EVALUATION OF A REAR-END COLLISION AVOIDANCE SYSTEM ON WINTER MAINTENANCE TRUCKS

By

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ABSTRACT

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Roadway winter maintenance trucks, commonly referred to as snowplows, operate in hazardous traffic conditions and pose a rear-end collision risk for motorists following them. In this study, a new prototype rear-end collision avoidance and mitigation system (CAMS) was tested on snowplows. The system, which detects position and speed of vehicles following the snowplow via a radar sensor and warns hazardous approaching situations via a flashing beacon light, was tested for its efficacy, operational effectiveness, economic viability, and impact on the followers' driving behavior. To this end, data were collected with two CAMS-equipped snowplows in the winter of 2018 in southeast Michigan and analyzed for the effect of the warning light.

Results generally favor the hypothesis that CAMS may improve traffic safety conditions by decreasing the likelihood of following drivers approaching too close to the plow, decreasing their reaction time by 0.83 seconds, increasing their average minimum time to collision by 0.24 seconds, and decreasing their maximum deceleration rate by 0.17 ft/s^2.

It is, however, also recognized that this technology needs more testing and operational improvements for practical feasibility. Recommendations include improving the sensor cleaning system, reducing vehicle detection error (particularly in the adjacent lane), and including distance-based thresholds in the warning activation mechanism to prevent tailgating.

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I am also grateful to the team at the Michigan Department of Transportation for sponsoring this project and supporting our team by providing access to their resources and the facility at Brighton, as well as the Federal Highway Administration State Planning and Research for providing ancillary funds for this project.

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KEY TO ABBREVIATIONS

AVL	Automatic Vehicle Location
CAMS	Collision Avoidance and Mitigation System
DOT	Department of Transportation
FHWA	Federal Highway Administration
ft/s; ft/s^2	Feet per Second; Feet per Second Squared
GPS	Global Positioning System
HSM	Highway Safety Manual
IVI	Intelligent Vehicle Initiative
LED	Light Emitting Diode
MDOT	Michigan Department of Transportation
MLR	Multiple Linear Regression
OHSP	Office of Highway Safety Planning
Q-Q	Quantile-Quantile (Plot)
RWIS	Road Weather and Information System
SPF	Safety Performance Function
SSAM	Surrogate Safety Assessment Model
SSM	Surrogate Safety Measure
TTC	Time to Collision

Chapter 1 - Introduction

1.1 Background

Winter maintenance of roadways remains a major challenge for roadway maintenance agencies in states with harsh winter climate. Traffic safety and operations are severely affected by poor visibility and snow or ice on the surface of the roadways. Recent research has found that traffic crash rates during winter periods are directly related to total snowfall levels (Heqimi et al., 2017; Usman et al., 2010). Snow removal and de-icing using winter maintenance trucks, commonly called snowplows or plow trucks, are the principal activities employed by transportation agencies to mitigate safety and operational issues associated with winter weather. As these operations are typically performed at reduced speeds directly in the roadway travel lanes, often under reduced visibility conditions, the risk of rear-end collision between the plow and trailing vehicles is elevated. Given the size of such vehicles, collisions involving snowplows can result in substantive property damage, vehicle repair, and medical costs.

To address these concerns, several state departments of transportation (DOTs) have invested in technology and public outreach programs that help in creating a safer operational environment for plow trucks. One method is to provide education to motorists to improve driving on ice- or snow-covered roads, particularly around plow trucks. For example, drivers are advised to accelerate and decelerate gradually, allowing extra time and distance to stop (Iowa.DOT, 2017a; Michigan.DOT, 2017). They are also advised not to follow snowplows too closely and to be mindful of the larger size of these vehicles, which results in potential blind spots, as well as lower travel speeds (Iowa.DOT, 2017b). Despite these efforts to optimize safety during winter maintenance, and particularly snow removal procedures, the number of crashes that involve a snowplow remains significant and represents an opportunity area for improvement.

This is especially true in Michigan where significant plowing and deicing operations occur statewide, particularly in the western and northern portions of the state that experience regular lake-effect snow. As part of this project, a review of crash reports in Michigan from 2012 through 2017 revealed an average of nearly 226 snowplow-involved crashes statewide per year (Zockaie et al., 2018). Many of these crashes involved a trailing vehicle colliding with the rear or side of the plow. Further assessment of the precipitating events and causal circumstances contributing to the collision suggested that approximately 50 percent of these crashes may have potentially been influenced by a rear-facing collision avoidance system.

The state legislature of Michigan has recognized the need for improving the operational safety conditions for snowplows and the general public affected by their operation. In 2017, the Michigan legislature passed a law allowing the use of "flashing, rotating, or oscillating amber or green lights" on winter maintenance vehicles, allowing for more visual means of attracting driver attention (Michigan, 2017). This also paved the way for the Michigan DOT (MDOT) to experiment with emerging technologies like collision avoidance systems that are currently principally used in consumer vehicles. In late 2017, MDOT procured the prototype of a collision avoidance and mitigation system (CAMS) from a private vendor and installed it on two of its snowplows. This study described herein was part of a greater project sponsored by MDOT that evaluated the practicality of expanding this CAMS system to a greater scale within Michigan.

a) MDOT vehicle with warning lights b) Green warning lights

Figure 1-1: Typical warning lights for winter maintenance vehicles in Michigan allowed since 2017

The said CAMS setup includes a rear-facing radar sensor mounted on the rear face of the snowplow that is able to detect vehicles up to 600 feet behind the truck and trigger an independent warning beacon also mounted on the rear of the plow truck upon detection of a vehicle encroaching too close to the plow. Such collision avoidance technology had not been previously implemented or tested for winter maintenance operations prior to this study as per the knowledge of the project team. As such, the effects of this technology on driver behavior and roadway safety remained uncertain and warranted evaluation. Moreover, more pragmatic concerns such as its ease of operation and economic feasibility were also not addressed. This study attempts to address these issues in detail.

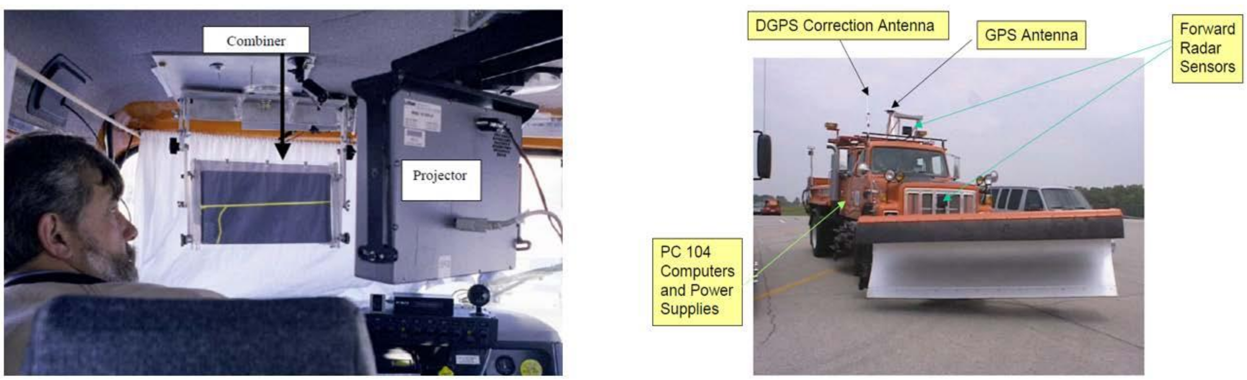
1.2 Literature Summary

Historically, a significant portion of winter maintenance research on improving technology has focused on its operational aspects, such as determining optimal routing strategies for snowplows in consideration of historical and forecasted traffic and weather data (Lemieux and Gampagna, 1984; Moss, 1970; Perrier et al., 2007; Robinson et al., 1990). Technologies like automatic vehicle location (AVL) and road weather information systems (RWIS) allow for real-time management of plowing and deicing operations. Studies conclude that AVL and RWIS are fundamental components of effective winter maintenance programs, although they need frequent calibration and modification (Kociánová, 2015; Schneider et al., 2017). More recent attempts in improving the operational characteristics of winter maintenance include an Internet of Things (IoT)-based approach with low-cost sensors gathering meteorological data (Chapman et al., 2014). However, it should be noted that IoT is currently a nascent technology and its use in assisting snow removal and deicing suffers the limitations of high deployment and maintenance costs (Chapman et al., 2014).

Despite significant advances in the research of operational and logistic characteristics of winter maintenance, there is limited documentation on its impact on traffic safety. Usman et al. analyzed the effect of weather, roadway conditions, and traffic volume on crash frequency and severity during periods of inclement weather in Toronto, Canada (Usman et al., 2010). With the help of negative binomial models, they concluded that roadway condition is a statistically significant factor in affecting crash frequency during severe winter. Since plow trucks function to improve roadway pavement condition, their positive effect in reducing crash frequency during severe winter may be implied.

Collision avoidance and advanced safety systems are part of an emerging technology that can help in reducing chances of crash occurrence during inclement winter weather conditions. These are part of advanced vehicle control and safety systems that make typically use of an array of electronic sensors to detect other approaching vehicles and warn motorists if they get too close (Zhang et al., 2014). This may include forward or rearward crash warning system and adaptive cruise control under the umbrella campaign of Intelligent Vehicle Initiative (IVI), which has been an active topic of research for the automotive industry (Ervin et al., 2005), although development in this field primarily revolves around algorithm development (Lee and Peng, 2005).

An important part of IVI is ‘in-cabin assistive systems’ for drivers. Figure 1-2 depicts a typical example of the use of a screen projector and image combiner placed inside the driver cabin of a snowplow that provides imagery of the roadway under low visibility conditions. These displays utilize data from antennas and sensors installed on the vehicle, as shown in Figure 1-2(b), which collect information about the environment, roadway, and weather conditions (Gorjestani et al., 2003). Based on the effectiveness of in-cabin assistance on snowplows in Minnesota, MDOT supported the use of in-cabin assistance in their CAMS to provide information to the snowplow driver besides providing information to the drivers following the plow should they approach too close to it.



a) Driver assistive system inside the vehicle   b) Driver assistive system outside the vehicle

Figure 1-2: Example of a snowplow driver assistive system with a screen projector

Technologies like IVI and CAMS appear to be useful aids in improving the safety of winter maintenance, but the research in these fields is relatively young. Moreover, the research in the integration of IVI is mainly limited to consumer vehicles and is scarce in specialized uses such as winter maintenance (Doi et al., 1994; Georgi et al., 2009; Harper et al., 2016; Zhang et al., 2014).

1.3 Study Objectives

The principal objective of this study is to assess the potential benefit of CAMS as an assistive technology for winter maintenance operations in terms of safety so that the feasibility of its large scale implementation, such as at the state level, may be evaluated in the short term. This broad goal entails the following specific objectives detailed in this study:

1. Driver safety analysis: Estimation of the safety impact of CAMS on drivers of the following vehicles with the help of surrogate safety measures (SSMs). The use of SSMs is usually sanctioned in the absence of sufficient crash data which are usually not available in the short term.
2. Driving behavior analysis: Analysis of the impact of this technology on driver perception and response to the presence of a snowplow using detailed trajectory and situational data.
3. Operational analysis: Testing the performance of the CAMS in field operations and issues of maintenance of the system itself.

1.4 Document Structure

The remainder of the document is structured as follows: Chapter 2 describes the components and working of the CAMS. Chapter 3 explains the field experiment carried out and the data collection procedure entailed.

Chapter 4 through 6 describe in detail the four analyses mentioned in Section 1.3. Chapter 4 describes the development of regression models of three surrogate safety measures that were derived from the vehicle trajectories.

Chapter 5 includes the definitions of and the analytical approach for the three driver behavior measures used – reaction time, response time, and encroachment rate – and the effect of the CAMS warning light on these measures. These measures are closely related to the SSMs mentioned in Chapter 4 but are obtained from a more refined dataset than that for the SSMs.

Chapter 6 describes the procedure used to quantify the performance of the warning system by estimating the proportion of false positive and false negative vehicle detection. It also explains the proxy method for quantifying the performance of the cleaning mechanism of the radar-camera box casing by comparing the occlusion of the casing with the quality of the resultant data.

Chapter 7 presents concluding remarks about the findings of this study, its limitations, the potential for system improvement, and scope for future work.

Chapter 2 - System Description

This section provides details of the CAMS evaluated in this research study as well as the data collection and processing scheme. The following sections provide details of the configuration and operation of the CAMS as well as the experiment involving the data collection in this study.

2.1 Components

The collision avoidance and mitigation system evaluated in this study is a set of removable equipment divided into a set of external and internal components which are respectively attached on to the rear face of the dumper of the snowplow and inside the driver cabin. CAMS is a modular and detachable system, which simplifies maintenance and allows for future technological upgrades and/or addition of components. The current system components are shown in Figure 2-1.

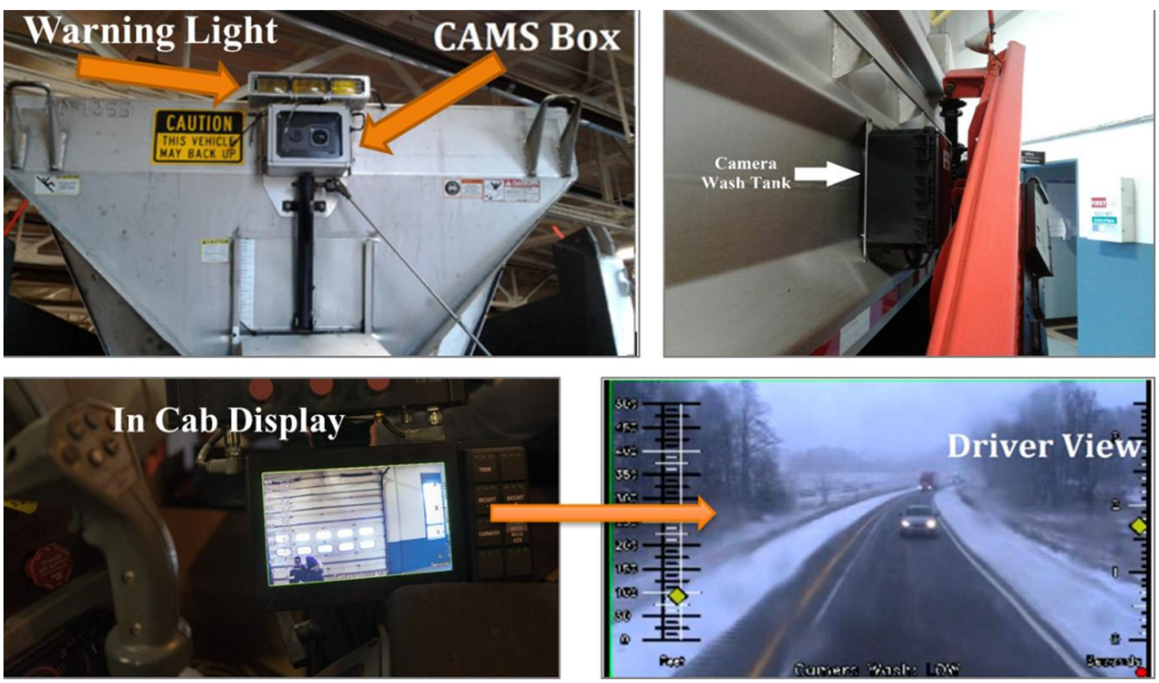


Figure 2-1: Illustration of components of CAMS installed on a snowplow

The external components include a sensor box, a beacon containing three amber lights, and an automated washing unit. The sensor box is a box with a transparent plastic window and encases two sensors – a radar transmitter and receiver, and a standard definition video camera. The radar sensor is the principal component of the CAMS that helps in the detection of vehicles in the rear of the snowplow. The warning beacon overlies the sensor box and consists of three LED lights in a horizontal row.

The rear-facing camera is not an integral but an optional part of the system that was installed only in this study to facilitate the capture of videos to be used for verifying the performance of the radar system in the detection of the following vehicles and their lateral position with respect to the snowplow. The camera also provides an in-cabin view of the rear of the vehicle and operations of the CAMS alert to the plow truck drivers, although the drivers were generally not involved with operation or validation of the CAMS alerts.

The system also includes an automated washing system connected to the sensor box. This was necessitated because of the regular need for cleaning the buildup of debris, mainly snow, ice, mud, and salt. The cleaning system consists of a defrosting grid on the camera and radar box, and nozzles that spray water and air at certain frequencies to keep the CAMS box clean while the plow truck is moving faster than a given threshold of 10 miles per hour. A wash tank container filled with water is connected to the nozzles and is connected through a pipe to the water tank of the plow truck. The frequent cleaning of the sensor box encasement was deemed necessary because debris can not only block the view of the camera but also hinder the performance of the radar sensor. This claim is proven as part of the operational assessment of the CAMS in Section 6.2.

The internal components of the system include an in-cab computer that includes a processor, display monitor, a removable hard disk for data storage, and the electrical connections to the sensor box as well as a GPS unit enabled with AVL technology. The AVL unit logs the coordinates of the plow truck at intervals of approximately once per every 6 seconds, though the recording frequency may vary depending on factors such as the truck's location, GPS signal strength, and atmospheric occlusion. The data of the truck's position is helpful in the programmatic detection of geometric features such as roadway curvature.

2.2 Data Collection

The system is plugged into the plow truck with the help of a direct current adaptor. The radar sensor is the principal component of the system that can detect motor vehicles in the rear field of view of the truck. It has a high longitudinal detection range of 600 feet and has a wide angle field of view capable of detecting vehicles in the adjacent lanes. When the CAMS is turned on, the radar system constantly records the trajectory of the following vehicles every 0.1 seconds, which includes – (a) the distance from the rear of the plow truck to the following vehicle, and (b) the relative speed of the following vehicle with respect to the plow truck. It decomposes these properties into two directions – longitudinal and lateral, based on the axis of motion of the snowplow. The details of the extraction procedure for the derived variables are provided in Section 4.2.

The trajectory information thus obtained is then fed to the onboard computer where it is processed to calculate relevant properties of all the detected vehicles at all times such as their time gap with the plow truck and the approximation of their lane position. This real-time information is then overlaid with the video and is both recorded and displayed to the truck driver, as illustrated in Figure 2-2. The figure depicts the various attributes of the CAMS video display, including the truck's rear exposure zone (defined in Section 4.2 and seen as the green grid in Figure 2-2), the longitudinal distance and relative speed of the detected vehicles (green and orange numbers on the scales on the left and right of the screen respectively), and time gap based on the relative speed and distance between the following vehicle and the rear of the plow truck.

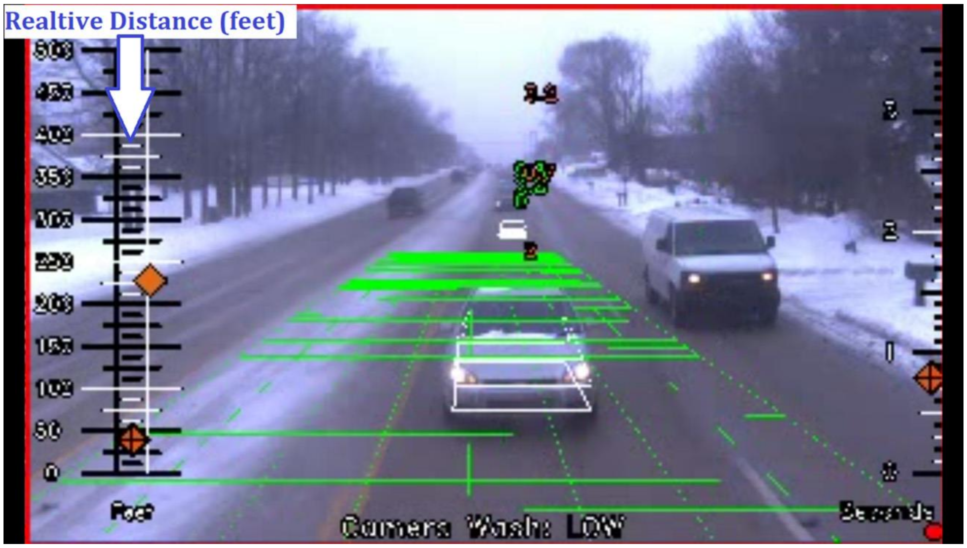


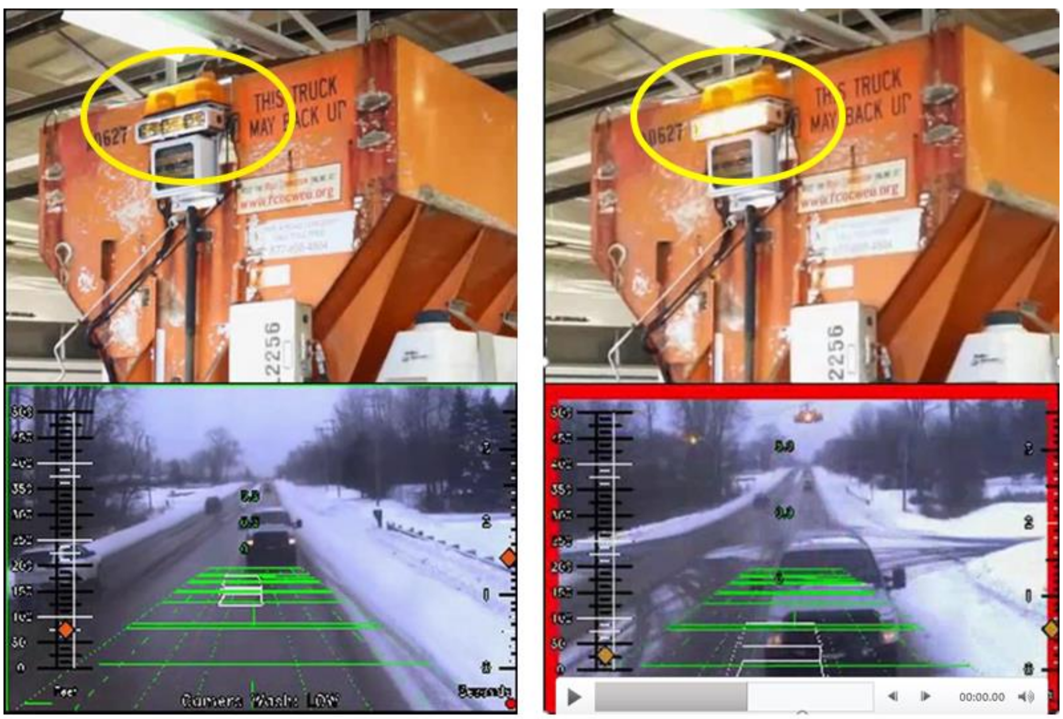
Figure 2-2: Screenshot of a typical CAMS video

Time gap is an important property discussed in this study and is similar in concept with time to collision and headway. It refers to the time after which the front bumper of the detected following vehicle would collide with the truck's rear bumper if the two vehicles continued to move at the same speed as of the time of detection. It is calculated as the negative of the ratio of relative longitudinal distance to relative longitudinal speed. This allows for negative values of gap in cases where the following vehicle recedes from the truck and can, therefore, be assumed to not be hazardous for the following vehicle regarding rear-end collision with the snowplow. Hence, by design, a warning is set off only when the following vehicle has a positive value of time gap.

2.3 Warning Light Operation

The system uses a two-level warning mechanism. This means that when a following vehicle is detected to have a time gap less than or equal to a pre-set threshold, the warning beacon located on top of the sensor box is activated to flash all the three amber lights simultaneously every 0.75 seconds in order to alert the driver to take precautionary actions like receding or changing lane. This is known as a 'level 1' warning.

The lights continue to flash until the subject vehicle either changes lanes, thereby moving out of the rear exposure zone, or recedes, thereby increasing the time gap to a value greater than the gap threshold. If the follower instead keeps on approaching closer to the plow truck and attains a time gap less than or equal to the second pre-specified gap threshold, a more aggressive warning ('level 2') is issued for reinforced feedback which involves a rapid alternate flashing of the three lights. Though a level 2 warning typically occurs after a level 1 warning has been initiated, a level 2 warning can be triggered independently of level 1 in the rare event of a vehicle moving close to the snowplow but in an adjacent lane suddenly swerving into the rear exposure zone of the snowplow and with a time gap that exceeds the level 2 threshold.



(a) (b)

Figure 2-3: Illustration of the working of the alarm warning with the follower (a) about to encroach and the beacon turned off, (b) exceeded the gap threshold leading to the trigger of warning level 1 with amber lights

Chapter 3 - Experimental Setup

3.1 System Calibration

Prior to this evaluation, the CAMS evaluated in this study had not previously been tested on plow trucks during winter maintenance operations. Thus, one of the initial study tasks was to perform a controlled field experiment consisting of a series of test runs using a CAMS instrumented plow truck and a following vehicle to calibrate the principal parameters of the CAMS, specifically the level 1 and 2 warning gap thresholds.

The values of gap thresholds for warning levels 1 and 2 were established after conducting test runs at different values of time gap, including the values 2, 3, and 5 seconds recommended by the manufacturer. All the test runs at this setting demonstrated that only the first threshold (e.g., 5 seconds) was useful, as the lower thresholds were triggered too close to the snowplow. Due to the short gap between the truck and following vehicle, it was observed that the that the maneuver initiated by the follower would occur irrespective of the CAMS warning alert due to uncomfortably close following distance. Therefore, in these cases with short time gap thresholds, it was not possible to activate the second threshold or even distinguish different patterns of the warning system as the second warning threshold was too close to the vehicle to be tested even in a controlled environment. Furthermore, even the initial 5 seconds threshold did not provide a large enough following distance, considering the aggressive braking required by the test driver. The field testing results indicated the use of a 7-second gap threshold for the level 1 warning and 5-second gap for level 2 warning. Thus, these level 1 and 2 warning thresholds were programmed into the CAMS prior to subsequent field data collection during actual snowplow operations.

3.2 Field Data Collection

The primary purpose of this study is to assess the effects of the CAMS warning system on motorist behavior during actual field operations. This was achieved using a case-control experiment, with the primary control being the presence or absence of the CAMS light. To this end, two MDOT snowplows equipped with CAMS collected data during usual winter maintenance operations under two different periods defined by whether the CAMS warning light was enabled. In the first period, the CAMS warning light was enabled (hereafter called 'CAMS light on'). In the second period, the light was disabled (called 'CAMS light off'), although all other systems components, including the camera, radar, and data collection capabilities were still operational. The details of the four resultant datasets are provided in Table 3-1.

Table 3-1: Description of the four data collection events

Dataset №	Truck ID	CAMS Light	Operation Period	Duration of Recorded Video (hr)	No. of Warnings Recorded
1	MDOT 4004	On	01/29/2018 - 02/07/2018	30.01	1387
2	MDOT 4005	On	02/09/2018 - 02/11/2018	33.70	813
3	MDOT 4004	Off	02/23/2018 - 03/08/2018	20.33	753
4	MDOT 4005	Off	02/23/2018 - 03/08/2018	12.82	351
				Σ = 96.86	**Σ = 3304**

The plow trucks operated along the same routes during both periods, which included arterials in Livingston and Washtenaw counties of Michigan near the cities of Brighton and Ann Arbor. The routes of the test trucks mainly included US-23 from Six Mile Rd to Hyne Rd and I-96 from N Burkhart Rd to Huron River Pkwy and are shown in Figure 3-1.

As mentioned formerly, the scenario with the CAMS light off served as the control condition, where the radar sensor operated and data were collected as intended, but the triggered warnings did not activate the warning light. The case and control data were collected during winter maintenance activities performed in late January 2018 (warning light enabled) and early March 2018 (warning light disabled).

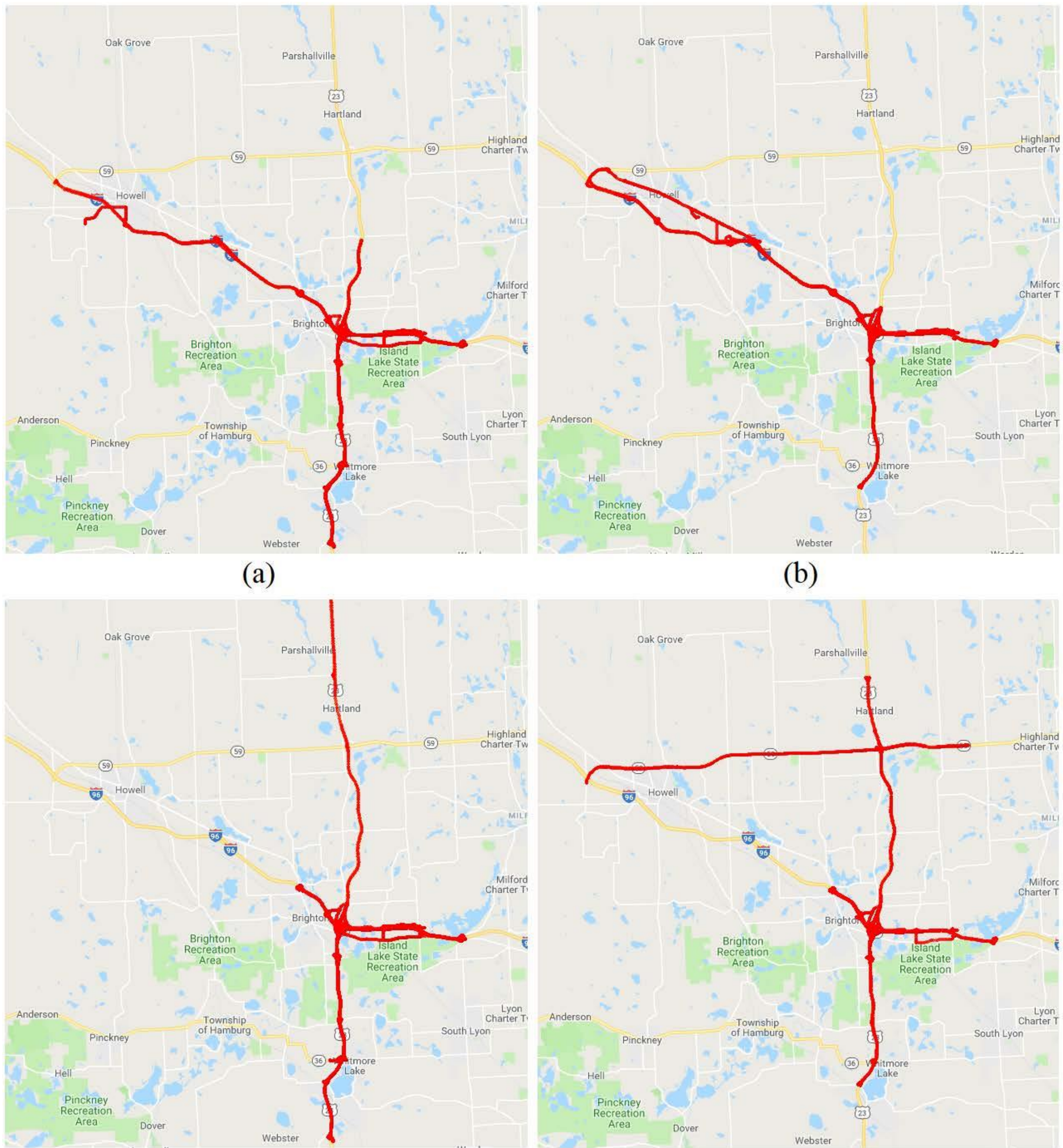


Figure 3-1: Trajectories of the snowplows MDOT 4004 and 4005 corresponding to dataset (a) 1, (b) 2, (c) 3, and (d) 4 [Map source: Google]

The three major datasets collected in this experiment were – (a) radar logs containing vehicle trajectory variables, (b) video footages throughout the data collection session, and (c) position and speed profiles of the snowplow. The details of data processing and analysis are provided in the subsequent chapters and the relevant associated scripts provided in the Appendix section.

Chapter 4 - Driver Safety Analysis

The primary purpose of all collision avoidance systems, whether in consumer use vehicles or public vehicles such as winter maintenance vehicles, is ameliorating traffic safety. Safety analysis of traffic facilities and operations typically uses frequency and severity information of crashes, whether observed or expected. The Highway Safety Manual (HSM) recommends the usage of safety performance functions (SPFs) to predict crash frequency in prespecified conditions (*Highway Safety Manual*, 2010). Traffic crashes, however, are rare events and therefore constitute a very small proportion of observed traffic events at a given place. The direct consequence of this rarity is the low expected frequency of crashes in a short period of, say, a year. The HSM, therefore, recommends crash data analysis of at least three years before and after an engineering treatment at a site in a typical before-after crash study for the establishment of statistically significant results (*Highway Safety Manual*, 2010). In cases such as this study, this is problematic because of further specifications such as specialized safety concerns and a short study period. In the absence of suitable SPFs as well as crash data to calibrate an SPF, surrogate safety measures (SSMs) are used in practice.

4.1 Surrogate Safety Measures

SSMs are employed to approximate the relative level of traffic safety by identifying traffic conflicts instead of crashes. According to the Federal Highway Administration (FHWA), a traffic conflict is defined as “an observable situation in which two or more road users approach each other in time and space to such an extent that there is a risk of collision if their movements remain unchanged” (Gettman and Head, 2007). A list of commonly used SSMs is shown in Table 4-1.

Table 4-1: Commonly used surrogate safety measures [Source: FHWA] (Gettman and Head, 2007)

Surrogate Safety Measure	Description
Gap Time	Time lapse between completion of encroachment by turning vehicle and the arrival time of crossing vehicle if they continue with same speed and path.
Time to Collision	Expected time for two vehicles to collide if they remain at their present speed and on the same path.
Encroachment Time	Time duration during which the turning vehicle infringes upon the right-of-way of through vehicle.
Deceleration Rate	Rate at which crossing vehicle must decelerate to avoid collision.
Proportion of Stopping Distance	Ratio of distance available to maneuver to the distance remaining to the projected location of collision.
Post-Encroachment Time	Time lapse between end of encroachment of turning vehicle and the time that the through vehicle actually arrives at the potential point of collision.
Initially Attempted Post-Encroachment Time	Time lapse between commencement of encroachment by turning vehicle plus the expected time for the through vehicle to reach the point of collision and the completion time of encroachment by turning vehicle.

SSMs like gap time, encroachment time, and post-encroachment time are well-suited for conflicts involving the angular intersection of the right of way of the conflicting vehicles, such as at intersections and on weaving segments. Car following behavior, such as following snowplows, however, does not involve right-of-way conflict directly in a manner similar to intersections. For this reason, the use of these SSMs is discouraged (Tak et al., 2018) and measures such as time to collision (and its modifications), proportion of stopping distance, and deceleration rate are used (Saccomanno et al., 2008; Son and Park, 2008; Tak et al., 2018).

Time to collision (TTC) is one of the most commonly used SSMs for rear-end and sideswipe crashes, which are the dominant type of crashes associated with snowplows. Different studies provide different approaches to TTC and its variants, such as its reciprocal (Chin et al., 1992; Kiefer et al., 2005) and time-integrated TTC (Chin and Quek, 1997). In general, TTC-based techniques rely on classification by comparing minimum TTC attained during a conflict with a preset threshold of safe TTC (El-Basyouny and Sayed, 2013). Surrogate Safety Assessment Model

(SSAM), a tool extensively used for comparative and complementary SSM analysis in conjunction with commercial traffic simulation tools like Paramics®, AIMSUN®, and VISSIM®, uses a default value of 1.5 seconds for safe TTC (Gettman et al., 2008). This value, however, corresponds to "normal conditions" that include moderate pavement, vehicle, and visibility conditions and driver alertness (Gettman et al., 2008). The more hazardous environmental conditions characteristic of winter maintenance operations on high-speed facilities seem to have found limited mention in the research literature. However, logic follows that the critical value of TTC for such conditions should be higher than 1.5 seconds to allow for more realistic abrupt braking.

4.2 Data Analysis

The data obtained from the four experimental field runs mentioned in Section 3.2 were processed to calculate the SSMs. The video footages were manually reviewed and data about the warning events were collected at the time of the beginning of flashing red of the video frame's window border. The radar logs were processed with a set of scripts written in R, two of which are provided in the Appendix (Sections I and II). A total of 3304 warning cases were collected, including information such as the time stamp (precise up to $1/10^{th}$ of a second), warning level, time of the day (subjectively classified as either 'day' or 'night'), and lane position of the alarm-causing vehicle (manually classified as 'same lane' or 'different lane').

The radar logs contain data of a maximum of 32 detected vehicles at each one-tenth of a second such as the distance (dx, dy) and speed (dvx, dvy) relative to the truck both along the longitudinal axis of the truck as well orthogonal to it (see Figure 4-1). These values were used to calculate relative distance ($ds = \sqrt{dx^2 + dy^2}$) and relative speed ($dv = \sqrt{dvx^2 + dvy^2}$). Time to collision, defined as the time taken for two vehicles to collide given constant speed as at the time of calculation (Gettman and Head, 2007), was calculated as the ratio of relative distance and the component of velocity along this distance ($TTC = \frac{|ds|}{|dv| \cdot cos\theta} = \frac{|ds|^2}{<ds,\ dv>}$) (see Figure 4-1). These data were joined with the truck speed profiles to obtain the absolute speed ($v = \sqrt{(dvx + v_{truck})^2 + dvy^2}$) and acceleration ($a(t) = (v(t) - v(t-1))/0.1\ s$) of the following vehicles.

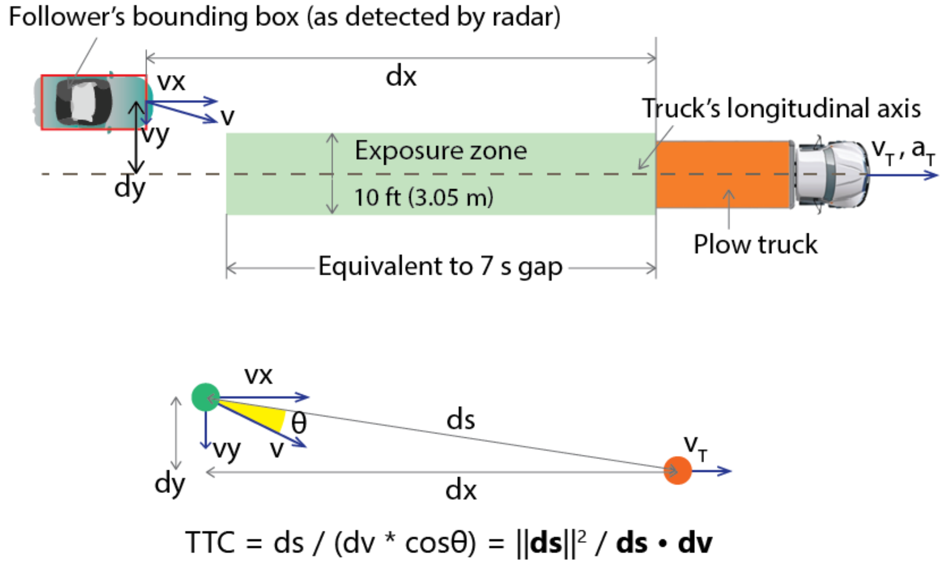


Figure 4-1: Illustration of trajectory variables captured in the radar log

The trajectory data were screened on the basis of the duration of their detection to account for their reliability and reduce noise in the observations. For this purpose, the preliminary analysis suggested the inclusion of only the observations lasting more than 3 seconds in an imaginary rectangular region 10 feet wide and with a length equivalent to 7 seconds of gap. This region is hereby called the 'exposure zone' and is illustrated as the shaded rectangle in Figure 4-1.

Moreover, since warnings can only be triggered by vehicles closing into the truck, only trajectories with strictly a negative speed profile ($dvx < 0$) were filtered, leading to a total of 40,275 trajectories. Also, for the sake of simplicity, cases of level 1 warning in which the subject vehicle was also issued a level 2 warning were removed to prevent the issue of data duplication.

Finally, the trajectory data were joined with the warning data to calculate measures such as minimum TTC, maximum deceleration, and maximum speed differential during the period of detection.

4.3 Results and Discussion

4.3.1 Summary Results

The refined dataset consisted of a total of 2328 warning cases and was used for modeling different SSMs. The variables used for modeling are described in Table 4-2 and their summary statistics are shown in Table 4-3. It should be noted that neither of the target variables and the covariates are overdispersed, with the coefficient of variability not exceeding unity, partially suggesting that multiple linear regression (MLR) models may describe the data adequately. Furthermore, the partly skewed distributions of the three target variables, shown in Figure 4-2, also suggest that linear regression may be used.

The descriptors were also checked for correlation to preclude model redundancy. The only pair of descriptors found to be significantly correlated based on t-tests conducted at a conservative significance level of 1 percent was {Truck Speed and Avg Before Speed}, with its Pearson correlation coefficient being as high as 0.66 (as seen in Figure 4-3). This may be attributed to the general rule of car following theory that followers generally aim to maintain a speed similar to the leading vehicle. This rationale was used to prevent the simultaneous inclusion of both these variables in the same model.

Table 4-2: Description of the variables in the modeling dataset for SSMs

Category	Variable	Description	Units/Range
Target variable	Min TTC	Minimum value of time to collision attained by a follower during the detection period	s
	Max Decel	Maximum deceleration attained after the issuance of the warning	ft/s^2

Table 4-2 (cont'd)			
Target variable	Max Speed Diff	Maximum speed differential between the follower and truck	mi/h
Covariate	Truck Speed	Speed of the truck at the time of warning	mi/h
	Avg Before Speed	Average speed of the follower before the instant of warning	mi/h
	Distance	Distance of follower from truck at the time of warning	ft
	Avg Before Lat Distance	Average lateral distance of the follower from the truck before the instant of warning	ft
Factor	CAMS Light On	Was the CAMS light enabled during the warning?	{0, 1}
	Is Dark	Was it "substantially" dark/night at the time of warning?	{0, 1}
	In Same Lane	Was the follower in the same lane as of truck?	{0, 1}
	Is Warning Level 2	Is the level of the warning 2 or level 1? 0: Level 1 1: Level 2	{0, 1}
	Warned Twice	Was the warning level 2 and issued after a level 1 warning?	{0, 1}

Table 4-3: Summary statistics of the variables in the modeling dataset for SSMs

Variable	Min.	1st Quartile	Median	Mean	3rd Quartile	Max.	Std. Dev.	CV*
Min TTC	0.053	0.832	1.209	1.609	1.859	16.746	1.437	0.89
Max Decel	0.070	0.699	1.119	1.398	1.748	5.942	1.293	0.92
Max Speed Diff	4.528	18.463	24.084	25.569	31.081	77.825	10.717	0.42
Distance	10.440	77.470	131.480	143.250	193.490	468.940	81.569	0.57
Avg Before Speed	8.062	52.142	62.121	59.329	69.288	102.428	14.129	0.24
Avg Before Lat Dist	-54.85	-24.35	-18.92	-16.72	-12.66	43.14	12.703	-0.76
Truck Speed	0.000	31.030	38.640	35.960	44.310	65.060	13.515	0.38
In Same Lane	0.000	0.000	0.000	0.165	0.000	1.000	0.371	2.25
CAMS Light On	0.000	0.000	1.000	0.677	1.000	1.000	0.468	0.69
Is Dark	0.000	0.000	0.000	0.241	0.000	1.000	0.428	1.78
Is Warning Level 2	0.000	0.000	0.000	0.429	1.000	1.000	0.495	1.15
Warned Twice	0.000	0.000	0.000	0.063	0.000	1.000	0.243	3.86

* CV: Coefficient of variability = ratio of the standard deviation with the mean

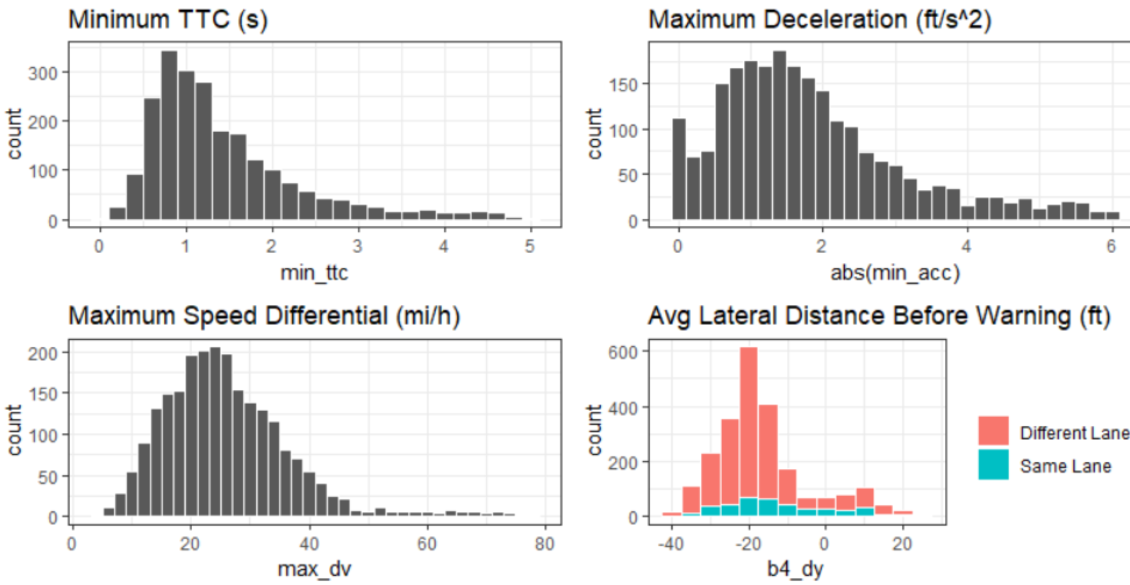


Figure 4-2: Distribution of the variables (a) Min TTC, (b) Max Decel, (c) Max Speed Diff, (d) Avg Before Lat Distance in the modeling dataset for SSMs

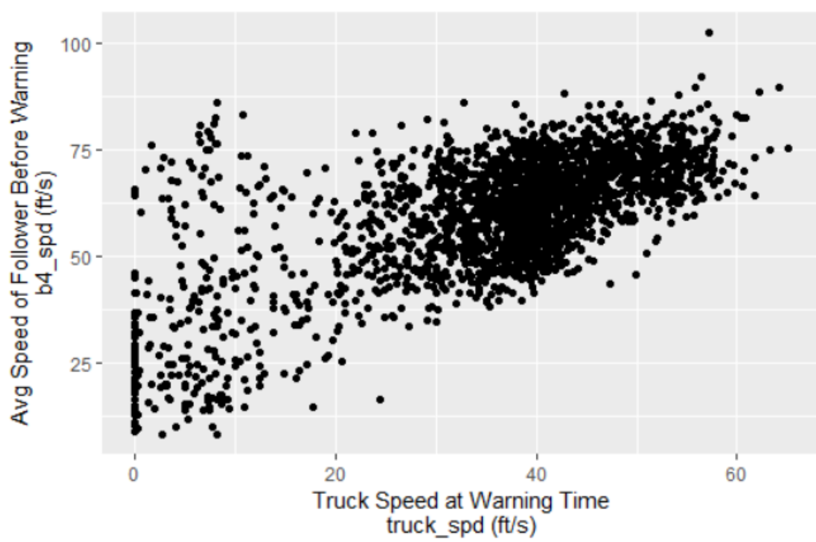


Figure 4-3: Scatter plot of the covariates Truck Speed and Before Speed showing a high degree of correlation (R = 0.66)

The preliminary warning dataset highlights the rarity of the event of triggering of a warning by the CAMS. With a total of 3306 warnings having been issued out of 40,275 strictly closing-in vehicle trajectories, it amounts to an incidence rate of 8.2 percent. Note that these warnings correspond to conflicts based on conservative thresholds of 5 and 7 seconds of TTC, which are significantly higher than the critical value of 1.5 seconds used by the Surrogate Safety Assessment Model (Gettman et al., 2008). For reference, only 1470 warnings correspond to the attainment of a minimum TTC of less than or equal to 1.5 seconds, amounting to a critical TTC incidence rate of 3.65 percent. This low incidence rate, along with the absence of any crash observed in the study period, hints at the rarity of the occurrence of unsafe driving with regards to snowplows and corroborates the general belief that most vehicles follow heavy vehicles such as snowplows at relatively acceptable gaps. A more rigorous analytical investigation, however, may provide better insight into this inference.

The distribution of maximum deceleration, the negation of minimum acceleration, in Figure 4-2(ii) is also noteworthy in its range spanning 0 to 6 ft/s^2, which is considerably lower than the 19.3 ft/s^2 and 24.1 ft/s^2 values of severe deceleration rate according to Dingus et al. (Klauer et al., 2006) and Nygard et al. (Nygård, 1999) respectively. This hints at the idea that while most drivers approached very low values of TTC in the worst situation, they did not brake sufficiently abruptly. This is somewhat unexpected of a newly introduced technological system like CAMS, where uninformed drivers are expected to decelerate more harshly in response to the flashing warning light.

4.3.2 Regression Analysis

Based on the features of the modeling dataset, three MLR models were fitted for the three response variables as shown in Table 4-2. In particular, the effect of the descriptor CAMS Light On was noted for all the three models. The estimates of the coefficients from these models are shown in Table 4-4, along with the standard error and p-value of these estimates at a significance level of 5 percent. The model summary statistics shown in Table 4-5 indicate that the models have significantly non-zero goodness-of-fit statistics.

Table 4-4: Estimates of coefficients of multi-linear regression models of the three target SSMs with significance values at α = 0.05

Variable	Estimate	Std. Error	T-value	$P(\|t\| > t_{cr})$
Model 1: Min TTC (s)				
(Intercept)	4.1114	0.1514	28.948	< 2.00E-16
Distance (ft)	0.0025	0.0003	7.520	7.75E-14
Avg Before Speed (mph)	-0.0435	0.0019	-22.612	< 2.00E-16
CAMS Light On 0: No 1: Yes	0.2382	0.0563	-4.235	2.38E-05
Is Warning Level 2 0: No, i.e., level 1 1: Yes, i.e., level 2	-0.2702	0.0554	-4.877	1.15E-06
In Same Lane 0: No 1: Yes	0.3398	0.0718	4.733	2.34E-06
Model 2: Max Decel (ft/s^2)				
(Intercept)	-2.7978	0.1436	-19.485	< 2.00E-16
Distance (ft)	0.0018	0.0003	5.504	4.12E-08
Truck Speed (mph)	0.0159	0.0020	8.031	1.51E-15
CAMS Light On 0: No 1: Yes	0.1673	0.0554	3.021	2.55E-03
In Same Lane 0: No 1: Yes	-0.4815	0.0702	-6.856	9.01E-12
Warned Twice 0: No 1: Yes	-0.2260	0.0941	-2.401	1.64E-02
Model 1: Max Speed Diff (ft/s)				
(Intercept)	0.7367	0.1260	-5.832	6.19E-09
Distance (ft)	0.0372	0.0023	16.303	< 2.00E-16
Avg Before Speed (mph)	0.2808	0.0129	21.747	< 2.00E-16
CAMS Light On 0: No 1: Yes	1.5009	0.3813	3.936	8.50E-05
Is Warning Level 2 0: No, i.e., level 1 1: Yes, i.e., level 2	6.7208	0.3761	17.869	< 2.00E-16
Warned Twice 0: No 1: Yes	-4.1963	0.6472	-6.484	1.08E-10

Table 4-5: Summary of the multi-linear regression models for the three SSMs

Summary Measure	**Model 1: Min TTC**	**Model 2: Max Decel**	**Model 3: Max Speed Diff**
Degrees of freedom	2365	2365	2365
Residual standard error	1.277	1.277	8.732
Multiple R-squared	0.2045	0.1011	0.3465
Adjusted R-squared	0.2021	0.0985	0.3446
F-statistic ($df.x = 7$)	86.83	38.02	179.2
P-value (at 95% confidence)	< 2.2E-16	< 2.2E-16	< 2.2E-16

It should be noted that all the three models show a consistent and significant relationship with the presence of CAMS light (CAMS Light On) as well as the distance at the time of warning (Distance). For minimum TTC (model 1 in Table 4-4), a positive coefficient indicates the widening of the safety buffer between the conflicting vehicles and therefore an increase in the apparent degree of safety. The presence of CAMS light, as depicted by its coefficient, arguably improves the safety of following behavior by increasing the minimum time to collision by roughly 0.24 seconds on average. Model 1 also shows the association of higher distances at the time of warning and presence of the follower in the same lane as of the snowplow with safer conditions, hinting at the possibility of lower prevalence of rear-end crashes than sideswipe crashes.

For minimum acceleration, or maximum deceleration (model 2), the positive coefficient of is_cams denotes a reduction in hard braking, which indicates a smoothed-out and safer approach in the following regime (Tak et al., 2015). Similar to model 1, warnings issued at larger distances tend to be associated with lower deceleration rates and thus safer conditions.

For maximum speed differential, model 3 suggests that the presence of CAMS light, in fact, increases the maximum speed difference between the plow truck and the follower by about 1.5 ft/s. Since higher speed differences are associated with higher crash risk and unstable car following behavior (Aarts and Van Schagen, 2006), the model intimates that the presence of CAMS light may be hazardous. However, this qualitative assessment needs a better statistical assessment for a reasonable qualification.

The presence of conflicting results in terms of these models, in general, necessitates a more rigorous approach to the estimation of the effects of the CAMS light. This is also reflected in the quantile-quantile (Q-Q) plots of the model residuals used to estimate the normality of model errors. Since linear regression assumes a normal distribution of errors with zero mean, a deviation from normality indicates the inadequacy of linear regression-based models. This is the case with all of the three models, as shown in Figure 4-4, where the distributions show a significant departure from the normal line at higher values of prediction errors. This observation, along with the contradictory interpretation of the effect of CAMS in these models, provides an opportunity for improvement. In general, however, it can be seen that the collision avoidance system tested on snowplows in this study has substantial potential in improving the safety of drivers following them.

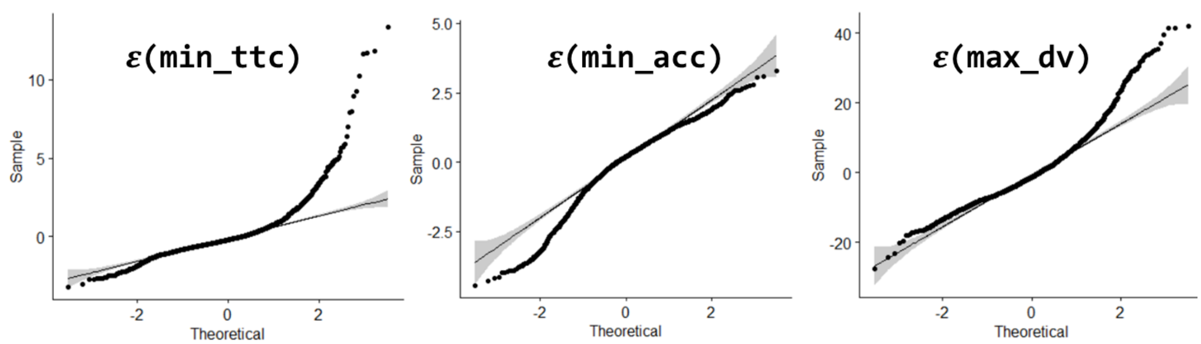


Figure 4-4: Q-Q residual plots of the three MLR models highlighting the different trends of normality of the errors

Chapter 5 - Driving Behavior Analysis

5.1 Analytical Approach

The effect of CAMS warning light on the behavior of the drivers following the subject snowplows was evaluated using a case-control study design with the warning light enabled and disabled. The behavior of the drivers following the CAMS-equipped snowplows was quantified in terms of three different measures – encroachment rate, reaction time, and response time, which are defined in Sections 5.2 and 5.3 respectively. The design of the study ensures that the differences in the behavior of these measures with the warning light enabled and disabled represent the measure of effectiveness provided by the CAMS warning light. These measures were analyzed across different roadway, geometric, and situational conditions. Predictive models using classification and regression tree analyses were developed to better understand the influence of each factor on the driver behavior metrics.

5.1.1 Data Description

Each dataset for the driving behavioral analysis consisted of detailed trajectory logs of the truck and the following vehicles along with the captured video for every five minutes. The recorded vehicular trajectory data logs were organized to obtain relevant kinematic variables such as relative and absolute longitudinal and lateral distance, speed, and acceleration (see Section I for the code). A combination of programmatic extraction and manual inspection was used to identify the vehicles responsible for triggering the recorded warnings. In the case of the warning light disabled, CAMS still recorded the issued warnings, although they were not reflected to the drivers of the encroaching vehicles. In both the scenarios, the trajectory data of the alarm-causing vehicles were extracted at four instants of time, along with roadway features such as the number of lanes and occupancy of the adjacent lane(s) and situational features such as the intention of the driver to either back off or change lane. These instants include – (a) warning level 1 issued, if at all, (b) warning level 2 issued, if at all, (c) when the minimum time gap was attained within the exposure zone, and (d) when the following vehicle reached the maximum deceleration after the instant of the warning (or the first instant of attaining a time gap less than or equal to 7 seconds in case of warning light off). These data points were used to calculate the target features as discussed later. Since this study concerns only with the effect of the warning light on the vehicles that triggered them, the resultant dataset was much sparser than the obtained trajectory data.

The target features of the analyses are defined in the subsequent sections. The statistically significant descriptive features extracted after preliminary analysis are listed in Table 5-1. Notably, three variables – number of lanes, occupancy of the adjacent lane, and the identified intended maneuver of the following vehicle's driver – were merged into one feature 'maneuver' in order to reduce the dimensionality of the problem.

5.1.2 Data Modeling

Besides the analysis of the distribution of the target features across different segments, maneuvers and gap thresholds, a modeling approach was used to identify the influence of CAMS warning light on the two target features relative to other potentially influential factors. The presence of largely categorical variables necessitated the use of a decision-making oriented modeling approach. As a result of this qualification combined with the issue of a small dataset, decision tree modeling was selected over other popular candidate methods, such as various types of regression models.

Decision tree modeling is a commonly used machine learning technique that represents a graphical tree with its branches depicting the splits constructed based on the amount of useful information its influential descriptive features create. These trees are a visually intuitive means of identifying the importance of descriptive features relative to each other. The features higher up in the tree's hierarchical structure tend to be more informative and hence more relevant in predicting the outcome of a query passed in as its "state", which, simply put, is denoted by each row of the dataset. A program was developed in R to execute the standard 'ID3' algorithm to construct these trees (see Section III for details).

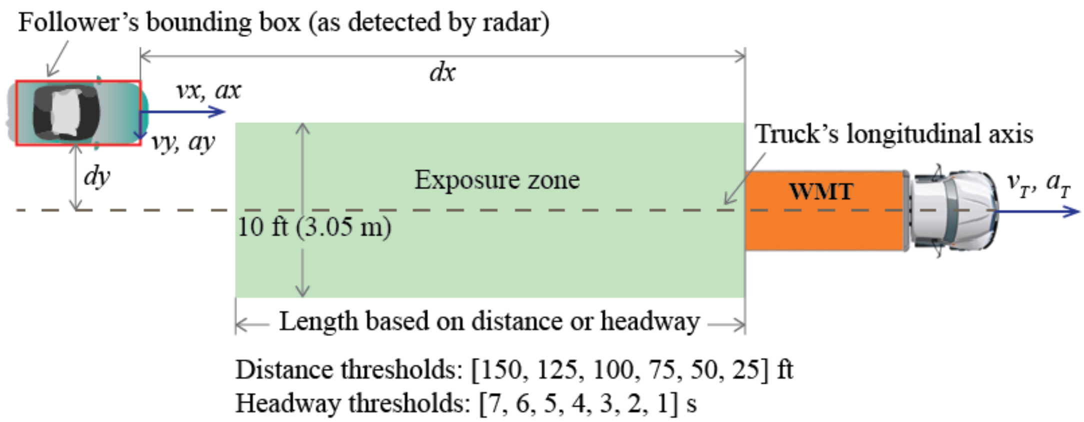
The two main categories of decision tree – classification and regression tree – differ in the type of their target feature as categorical and continuous, respectively. Therefore, a classification tree was produced for encroachment whereas regression trees were produced for reaction and response times. All three models were developed with the same descriptive features in order to maintain uniformity of inference. They are described in Table 5-1.

Table 5-1: Descriptive features used in the modeling of driver behavior

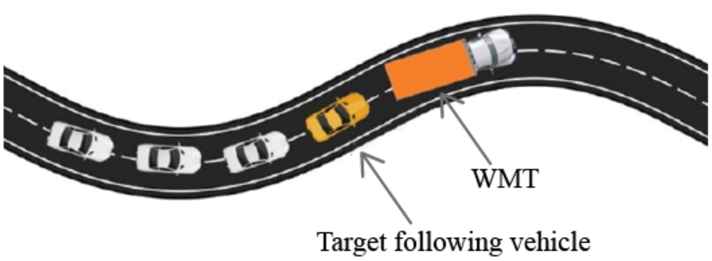
Variable	**Description**	**Levels**
Light	Indicates the presence or absence of the CAMS light when the warning was triggered.	1. On 2. Off
Warning Level	The activated warning level based on the time gap threshold.	1. Level 1 only 2. Level 2 only 3. Both level 1 and 2
Geometry	The physical environment of the site/segment.	1. Straight/tangent segment 2. Left/right turn 3. On/off-ramp 4. Merge/diverge lane
Maneuver	Characteristics such as space availability in the adjacent lane and the desired maneuver in response to closing in towards the plow.	1. Single lane road, follower backing off 2. Multi-lane road, adjacent lane occupied, follower backing off 3. Multi-lane road, adjacent lane occupied, follower changing lane 4. Multi-lane road, adjacent lane vacant, follower backing off 5. Multi-lane road, adjacent lane vacant, follower changing lane

5.2 Encroachment Rate

The concept of encroachment was used to understand the patterns of following a plow truck exhibited by the following vehicles subject to different conditions, especially the influence of flashing warning light. Encroachment in this study was defined as the action of a driver entering into and staying in an exposure zone behind the plow truck for a duration greater than a specified dwell time. This is based on the general understanding that a driver should keep a safe distance or gap with the truck at all times. Encroachment rate was accordingly defined as the ratio of the number of vehicles crossing a certain threshold of either distance or time gap to the total number of vehicles detected over a unit period of time. A series of gap thresholds were established for analytical purposes which are listed in Figure 5-1. Distance gap was studied over the range of up to 150 feet at 25-feet intervals, while time gap ranged over 7 seconds at 1-second intervals.



(a) Straight segment



(b) Curved segment

Figure 5-1: Definition of exposure zone for (a) straight segments, (b) curved segments

Some parameters related to the snowplow's exposure zone were established after rigorous manual inspection. Specifically, dwell time and zone width were set at 3 seconds and 10 feet, respectively. However, based on preliminary inspection, the exposure zone was defined differently for straight and curved segments (see Figure 5-1). For straight segments, it was defined as an imaginary rectangle extending from the truck's rear for different lengths corresponding to the aforementioned values of distance and time-based gaps. For curved segments, such a rectangular exposure zone could not effectively capture the reality of warning-causing vehicles due to numerous cases of false negative detection. Therefore, only the nearest following vehicle was considered for the encroachment analysis of curved segments.

The variation in encroachment rate was analyzed based on the cumulative relative frequency distribution. For the purpose of modeling, it was posed as a simple yes/no question – "given a situation of the driver following the snowplow, did the driver encroach beyond the specified time gap threshold?" This was deemed necessary because the measure could then be modeled for different thresholds of gap and the most relevant value of a 'safe gap' could be obtained.

5.2.1 Results

5.2.1.1 Frequency Distribution

The encroachment rate of following vehicles was analyzed for both space and time-based gaps for both trucks. The frequency distribution of encroachment rate is shown in Figure 5-2. The frequency is labeled as cumulative in these figures because of its cumulative nature, that is, a vehicle having crossed, say, 50 feet of space gap has already crossed 100 feet. The sample sizes of the control and study cases are also labeled in the figures. The small sample sizes are indicative of both the rare nature of the event in general, as well as the limited available datasets.

The results generally show that a larger proportion of drivers cross smaller thresholds of distance and time-based gaps when the warning light is disabled as opposed to when it is enabled. This can be verified by the general trend of the plots for 'light off' period appearing higher than that of light 'on' on the vertical axis. This suggests that the CAMS warning light system might be effective in pushing drivers to safer gaps. Evidence from the videos also support this claim, but also inform that the presence of a flashing light signal redirects them to the adjacent lane in most cases where the difference in cumulative frequency is very high.

The patterns also differ significantly by segment geometry, as can be differentiated in Figure 5-2. This may be attributed to the different selection criteria of exposed and warning-causing vehicles. This difference is exacerbated by the small number of warning observations of truck 2 in both the cases of warning light – on and off. In general, however, these results suggest that once the warning alarm was provided to the following vehicles, relatively fewer vehicles crossed the lower and riskier thresholds of gap with the plow truck. In the absence of supplementary crash information, it can be intuitively assumed to lead to safer maintenance operations. However, it is crucial to have more observed data supporting this assumption.

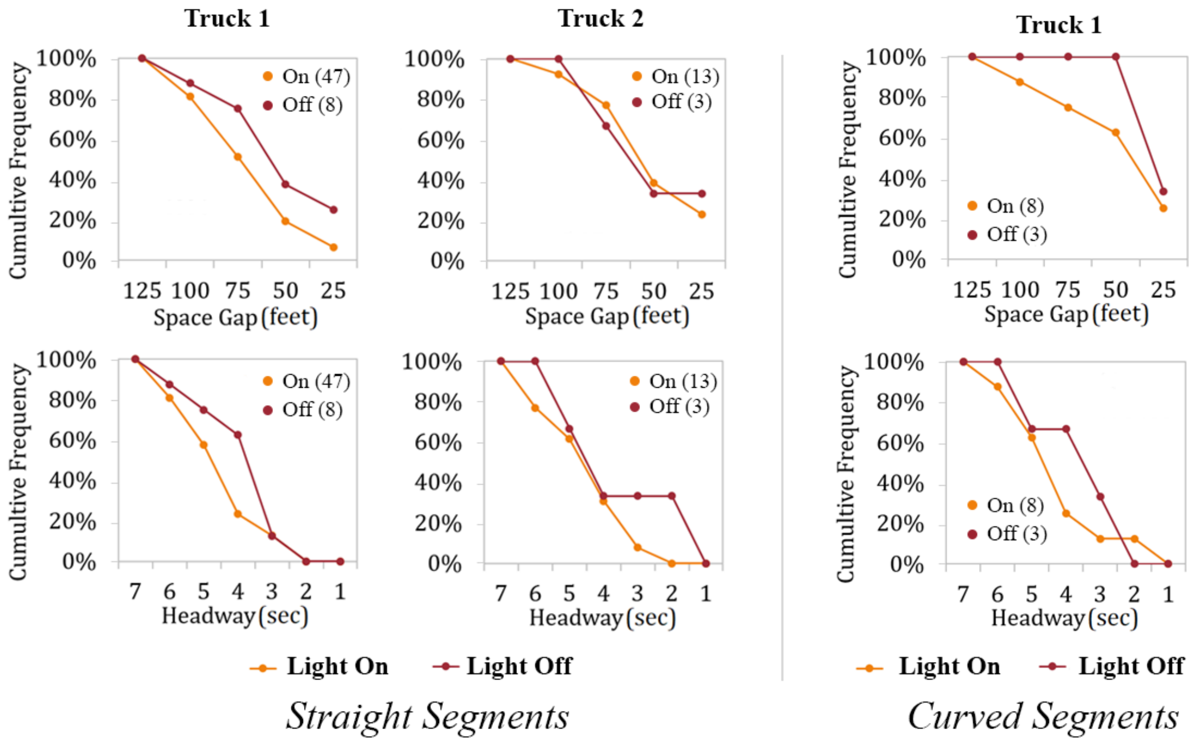


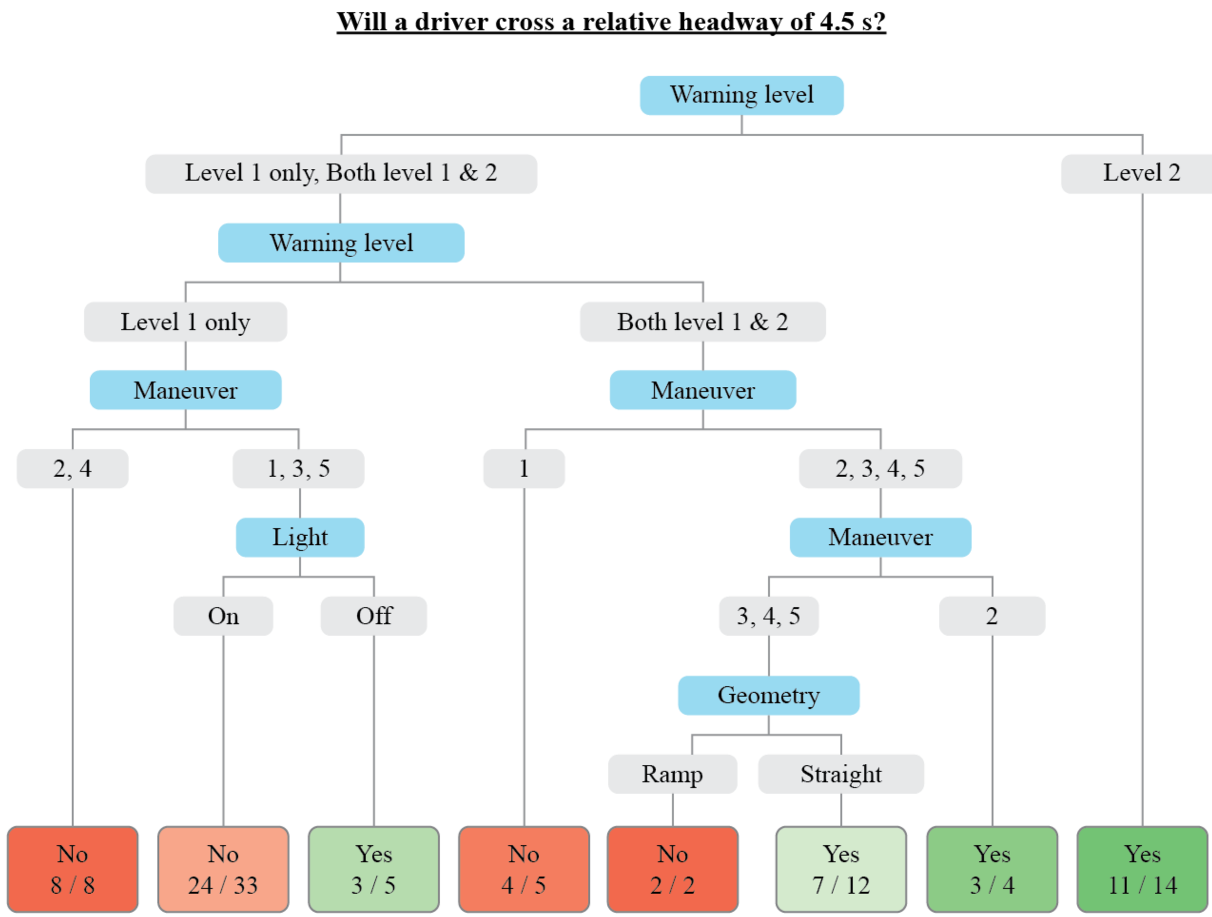
Figure 5-2: Cumulative frequency distribution of encroachment rate on straight and curved segments

5.2.1.2 Decision Tree

The decision tree of the encroachment likelihood for a specific "safe gap" value of 4.5 seconds is shown in Figure 5-3. This value was set as a model parameter and was regulated for different trials. It was observed that a low value of this safe gap such as 2 or 3 seconds would lead to the aggregation of observations under the most important factor: *warning level* and the subsequent dropping of other influential factors. Similarly, a higher value of this parameter led to the development of unrealistic decision sequences. Values of 4 and 4.5 seconds describe the influence of the descriptive features more accurately.

It was observed that the presence of light prompted drivers to not go closer than the safe gap of 4.5 seconds. This is evidenced by the observation that 24 out of 33 alarm-causing vehicles were repelled by the warning to fall back of 4.5 seconds as opposed to 2 out of 5 in the absence of the light. A similar observation was made in case of a threshold of 4 seconds. Based on these observations, it can largely be concluded, though not without qualification, that the warning light may be effective in changing the drivers' decision to stay at safer gaps.

The structure of the decision tree also provides important information. According to Figure 5-3, the most informative descriptive feature was observed to be *warning level*, followed by *maneuver* and then by the presence of *light*, which was found relevant for only level 1 warnings. This sheds light on the possibility that the presence of light itself did not lead to a drastic change in drivers' likelihood of crossing a certain threshold of time gap, at least not more than warning level issued to them and their intended maneuver. However, this inference should be held with caution as the structure of a decision tree is highly sensitive to the size of the dataset, especially for smaller datasets.



Note: The numbers represent the confidence of classification as x/y, where x = no. of warning cases fitting that classfication, y = total no. of cases. The depth of shade of the leaf nodes depicts the same.

Figure 5-3: Classification tree of encroachment likelihood for time gap level of 4.5 seconds

5.3 Reaction and Response Times

Reaction time is a fundamental concept in the study of driver behavior. Its conventional definition takes into account the total time taken by a driver to perceive, interpret, and judge the situation, and finally act, most commonly by applying brakes (Gerlough and Huber, 1975). In this study, however, reaction time was defined in the context of the issued warning alert as the time difference between the instant of triggering of a warning and the instant when the following vehicle attained its maximum negative acceleration (i.e., deceleration) while occupying the exposure zone.

This modification in its definition is attributed to the availability of only the physical state of the following vehicles, such as their speed and acceleration.

In conjunction with reaction time, another related parameter called response time was considered for understanding driver behavior. It was defined as the time taken by the driver to maneuver to a perceivably safe gap with the snowplow after the issuance of the warning. Per the observations, the minimum time gap between the truck and the vehicle during its stay in the exposure zone was considered the aforementioned safe gap. After the attainment of the minimum time gap, the distance between the subject vehicle and the snowplow would increase, intuitively implying a reduction in the risk of crash occurrence.

Reaction and response times are closely linked to each other and were observed to be highly positively correlated in all cases. Therefore, they may be interpreted in conjunction with each other. They are mathematically expressed by equations 1 and 2, respectively.

$$t_{react} = \left|t_{\min(\hat{a})} - t_{warn}\right| \tag{1}$$

$$t_{resp} = \left|t_{\min(dt)} - t_{warn}\right| \tag{2}$$

5.3.1 Results

5.3.1.1 Aggregate Changes

The average values of reaction and response time across different combinations of segment geometry (a physical property) and intended maneuver (a behavioral property) are tabulated in Table 5-2. The effect of the warning light was positive in reducing both of these values. The average reaction time on straight segments reduced from 2.30 seconds in the base case to 1.47 seconds when the warning light was enabled. The 0.83 seconds (36 percent) change in reaction time is a considerable reduction that may indicate improvement in driving behavior. The mean response time on straight segments also reduced from 2.71 to 2.16 seconds, a reduction of about

20 percent, indicating a positive change in favor of safe driving behavior. Note that these values are significantly higher than standard mean values of braking reaction time, which usually lies in the range of 1.1 to 1.4 seconds for drivers facing an unexpected situation (Chang et al., 1985; Gerlough and Huber, 1975; Sivak et al., 1982) and even higher than the design reaction time of 1.5 seconds as prescribed in the AASTHO Green Book (AASHTO, 2001). This inconsistency may be attributed to a different definition that is used in these documents compared to this study, which relies on the observed change in the sign of the values of acceleration.

Although the difference in these values between the two cases of the warning light (on versus off) was found to be numerically significant, the statistical significance of this inference is questionable due to the small number of observations in the case of light disabled. Similarly, too few observations of curve segments imply the statistical insignificance of the results of curve segments.

Table 5-2: Average values of reaction and response time for different segment geometries and intended maneuvers

Maneuver	**Light**	**Straight segments**		**All Segments**	
		Average value (s)	**No. of observations**	**Average value (s)**	**No. of observations**
Reaction Time					
Both maneuvers	On	1.47	33	1.53	37
	Off	2.30	7	2.30	7
Lane change only	On	1.55	23	1.55	24
	Off	2.40	5	2.40	5
Back off only	On	1.29	10	1.48	13
	Off	2.04	2	2.04	2
Response Time					
Both maneuvers	On	2.16	36	2.17	42
	Off	2.71	7	2.46	8
Lane change only	On	2.42	25	2.39	26
	Off	2.94	5	2.57	6
Back off only	On	1.56	11	1.82	16
	Off	2.13	2	2.13	2

5.3.1.2 Decision Tree

The regression trees of the reaction and response time are given in Figure 5-4 and Figure 5-5 respectively. The leaf nodes in shades of red indicate the average value of the target feature with the query state outlined in the branches above them. According to Figure 5-4, the presence of warning light decreased the reaction time of drivers executing maneuvers 2, 3 and 5, all pertaining to multi-lane road segments, compared to the absence of the warning light. The average difference of 1.57 seconds of reaction time corresponds to a subset of observations with a higher difference than the overall observed difference of 0.83 seconds. These models corroborate the hypothesis that the CAMS warning light can be effective in reducing the reaction and response time, which in turn can be reasonably conjectured to be associated with an improvement in the following driver behavior. Similar to previous inferences, a more statistically significant analysis should be performed with the help of a richer dataset.

Reaction time (s)

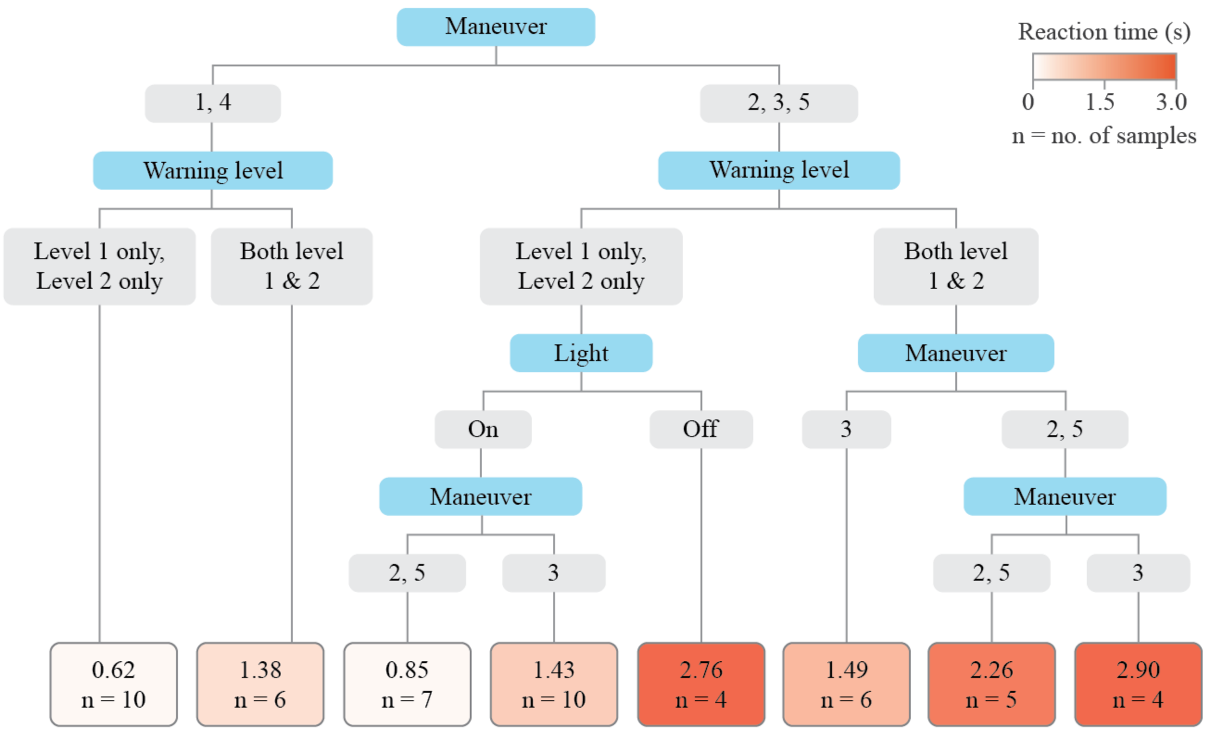


Figure 5-4: Regression tree of reaction time

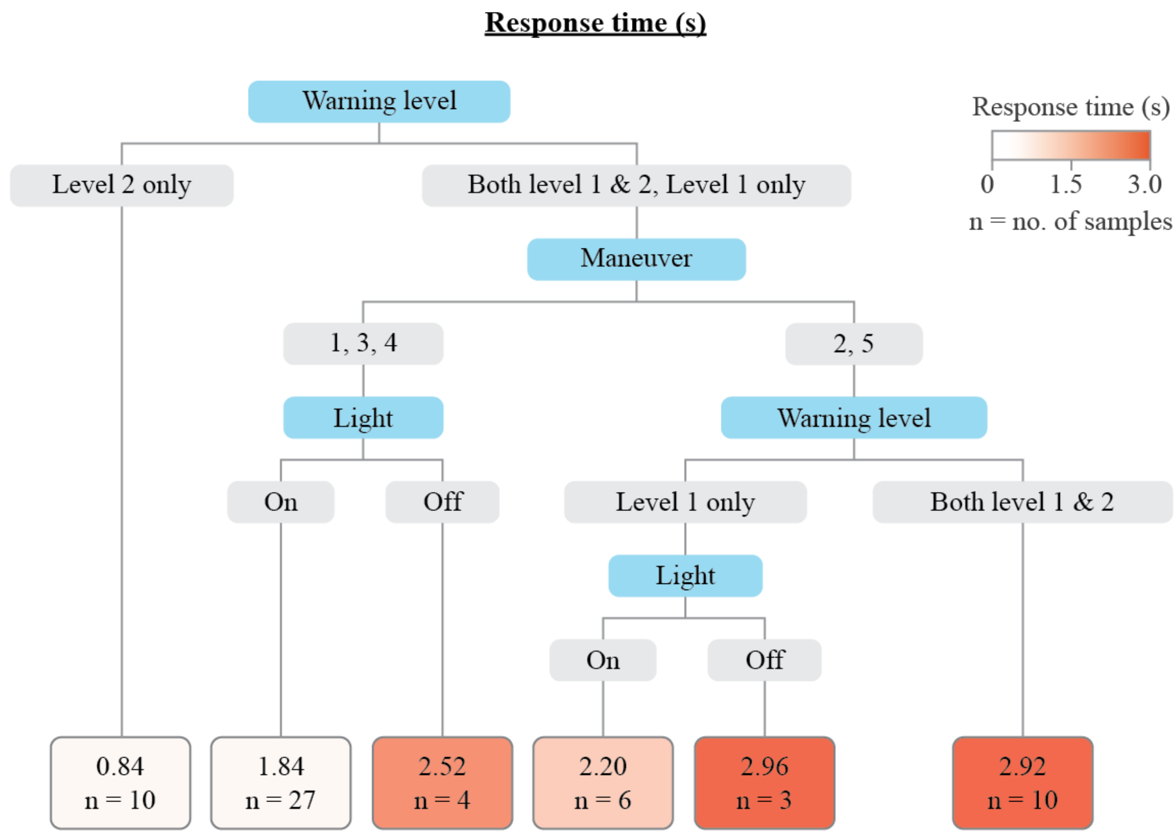


Figure 5-5: Regression tree of response time

Chapter 6 - Operational Analysis

This chapter looks at the performance of the warning as well as the washing system of the CAMS as inferred from analysis of the video and radar data. While the former is fundamentally important to diagnose the efficacy of the system itself, the latter is important in practice if not as much in concept.

6.1 Performance of Warning System

A well-designed alarm system is central in accurately and effectively delivering information to distracted drivers encroaching towards the snowplow. To test the accuracy of the alarm system, the distribution of the time gap between the plow and the following vehicles was analyzed for cases where the alarm was triggered. With the given two-level warning system, it was expected to observe time gap equal to the warning thresholds (i.e., 7 and 5 seconds for level 1 and 2) at the time of the issuance of the warnings, but the collected data sets showed a non-uniform distribution in the observed values of gap. The time gap distributions of level 1 and level 2 warnings that were triggered due to the vehicles traveling in the same lane of the plow (true positive warnings) are shown in Figure 6-1. In this figure, the data collected during the night and day times and also for the tangent and curved segments of the roadway are presented separately. Note that the case of videos recorded on curved segments during nighttime is excluded since no warning was detected by the system in that dataset. The figure indicates that the system showed a significant departure from its design gap thresholds, with up to 2 seconds delay in activation.

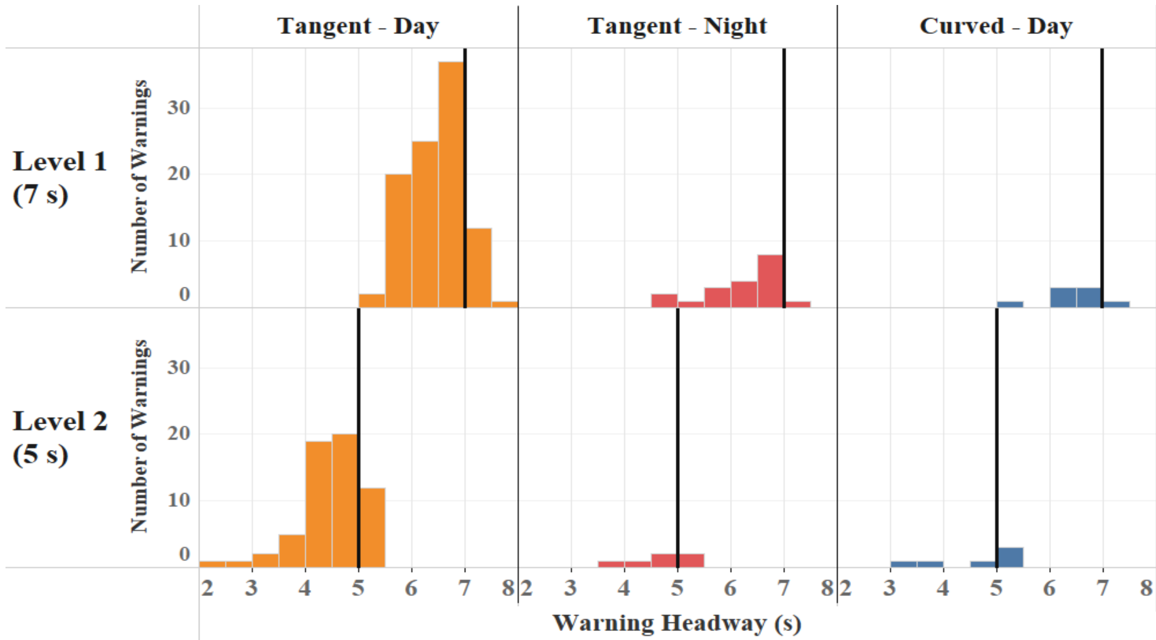


Figure 6-1: Time gap distribution for all level 1 and level 2 warnings for three categories of warning with reference to design gap thresholds

6.1.1 False Positive Alerts

The CAMS is designed to issue warnings only to encroaching vehicles in the same lane as that of the plow truck. In some cases, however, warnings were issued by vehicles passing in an adjacent lane. These cases were labeled as false positive. A common observation of these cases was the presence of a vehicle freely closing the gap with the truck in the adjacent lane alongside a vehicle in the same lane not encroaching the truck. This observation is illustrated in Figure 6-2. An analysis of the video snippets of these cases revealed an issue with the alarm activation mechanism instead of inaccurate radar detection. This suggests that revising the detection and alert algorithm in the warning system to exclude adjacent lane vehicles should resolve this issue.

Figure 6-2: Example of a false positive warning caused by a vehicle in the adjacent lane

6.1.2 False Negative Alerts

False negative cases were defined as those in which a following vehicle crossed at least one of the two warning gap thresholds, but the system did not activate the alarm. Such cases were studied by analyzing the time gap profiles of in-lane following vehicles when they dropped below the warning gap threshold of 7 seconds. Figure 6-3 shows a higher propensity of observing false negative cases on curved segments than on straight segments. This peculiar observation, however, can be attributed to a higher rate of misclassification of the lane position of the following vehicles on curves than on straight segments because of the simple criterion used for classification of lane position. Even discounting these misclassification error cases, a large number of observed false negative cases suggests the need for substantial improvement in the CAMS detection mechanism.

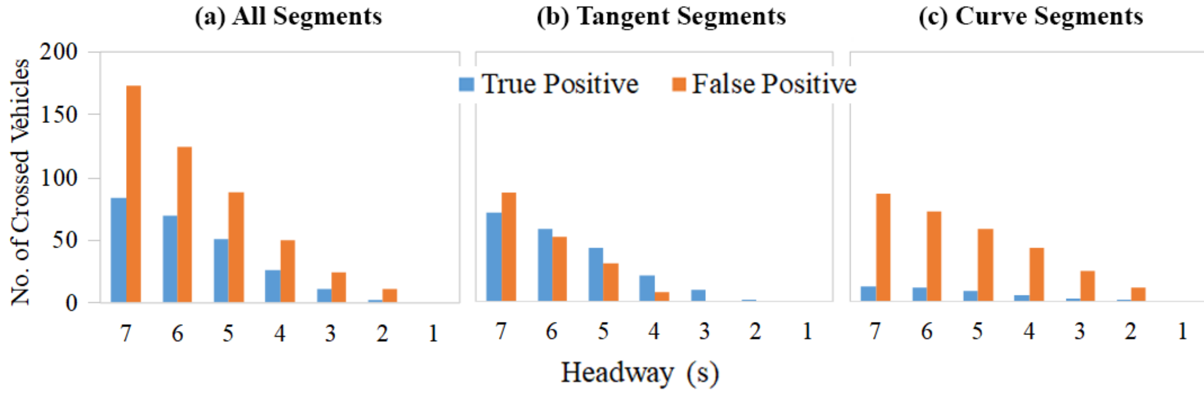


Figure 6-3: Number of true positive and false negative warnings for the time gaps less than 7 seconds by segment curvature

6.2 Performance of Cleaning System

The position of the radar sensor outside of the plow truck exposes it to snow, ice, and dirt/grime. The sensor is designed to be capable of detecting objects even with slight occlusion of the sensor box encasement by snow or raindrops. However, it can easily accumulate multiple layers of ice, snow, grime, and salt once the washing system malfunctions.

By association, it was hypothesized that the performance of the washing unit should be positively correlated to the accuracy of object detection by the CAMS and the timing of the warnings. This hypothesis was tested in two ways – (a) based on the number of triggered warnings in different conditions of visibility, and (b) based on the size of data logged by the radar system. To this end, about 200 hours of videos recorded by the CAMS camera under different lighting conditions were manually analyzed. The degree of blockage of the camera lens was arbitrarily classified into four levels based on the ease of identification of approaching vehicles (or their headlights in the dark) as shown in Figure 6-4. It served as a measure of the effectiveness of the washing system.

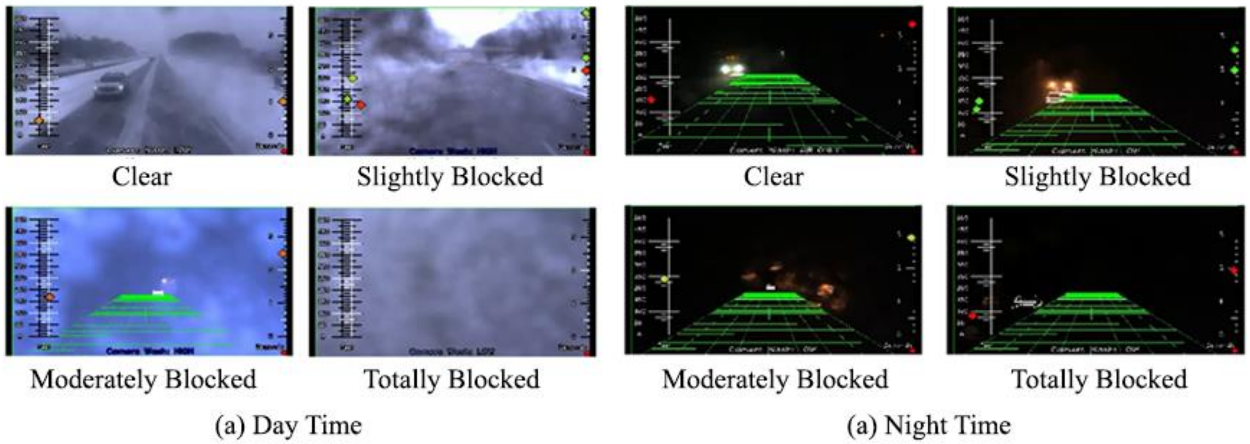


Figure 6-4: Four levels of camera view quality observed in test operations during (a) daytime, and (b) nighttime

6.2.1 Camera Blockage versus Warnings

The operational performance of the CAMS was assessed with respect to the level of blockage of the radar-camera box by snow. To this end, five data sets were collected by three CAMS-enabled plow trucks across two broad time periods and grouped into two levels of ambient snowfall. All of the five data sets had very similar geographic coverage and were therefore considered comparable. The amount of logged data for each category of camera lens blockage was calculated and compared with the total number of warnings in each dataset. The dataset description is depicted in Figure 6-5. In this figure, the left vertical axis shows the duration of the observations in hours (only for daytime) and the right axis shows the total number of recorded warnings by CAMS, including both level 1 and level 2.

It can be seen that the duration of observation is very similar in sets 1, 2, and 3, but set 1 has a substantial lower duration of partially or totally blocked camera views compared to sets 2 and 3. This coincides with the significant difference in the total number of warnings between set 1 and sets 2 and 3. Similarly, this pattern does not exist for datasets 4 and 5 where the effect of snow is negligible. This correlation of performances of the camera and the radar suggests that the radar unit also gets occluded by snow along with the camera.

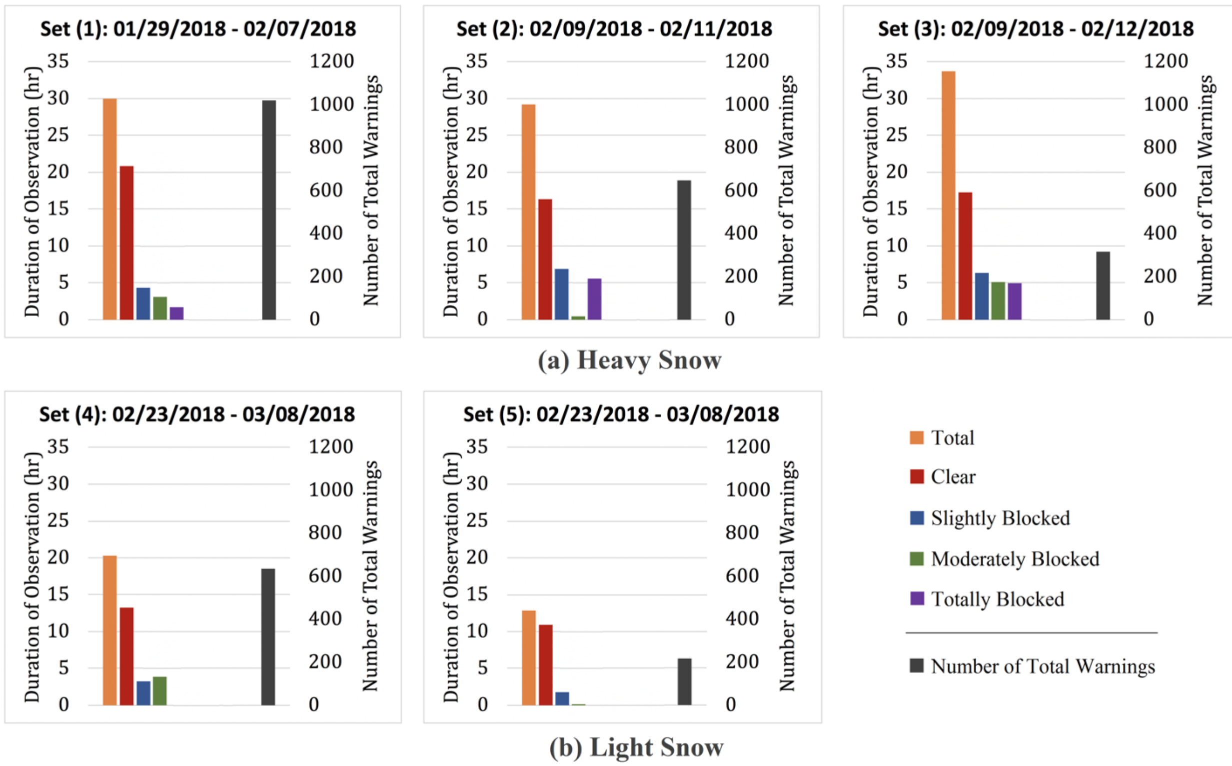


Figure 6-5: Distribution of observation duration and the total number of recorded warnings in different data sets during daytime: (a) heavy snow, and (b) light snow

The radar system occlusion by snow is also supported in Figure 6-6, which directly compares the distributions of the duration of recorded videos and the number of warnings with respect to the different levels of view blockage. Sets 4 and 5 (with light snow) were categorically removed because the duration of totally blocked time was zero for them. The ratio of the percentage of recorded warnings to that of the duration of observations during the totally blocked time was considered a parameter of comparison. This ratio came out to be 0.65, 0.24, and 0.15 respectively for sets 1, 2 and 3. These values show that only a small portion of warnings was recorded during the totally blocked time, which strengthens the idea that the radar performance is negatively affected by camera blockage and by extension the performance of the washing system that is responsible for cleaning this blockage.

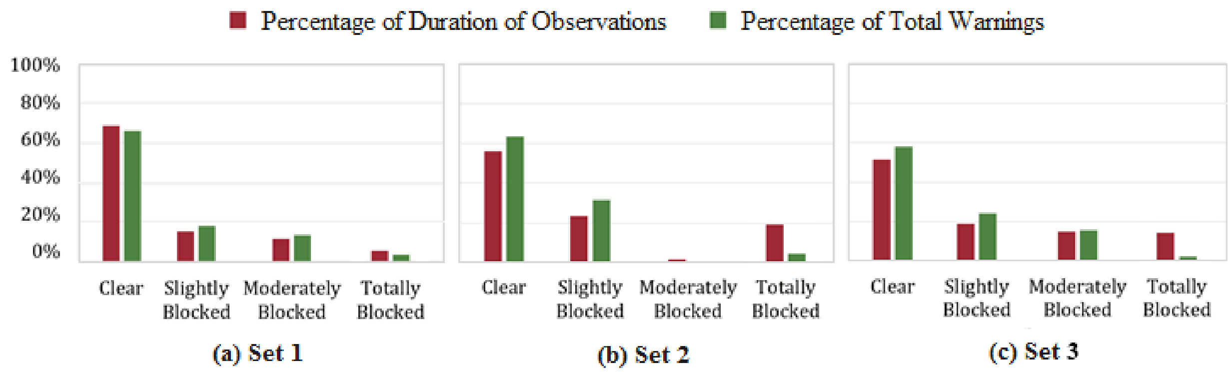


Figure 6-6: Comparison of camera observation and number of warnings for sets 1, 2 and 3 for different levels of camera lens blockage

6.2.2 Radar Data Size

The results presented in the previous section demonstrate that the CAMS box was blocked for a significant portion of maintenance operations during adverse weather conditions, coinciding with lower rates of triggered CAMS warnings. This relationship was further investigated using the size of non-null data logged by the radar unit as a measure of its performance, since the radar unit logs empty or "zero" data when its sensor is blocked. The percentage of non-zero values ($p_{\neq 0}$) in the radar log was found to be roughly directly proportional to the number of objects detected in most cases and was measured under different visibility conditions. A base value of 6.8 percent of $p_{\neq 0}$ was found in all log files, which corresponds to constant information about the truck and the environment.

Figure 6-7 shows the percentage of the non-zero values in the data files logged at every 5 minutes against the percentage of totally blocked duration for dataset group 1 that is characterized by heavy camera occlusion due to snow. All the profiles show that the value of $p_{\neq 0}$ drops exactly or very close to its base value of 6.8 percent (marked as a red horizontal line) when the level of total camera blockage increases. It can be observed that there are multiple contiguous blocks of time with totally blocked camera lens and long durations (minimum of 35 minutes). Since it is impractical to assume that no vehicle would have moved behind the truck in these long stretches of time in reality, it was concluded that no following vehicles were detected by the radar system despite their presence on the road. This observation provides strong evidence that the performance of the radar system is negatively affected by occlusion due to snow and ice. In practice, it implies that manufacturers and associated authorities should verify the quality of the washing system to ensure adequate performance of the CAMS upon large-scale deployment of this technology.

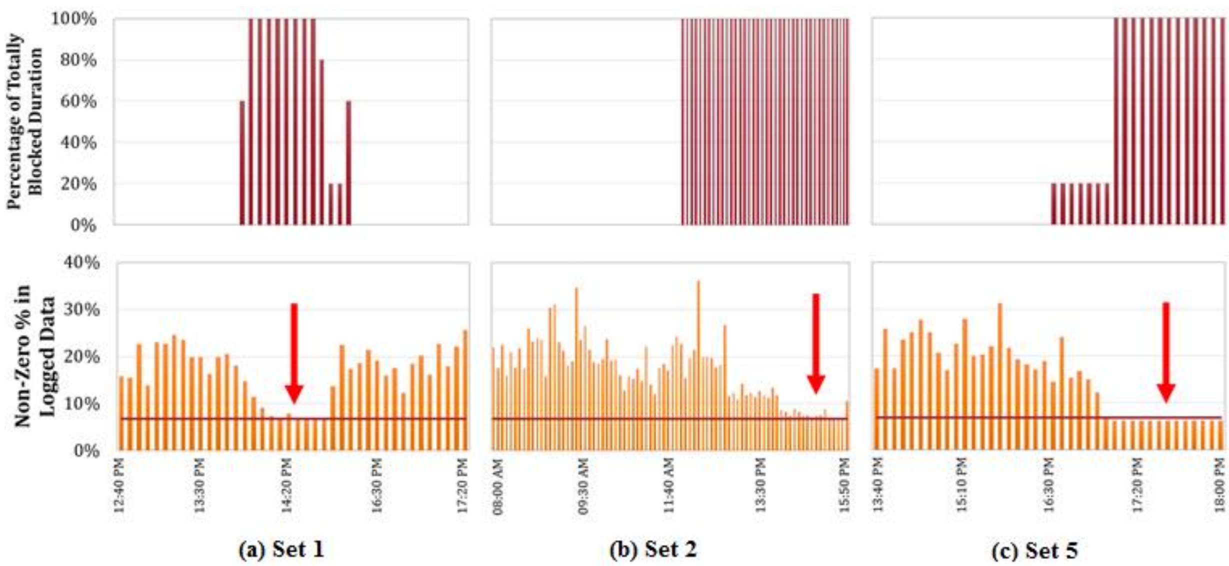


Figure 6-7: Relationship between camera view blockage and radar data logger for datasets 1, 2, and 3 (heavily occluded due to snowfall)

Chapter 7 - Summary and Recommendations

7.1 Summary

Collision avoidance systems are designed to improve traffic safety by preventing certain types of crashes, including rear-end and sideswipe. While collision avoidance systems are becoming increasingly common on vehicles, such systems have not experienced extensive implementation or testing on winter maintenance trucks, commonly referred to as snowplows or plow trucks.

The Michigan DOT recently installed a new prototype collision avoidance and mitigation system (CAMS) for testing on snowplows which warns drivers following them by triggering a rear-facing flashing LED light upon detection of a vehicle encroaching too close to the plow truck in terms of time gap. As this collision avoidance technology had not previously been implemented or tested for winter maintenance operations, this study sought to determine the extent to which CAMS may improve traffic safety mainly in terms of drivers' response when approaching snowplows from the rear. Besides this, it also sought to assess more pragmatic concerns associated with this technology such as the issues encountered with regular operations and maintenance. This was segregated into three analyses that are summarized below.

7.1.1 Driver Safety

The safety impacts of this technology were tested by conducting a case-control experiment using two test snowplows equipped with CAMS with the warning light enabled and disabled to control for external biases, with the other conditions controlled. Trajectories of vehicles following the snowplows were recorded in the same manner for both the cases and processed to obtain the distributions and linear regression models of three surrogate safety measures – minimum time to collision (TTC), maximum deceleration, and maximum speed differential between the plow truck and the following vehicle.

The results show mixed effects of the warning light. The minimum TTC with the light enabled was found to be 0.24 seconds than with the light disabled and the maximum deceleration about 0.17 ft/s^2 more, which indicate mild safety improvement. On the other hand, the warning light is also associated with a widening of the maximum speed differential by about 1.5 ft/s, which provides for conflicting results.

7.1.2 Driver Behavior

The effects of the warning light were also studied for a more refined dataset of manually reviewed warning events to account for environmental and event-specific conditions. Specifically, properties related to driver behavior, namely their decision for encroaching close to the plow truck and their reaction and response times in the event of doing so, were observed across different roadway, geometric, and situational conditions. Descriptive models using classification and regression tree modeling were developed to better understand the influence of each factor on the driver behavior metrics.

The results indicate positive effects of the CAMS warning light on improving both of the behavioral metrics. The reaction time reduced from 2.30 to 1.47 seconds, reducing by 36 percent. The response time reduced from 2.71 to 2.16 seconds, a remarkable reduction of 20 percent. The warning light was also found to be effective in improving the likelihood of drivers encroaching beyond safe headway thresholds of 4 and 4.5 seconds. However, these figures are based on a small subset of warning events and may not be representative of some real situations.

7.1.3 Operational Performance

The operational performance of the system was tested by evaluating two measures – (a) the accuracy of the CAMS responsible for detecting following vehicles and issuing warnings appropriately, and (b) the relationship between the effectiveness of the radar unit and that of the washing system intended to clean it from snow and dirt buildup.

The detection and alarm activation mechanism of the CAMS was found to have a few issues that may need to be fixed for practically feasible utilization. It shows a high misclassification rate when multiple following vehicles in different lanes simultaneously close in on the plow truck, giving rise to numerous false positives. It also has difficulty detecting the alarm-causing follower in many cases, especially on curved segments where lane detection becomes difficult.

The performance of the washing system was found to be positively correlated to that of the CAMS in terms of object detection. The pattern in the data logged by the radar unit was found to coincide with the pattern of occlusion of the camera view, which is the direct result of the inefficacy of the washing unit. Similarly, the markedly small number of warnings issued during the phase of significant camera occlusion also hinted at this idea. This suggests that an effective washing system is a necessary requirement of the CAMS technology.

7.2 Study Limitations

It should be noted that there are certain limitations associated with the analyses conducted in this study. These limitations may be rectified by using better-designed experiments that deliver larger and more comprehensive datasets.

1. The data used for developing the SSM models lack some relevant environmental and event-specific variables that may have affected the resultant target measures as well as the correlation between the descriptive variables. Specifically, the estimates of the

three SSMs are themselves based on assumptions rooted in the lack of actual information. For instance, the maximum speed differential between the snowplow and the following vehicle is assumed to have been attained after the issuance of the warning, but the data lacks any qualifier for screening events where it was attained prior to the warning.

2. The sample size in the analysis of driver behavior is reasonably small. Small samples readily affect the results of supervised models like decision trees developed in this analysis.
3. The behavioral analysis might be biased due to different weather conditions during the light enabled (heavy snow events including low visibility periods) and light disabled (light snow events mostly high visibility) cases.
4. The effect of potentially important environmental factors such as visibility, precipitation, and roadway conditions and human factors like age, gender, driving experience, and physiological state could also not be assessed.
5. The number of observed true positive warning light activations (i.e., when vehicles traveling in the same lane of the snowplow cross the activation threshold and the warning light is activated) is not large enough to draw statistically valid conclusions regarding the effects of the CAMS on drivers' behavior.
6. The washing system failure during the heavy snow conditions interferes with the operation of the radar unit and obstructs the camera view. This prevents the assessment of the performance of the CAMS during periods when it would typically be most beneficial.

7.3 Recommendations

Overall, this study suggests that there may be potential safety benefits associated with the broad deployment of the CAMS. However, the current prototype requires additional modification and testing prior to widespread deployment. This is largely due to the operational issues for both the radar unit and the associated cleaning system that persisted during field testing and inhibited reliability. The following list of recommendations should be considered prior to further implementation of the CAMS. After these changes have been made, a follow-up study is recommended to further evaluate the performance of the modified CAMS.

1. Collect additional driver behavior data during comparable weather events with the warning light enabled and disabled. To reduce selection bias during data collection, it is suggested to alternate between the phases of light enabled and disabled during each maintenance operation (e.g. alternating between enabled and disabled operation hourly). This would make the conditions as consistent as possible during enabled and disabled data collection in terms of weather, roadway, and traffic conditions, and result in a more accurate assessment of the impacts of the warning light on safety and behavioral measures.
2. Incorporate an absolute distance-based threshold for warning alert activation in addition to the time gap thresholds currently used to activate the warning alert. This may help prevent tailgating and keep vehicles away from the rear zone of the snowplow, regardless of the associated speed differential.
3. Resolve issues with the inconsistency/imprecision of the warning light activation. Although the data log suggests that the radar properly identified the location and speed of vehicles, the warning light was often activated at inappropriate times or not

activated when it should have been. The specific issues included: warning light activated by an adjacent lane vehicle, delays in warning light activation of up to 2 seconds, and warning light not activated at all.

4. Modify the CAMS to better assist the snowplow drivers during winter maintenance operations. This may include better blind spot coverage, which would require inverting the mirrored camera view, and providing an improved driver assistive system to encourage the plow drivers to maintain the system during the operations. Alternatively, it may also be appropriate to remove the camera and in-cab display, as doing so has no impact on CAMS operations.

APPENDIX

CODES/PROGRAMS

I. Read Vehicle Trajectory Data from Radar Log

```
# Language: R
# Author: Rajat Verma
# Description: Read the vehicle data from all 5-min data sheets in the data source for both the plow & the following vehicles & store as combined RData file

# Packages
require('tictoc') # for checking time consumption
require('data.table') # for batch-processing data
require('dplyr') # for more dataframe manipulation

tic()

# I/O
# main data directory
data.dir <- 'CAMS Data/T1 - 4004 - ON'
# path of the output file
outfile <- file.path(data.dir, 'RData/veh_data.RData')

# Inputs
# divide the process into batches to prevent memory overloading
file.num.range <- 1:100

# Preprocessing
# select only the files relevant to the snowplow data
truck.files <- dir(file.path(data.dir, 'Truck Log'), '*.csv', full.names = T)
# “” relevant to the detected vehicles
car.files <- dir(file.path(data.dir, 'Car Log'), '*.csv', full.names = T)
# every 5 minutes should have exactly one car and one truck file
if (length(truck.files) != length(car.files))
  {warning('#(car files) != #(truck files)')}
# filter the relevant columns in the car files that contain dx, dy, vx, etc.
car.rel.cols <- c(2, sort(unlist(lapply(c(3,4,5,6,13), seq, by = 18,
                                        length.out = 32))))
error.files <- character()

# Read car data
read.car.log <- function(file) {
  car.raw <- tryCatch({
    return(fread(file, select = car.rel.cols))
  },
  error = function(e) {
    print(sprintf('(Skipped) %s', file))
```

```
    error.files <<- c(error.files, file)
    return(NULL)
  })
  return(car.raw)
}
time.car <- system.time(
  car.log <- rbindlist(lapply(car.files[file.num.range], read.car.log),
                       fill = F))

# Read truck data
read.truck.spd <- function(file) {
  truck.spd <- tryCatch({
    return(as.data.frame(fread(file, select = c(2,3)) %>%
      group_by(epochTime) %>%
      summarize(speed_mph = mean(Vehicle.MPH10)/256)))
  },
  error = function(e) {
    print(sprintf('(Skipped) %s', file))
    error.files <<- c(error.files, file)
    return(NULL)
  })
  return(truck.spd)
}
time.truck <- system.time(
  truck.spd <- rbindlist(lapply(truck.files[file.num.range], read.truck.spd),
                         fill = F))

# Save the two data structs
save('car.log', 'truck.spd', 'time.car', 'time.truck', 'car.files',
     file = outfile)
toc()
# ……………………………………………………………………………………………………………...
```

II. Create Filtered Dataset of Non-Null Trajectories

```
# Language: R
# Author: Rajat Verma
# Description: Create detected object & follower data clusters detected in truck zone using car and truck
RData

t0 <- Sys.time()

# Packages
require('dplyr')
require('data.table')

# Input
DS <- 4 # dataset number

# I/O
data.dir <- sprintf('../Data') # data directory
# condensed rdata file containing truck & following car trajectories
veh.data.file <- sprintf('%s/DS%d Veh Data.RData', data.dir, DS)
avl.file <- sprintf('%s/DS%d AVL.csv', data.dir, DS) # AVL data file
obj.df.file <- sprintf('%s/DS%d Object DF.rds', data.dir, DS) # result df

# Constants
dwell.time <- 3 # min duration of stay (sec) to filter detected veh observ/ns
time.factor <- 10 # record frequency = no. of records per second

# Load the data
# - load the following car data
if (!exists('car.log')|!exists('truck.spd')) load(veh.data.file)

# - add decimal place to the epoch time (with some approximation/assumptions)
car.log[, epoch := epochTime +
        seq(0.0, by = 0.1, length.out = as.integer(.N)), epochTime]

# Main loop
# - initialize the dataframe containing all trajectories
obj.df <- data.frame()
# - for each detectable object
for (obj.id in seq(32)) {
  # - get indexes of relevant cols
  col.ids <- seq(5*obj.id - 3, 5*obj.id + 1)
  # - filter the data of the relevant columns
  data <- car.log[, c(ncol(car.log), col.ids), with = F]
  # - rename the df columns
  colnames(data) <- c('t','dx','vx','dy','ax','vy')
```

```
  # Filter continuous blocks of observation data (i.e. non-zero 'dx')
  # - filter the non-null data from the sparse df
  non.0.idx <- which(data$dx != 0)
  non.0.df <- data[non.0.idx,]
  # - add the object number (1-32) & observation number for future reference
  non.0.df$obj.num <- obj.id
  non.0.df$obs.num <- factor(cumsum(diff(c(0, non.0.idx)) != 1))

  # Filter observation numbers which have been detected for > dwell time
  filt.obs.nums <- non.0.df %>%
    group_by(obs.num) %>%
    summarize(n = n()) %>%
    filter(n >= dwell.time * time.factor) %>%
    select(obs.num) %>%
    pull()
  filt.obs.df <- non.0.df %>% filter(obs.num %in% filt.obs.nums)

  # Append the filtered df of object cluster data
  obj.df <- rbind(obj.df, filt.obs.df)
  print(paste('Obj', obj.id))
}
# Finalize the resultant object by fixing data types & units
obj.df <- data.table(sapply(obj.df, as.numeric))[order(obs.id, t)]
obj.df[, `:=`(epoch = t, t = lubridate::as_datetime(t), dx = dx/16 * 3.28084,
              dy = dy/64 * 3.28084, vx = vx/16 * 2.23694,
              vy = vy/16 * 2.23694, ax = ax/32 * 2.23694)]
setcolorder(obj.df, c('obs.id','ds','obs.num','obj.num','epoch',
                      't','dx','dy','vx','vy','ax'))

# Save the resultant dataframe
saveRDS(obj.df, file = obj.df.file)

print(sprintf('Time elapsed: %.3f', Sys.time()-t0))
# ………………………………………………………………………………………………………………...
```

III. Decision Tree Model for Reaction and Response Time

```
# Language: R
# Author: Rajat Verma
# Description: Develop regression tree models of the driving behavior measures with the help of input
data CSV file created after manual video review

# Packages
require('dplyr') # for data manipulation
require('rpart') # for creating the decision tree
require('rpart.plot') # for customizing the appearance of the tree

# I/O
input.file <- '../Data/Modeling Input Raw.csv'

# Input
# - set the target variable: can be ‘react time’ or ‘resp time’
targ.var <- 'resp time'

# Parameters
dwell.time <- 0.25 # filter value of target variables
minsplit <- 2 # min no. of splits in the tree
minbucket <- 3 # min size of the leaf node

# Get the data
# - read the data
raw <- read.csv(input.file)
# - assign the fields
fields <- c('Warning', 'Maneuver', 'Light', 'Geometry')
# - create the input matrix
X <- raw[,fields]
# - convert the input to factor to facilitate splitting
X[] <- lapply(X, factor)
# - set the target variables
t.react <- as.numeric(raw$ReacTime)
t.resp <- as.numeric(raw$RespTime)
# - dataset contains the two target vars & the input data
data <- data.frame(ReacTime = t.react, RespTime = t.resp, X)

# Train the model
if (targ.var == 'react time') {
  # - filter the data for reaction time greater than the preset threshold
  filt.data <- filter(data, ReacTime >= dwell.time)
  plot.title <- 'Reaction Time (s)'
  tree.controls <- rpart.control(minsplit = minsplit, minbucket = minbucket)
  fit <- rpart(ReacTime ~ Warning + Maneuver + Light + Geometry,
            data = filt.data, method = 'anova', control = tree.controls)
```

```
} else if (targ.var == 'resp time') {
  filt.data <- filter(data, RespTime >= dwell.time)
  plot.title <- 'Response Time (s)'
  tree.controls <- rpart.control(minsplit = minsplit, minbucket = minbucket)
  fit <- rpart(RespTime ~ Warning + Maneuver + Light + Geometry,
              data = filt.data, method = 'anova', control = tree.controls)
}

# Plot the tree
rpart.plot(fit,
           main = plot.title,
           type = 3, # type of display
           extra = 1, # use this arg for no. of obs/ns
           fallen.leaves = T,
           tweak = 1.25,
           digits = 3,
           box.palette = 'Reds',
           round = 1,
           split.box.col = '#88E9FF',
           split.round = 1,
           ygap = 0.2,
           Fallen.yspace = 0.3,
           # split.space = 0,
           split.yspace = 0.3,
           yspace = 0.1
)
# legend(0.05,0.6,legend=seq(0,1,by=0.2), fill=seq(0,1,by=0.2),
#        title = "Reaction Time")

# Predict for a query
# - change the input variables to manually test the model prediction
query <- data.frame(
  WarnLev = 1,
  Maneuver = 2,
  Light = 1,
  TurnFlag = 0)
predicted <- predict(fit,lapply(query,factor))
print(predicted)
# ……………………………………………………………………………………………………………...
```

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REFERENCES

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