSDS. However, the R^2 of the linear regression model was very low (0.324) because most of the variables were ordinal or nominal. Because speed alteration is ordinal, the research team used it as the dependent variable. Consequently, R^2 improved to 0.654.

The research team complemented the study by constructing a BN and performing a more detailed sensitivity analysis. In addition, the research team developed a better compliance prediction model since the BN error rate was lower than the regression model. Similar factors affected the Compliance After. For example, the regression model indicated that a speed limit increase would decrease Compliance After. However, the BN specified how much each compliance category would change when the speed limit changed from 25 to 45 mph.

The BN construction was based on road-related data. Information about drivers, such as their behavior, attitudes, and socioeconomic information, was not considered in the BN because it was not available. In order to find the effect of driversô socioeconomic information and attitudes on speed compliance, the research team developed a multinomial logit model using the survey questionnaire data. Surprisingly, none of the coefficients were significant. Therefore, the research team concluded that driversô socioeconomic information and attitudes did not have a significant effect on speed compliance downstream of DSDS. Thus, the developed BN is a reliable model.

CONCLUSIONS

This study collected speed data upstream and downstream of a DSDS on three corridors with different speed limits: 25, 35, and 45 mph. The 25 mph site was a school zone. The data was collected with a digital counter for at least one week. After analyzing the data with different statistical models, the research team concluded that DSDSs are effective. However, a DSDS should be used as a temporary solution because its effectiveness reduces with time. The research team also concluded that a DSDS is effective only for short distance, as drivers increase their speed after passing the DSDS. Therefore, DSDSs should be used on critical points. A critical point could be defined as an area where the probability of crashes is high or safety is very important (e.g., work zones or school zones). When a DSDS is combined with another speed control device, such as a speed camera, its effectiveness increases.

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