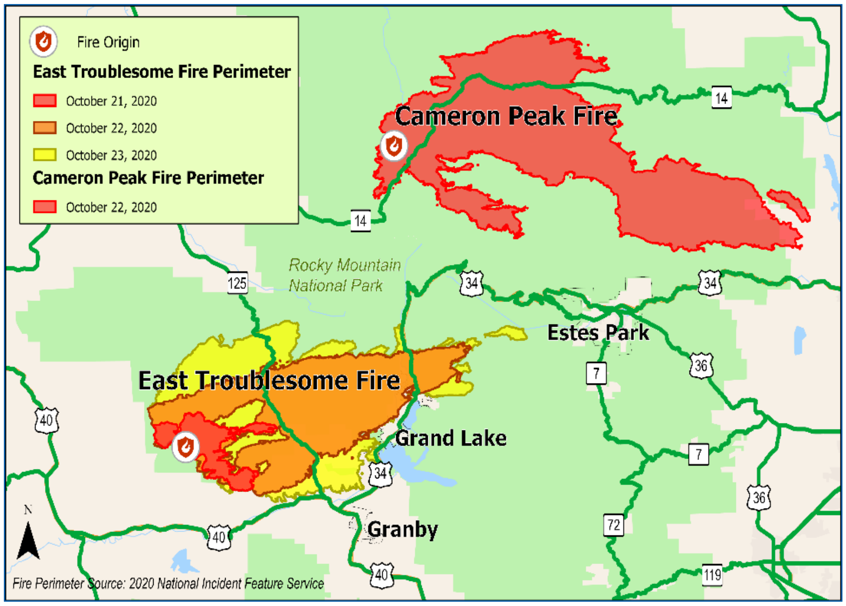
MOUNTAIN-PLAINS CONSORTIUM

MPC 23-509 | P. Lu and Y. Huang

REGIONAL EMERGENCY EVACUATION ANALYSIS IN TRAFFIC WITH CONNECTED AND AUTONOMOUS VEHICLES



A University Transportation Center sponsored by the U.S. Department of Transportation serving the Mountain-Plains Region. Consortium members:

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Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
MPC-685		

4. Title and Subtitle	5. Report Date
Regional Emergency Evacuation Analysis in Traffic with Connected and Autonomous Vehicles	December 2023
	6. Performing Organization Code
7. Author(s)	8. Performing Organization Report No.
P. Lu, Y. Huang, A. Ali, S. Ahmad, X. Yang, Y. Ren and H. Ahmed	MPC 23-509
9. Performing Organization Name and Address	10. Work Unit No. (TRAIS)
North Dakota State University NDSU Dept 2880, PO Box 6050 Fargo, ND 58108-6050	11. Contract or Grant No.
12. Sponsoring Agency Name and Address	13. Type of Report and Period Covered
Mountain-Plains Consortium North Dakota State University PO Box 6050, Fargo, ND 58108	Final Report
	14. Sponsoring Agency Code

15. Supplementary Notes

Supported by a grant from the US DOT, University Transportation Centers Program

16. Abstract

In an ever-evolving world characterized by environmental challenges and technological advancements, the confluence of natural disasters, particularly increasing wildfire threats, and the role of connected and autonomous vehicles (CAVs) stands as a critical focal point for research and innovation. This study embarks on a comprehensive exploration of this dynamic landscape, encompassing disaster management strategies, wildfire evacuation, and the integration of innovative CAV technology. Additionally, it delves into the intricate tapestry of public attitudes and perceptions surrounding CAVs, shedding light on the nuanced dynamics that influence technology acceptance. As our planet grapples with the escalating risks of natural disasters driven by climate change, and CAVs become an emerging reality, this research seeks to unravel the potential these vehicles hold in enhancing disaster response and reshaping the transportation landscape.

To understand how individuals perceive CAV technology, the research conducts a stated preference survey in distinctive environments, such as medium-sized towns marked by cold climates and significant academic populations. It reveals that the acceptance of CAVs is intertwined with factors like the perceived utility, perceived risk, and the potential for safety improvements under adverse weather conditions. These insights underscore the multifaceted nature of public sentiment and acceptance surrounding CAVs, highlighting the importance of grasping user perspectives in diverse urban settings.

In sum, this research navigates the complex terrain of natural disaster management and the burgeoning CAV technology landscape, uniting technology's transformative capabilities with the intricate interplay of human attitudes, and offering a comprehensive view of a world evolving in response to both environmental challenges and technological innovations.

17. Key Word	18. Distribution Statement
Autonomous Vehicles, Emergency Evacuation, Wildfires, Natural Disasters, Connected Vehicles	Public distribution

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	34	n/a

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

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Acknowledgments

This research was made possible with funding supported by the U.S. Department of Transportation through the Mountain-Plains Consortium (MPC) Transportation Center. The authors express their gratitude to the U.S. DOT and MPC.

Disclaimer

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented. This document is disseminated under the sponsorship of the Department of Transportation, University Transportation Centers Program, in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.

Six publications based on this research were published before this report was finalized, and each acknowledged this project. These journal papers are as follows:

1. Ahmed, H. U., Huang, Y., Lu, P., & Bridgelall, R. (2022). "Technology Developments and Impacts of Connected and Autonomous Vehicles: An Overview." *Smart Cities*, 5(1), 382–404. https://doi.org/10.3390/smartcities5010022 [Impact factor: 6.4]

2. Mirzazadeh, B., Huang, Y., & Motuba, D. (2022). "The attitudes towards autonomous vehicles in a medium-sized academic-dominated US metropolitan area with cold winters." *International Journal of Human–Computer Interaction*, 1-16. https://doi.org/10.1080/10447318.2022.2074646 [Impact factor: 4.7]

3. Ahmad, S., Ali, A., Ahmed, H. U., Huang, Y., & Lu, P. (2023). "Evaluating Traffic Operation Conditions during Wildfire Evacuation Using Connected Vehicles Data." *Fire*, 6(5), 184. https://doi.org/10.3390/fire6050184 [Impact factor: 3.2]

4. Ahmad, S., Ahmed, H. U., Ali, A., Yang, X., Huang, Y., Guo, M., Y. Ren, & Lu, P. (2023). "Evaluating driving behavior patterns during wildfire evacuations in wildland-urban interface zones using connected vehicles data." *Fire Safety Journal*, Volume 142, January 2024, 104015. https://doi.org/10.1016/j.firesaf.2023.104015 [Impact factor: 3.1]

5. S. Ahmad, J. Rogers, M. Nelson, Y. Huang, B. Ajmera, & P. Lu, "Evaluating the Mobility Performance of Autonomous Vehicles at a Signalized Traffic Intersection," Proceedings of SPIE Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2022, Vol. 12046, pp. 120460Z, DOI: 10.1117/12.2606614, (2022).

6. Xinyi Yang, Hafiz Ahmed, Ying Huang, & Pan Lu, "Cumulatively Anticipative Car-Following Model with Enhanced Safety for Autonomous Vehicles in Mixed Driver Environments," *Smart Cities*, 6(5), 2260-2281, 2023 https://doi.org/10.3390/smartcities6050104

ABSTRACT

In an ever-evolving world characterized by environmental challenges and technological advancements, the confluence of natural disasters, particularly increasing wildfire threats, and the role of connected and autonomous vehicles (CAVs) stands as a critical focal point for research and innovation. This study embarks on a comprehensive exploration of this dynamic landscape, encompassing disaster management strategies, wildfire evacuation, and the integration of innovative CAV technology. Additionally, it delves into the intricate tapestry of public attitudes and perceptions surrounding CAVs, shedding light on the nuanced dynamics that influence technology acceptance. As our planet grapples with the escalating risks of natural disasters driven by climate change, and CAVs become an emerging reality, this research seeks to unravel the potential these vehicles hold in enhancing disaster response and reshaping the transportation landscape.

To understand how individuals perceive CAV technology, the research conducts a stated preference survey in distinctive environments, such as medium-sized towns marked by cold climates and significant academic populations. It reveals that the acceptance of CAVs is intertwined with factors like the perceived utility, perceived risk, and the potential for safety improvements under adverse weather conditions. These insights underscore the multifaceted nature of public sentiment and acceptance surrounding CAVs, highlighting the importance of grasping user perspectives in diverse urban settings.

In sum, this research navigates the complex terrain of natural disaster management and the burgeoning CAV technology landscape, uniting technology's transformative capabilities with the intricate interplay of human attitudes, and offering a comprehensive view of a world evolving in response to both environmental challenges and technological innovations.

EXECUTIVE SUMMARY

This research addresses the urgent need for enhanced emergency evacuation strategies in the MPC region during natural disasters, particularly wildfires, by capitalizing on data from connected and autonomous vehicles (CAVs). Leveraging a dataset from connected vehicles, the study evaluates driving behavior and traffic conditions during wildfire evacuations, providing crucial insights for disaster response. Furthermore, it investigates the role of CAVs in disaster management and assesses public attitudes toward their integration in a medium-sized metropolitan area with cold weather. This research offers a data-driven foundation for optimizing emergency evacuation plans and underscores the potential of CAVs in improving disaster response, highlighting the importance of public perception in realizing this potential.

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1. INTRODUCTION

Natural disasters have become more common and expensive in recent years. Extreme and no-notice disasters, defined as events that occur with little to no official warning, pose a significant threat to human life, property, and integrity of the ecosystem. These catastrophic damages are often caused by wildfires, which are uncontrolled fires that spread quickly under extreme weather conditions such as severe drought and high wind and in the presence of dry vegetative fuel and steep topography. Unfortunately, because of climate change, these conditions are becoming more common, particularly in the western United States [1], [2]. Large-scale wildfires can cause mass evacuations which can create social disruption, long-term infrastructure damage, and injuries or deaths of evacuees and first responders [3], [4]. Statistics show that between 1980 and 2007, there were, on average, 20 evacuations per year in Canada with some years recording as many as 53 evacuations [5]. Moreover, in recent years the state of California witnessed more than one million people evacuate their neighborhoods and about 30,000 structures destroyed due to fire incidents [6]. Additionally, communities living near undeveloped wildlands or vegetative fuels, constituting wildland-urban interface (WUI) zones, are most vulnerable to fire due to their proximity to flammable vegetation and limited egress routes [7], [8]. Many of these communities are experiencing rapid population growth, but the traffic infrastructure and number of exits are unable to keep up with the rising traffic demand, putting the lives of residents at risk (Cova et al., 2021) [9].

In the event of an emergency evacuation such as in WUI areas, having a reliable transportation system is necessary. It gives residents safe passage out of the affected area and essential timely access for first responders to reach the impacted region. Large-scale hazardous events (such as wildfire, tornado, hurricane, earthquake, flood, or chemical spill) often require mandatory evacuation of residents [10]. In these situations, the amount of time available for evacuation is critically important, especially in the event of wildfire where evacuees must watch out for smoke, flying debris, and flames, as well as avoid conflict with emergency services [11], [12]. The population density and traffic infrastructure of the area affected by the fire also have a significant impact on the safe and well-planned evacuation of people. When there is a sudden evacuation, high-density areas can cause more traffic congestion and create longer vehicular queues on the exiting routes, endangering the lives of stranded evacuees [13], [14]. The response of the local authorities and first responders is also considered important in determining the behavior of residents during an evacuation. Pre-evacuation warnings and explicit instructions from emergency personnel can help evacuees make thoughtful decisions about the fire risk and safely depart the affected area [[15], [16]]. Additionally, the population's demographics, including household size, income, education level, ownership of a car or home, ethnicity, and previous experience with mass evacuations, can have a significant impact on the evacuation rate [17], [18]

In the context of wildfire evacuations, the integration of connected and autonomous vehicles (CAVs) represents a promising advancement that can significantly enhance the evacuation process. These vehicles, equipped with real-time communication capabilities and autonomous navigation systems, bring efficiency and safety to evacuations. Connected vehicles can share critical information about traffic conditions, road closures, and alternate routes, while autonomous vehicles can adapt swiftly to changing circumstances, selecting the safest and most efficient evacuation routes. The coordination between CAVs not only optimizes traffic flow but also prevents congestion and bottlenecks, which are essential steps during large-scale evacuations. Furthermore, CAVs can provide accessible transportation for individuals with mobility challenges, ensuring inclusivity in evacuation efforts. Additionally, the data collected by these vehicles can be invaluable for emergency response teams and future evacuation planning. By reducing the risk of human error, enhancing traffic management, and improving accessibility, CAVs offer a new dimension of safety and efficiency to wildfire evacuations, potentially saving lives and mitigating the impact of these disasters on communities.

This project proposes to address the MPC region's urgent need for emergency evacuation analysis during natural disasters such as wildfires by taking advantage of the rapid development of data collection from CAVs. Such an analysis is expected to provide emergency evacuation officials and residents with a suggested action plan based on the simulation predictions of a hazard spreading. Specifically, three objectives will be aligned to achieve such an overarching goal:

1. Obtaining and transferring the real-time data from the database obtained from connected and autonomous vehicles, followed by converting the data into the appropriate format for microsimulation software.
2. Setting up and validating the microsimulation model for emergency evacuation analysis based on the collected traffic data during previous evacuation experiences within the MPC region. The focus will be given to the states of Wyoming, Colorado, and Utah based on those states' higher frequency of wildfire disasters.
3. Predicting and making recommendations for future evacuation needs.

In addition, the team will use the results from this development to enhance curricula that would engage and mentor students in the practice of developing safe smart cities. This project will involve 10 graduate students and several undergraduate students. The trainings through this project will prepare students for potential careers in smart city development.

Thus, this report is organized according to objectives. Chapter 2 provides a brief introduction to the real-time data extraction and conversion for microsimulation. Chapter 3 introduces the microsimulation model validation for wildfire emergency evacuation. Chapter 4 explains future evacuation needs and gives recommendations. Chapter 5 shows the curriculum and educational development of this project, including student mentoring and outreach activities. Finally, Chapter 6 summarizes the conclusions and recommendations from the study.

2. REAL-TIME DATA EXTRACTION AND CONVERSION FOR MICROSIMULATION

2.1 Connected Vehicles (CVs) Data

Over the last decade, large sets of data about human mobility, facilitated by extensive use of sensors, such as global positioning system (GPS) devices in many modes of transportation and mobile phones, have become the fundamental component of the new smart cities paradigm [19]. Detailed information about a driver's location, speed, and other information can be gathered from a mobile device or vehicle by a public or private entity and can be used to obtain travel times [20]. Many independent third-party companies compile large amounts of crowdsourced data and provide high-quality real-time traffic information [21-24]. Moreover, modern vehicles, known as connected vehicles (CVs) produced by leading automobile manufacturers, are equipped with sensors that record temporal and spatial information about the vehicle trajectory and the surrounding environment and transmit it to the cloud computing databases [25]. Several big data companies have also emerged (such as Otonomo, Wejo). These companies segregate and normalize historical CV data and share it with vehicle manufacturers, researchers, and technology developers for research and development [26]. For instance, Wejo has partnered with multiple global automobile manufacturers that record vehicle trajectory data from vehicle onboard sensors. The data are collected at 3-second intervals and each data-point is recorded within a 3-meter radius with an accuracy of 95%. Each data point includes a unique identifier, the location of the data point, a timestamp, the vehicle's speed, and its direction of movement.

2.2 Elevating Data Insights: The Superiority of CV Data

Although the anonymized CV dataset has recently become available to explore historical traffic patterns at the location of interest, several researchers have already tested Wejo's vehicle movement dataset. Li et al. (2021) estimated border crossing time at Paso del Norte International Bridge in El Paso, TX, using Wejo's CV dataset and observed a correlation rate of around 0.8 with the existing Bluetooth-generated border crossing time information system. They also discovered that the temporal coverage rate of Wejo's dataset was around 60% to 70% for estimating border crossing time at the selected site [27]. In another study, Desai et al. (2021) used this dataset to study the impact of interstate construction work zone diversions on traffic signal performance measures [28] Khadka et al. (2022) identified queue propagation at freeway bottlenecks and arterial traffic intersections using these CV data [29]. Furthermore, Saldivar Carranza et al. (2021) estimated operational performance measures for various traffic signals in Indianapolis, and Abdelraouf et al. (2022) developed a sequence-to-sequence deep learning model to forecast traffic volume and speed on four expressways in Orlando, FL [30], [31]. Hence, because of the lack of empirical data on WUI fire evacuation clearance times and the inability of existing travel data collection technologies to comprehend such data, the CV datasets provide an opportunity to evaluate traffic delays resulting from historical wildfire events.

2.3 Conversion of CV Data for Analysis in GIS

The dataset was delivered in smaller parcels of JSON files to Amazon Web Services (AWS) S3 cloud storage; the parcels were stored in the local storage using the AWS Command Line Interface (CLI). Initially, the stored JSON files were pre-processed into CSV files and compiled together in MS Excel to create a readable format for later use. Next, to visualize the processed tabular data, it was imported into the ArcGIS Pro software, and the location attributes of the data (i.e., latitude and longitude) were utilized to create a feature class of the entire dataset.

2.4 Evaluation of Driving Behavior During Evacuation

For the selected study areas, the connected vehicle driving events data (i.e., hard-braking and hard-acceleration) provided by Wejo Data Services, Inc., were used to analyze the behavior of drivers in a mass evacuation. To analyze the extent of aggressive driving in the selected wildfire evacuation cases, the period of data collection consisted of evacuation as well as non-evacuation time frames to allow us to evaluate driver behavior under varying driving conditions. Considering that Saratoga Springs in Utah was evacuated on June 28, 2020, data were collected for the period of June 20-30, 2020. Three towns in Colorado were evacuated on October 21, 2020, (Grand Lake) and October 22, 2020 (Granby and Estes Park), so data were collected from three days in September and five days in October, as detailed in Table 2.1.

Table 2.1 Driving events data collection

S No.	City	Fire event	Date of evacuation	Data collection period
1	Saratoga Springs, UT, USA	Knolls Fire	June 28, 2020	June 20, 2020 – June 30, 2020
2	Grand Lake, CO, USA	East Troublesome Fire	Oct. 21, 2020	Sept. 23, 2020 – Sept. 25, 2020, Oct. 21, 2020 – Oct. 25, 2020
3	Granby, CO, USA	East Troublesome Fire	Oct. 22, 2020	Sept. 23, 2020 – Sept. 25, 2020, Oct. 21, 2020 – Oct. 25, 2020
4	Estes Park, CO, USA	Cameron Peak Fire & East Troublesome Fire	Oct. 22, 2020	Sept. 23, 2020 – Sept. 25, 2020, Oct. 21, 2020 – Oct. 25, 2020

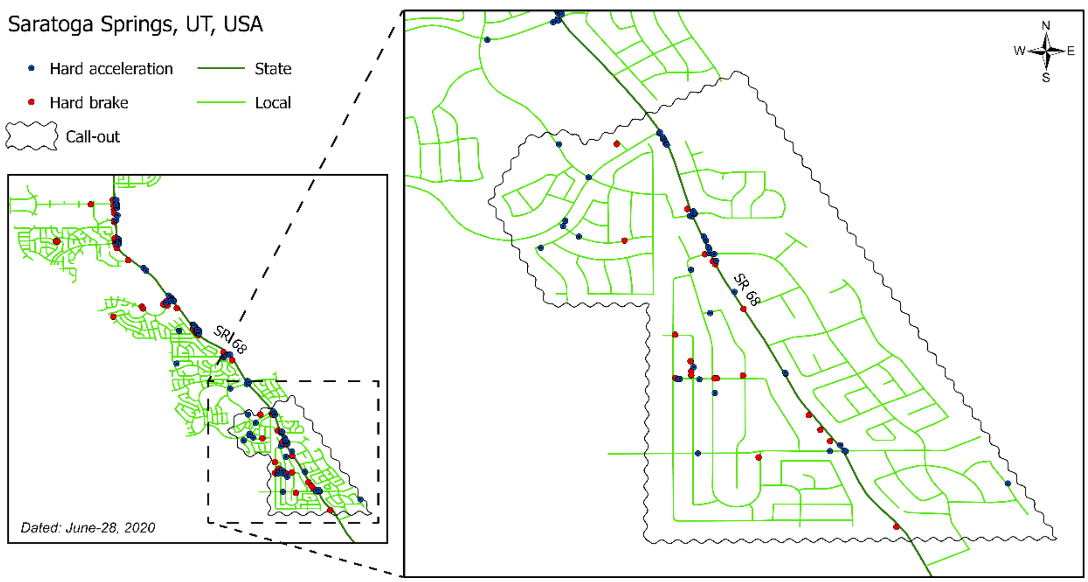
2.4.1 Data Collection and Analysis

The data were delivered in smaller parcels consisting of around 14,000 JSON files to AWS S3 cloud storage and were stored in the local storage using the AWS CLI. The key attributes of the data used for processing and analysis are listed in Table 2.2.

Table 2.2 Key driving events data attributes

S No.	Data attributes	Definitions
1	Data-point ID	Records a unique data-point whenever a vehicle applies a HB or a HA event.
2	Captured date & time	Records the time and date of the event when a data-point is recorded in Universal Coordinated Time (UTC).
3	Time zone offset	Records the location time zone offset for the data-point. The time zone offset of (UTC - 6 hours) was used for all study areas for the collected data period.
4	Latitude	Provides the north-south positioning of the vehicle on the Earth's surface.
5	Longitude	Provides the east-west positioning of the vehicle on the Earth's surface.
6	Acceleration change type	Signifies an HA event when a vehicle detects an acceleration of over 2.77 m/s^2 or an HB event when a vehicle detects a deceleration of over 2.77 m/s^2.

The study area analyzed for the city of Saratoga Springs consisted of five miles of SR-68 between mile markers (MM) 25 and 30 along with the residential neighborhoods evacuated during the 2020 Knolls Fire, as illustrated in 1(a). As can be seen in 1(b), the analysis of the data for this city revealed that the day of evacuation (June 28, 2020) observed almost twice as many HA events and more than twice as many HB events as the reference day the week before (Sunday, June 21, 2020). This suggests that the residents reacted aggressively to the short-notice evacuation orders and drove their vehicles with higher acceleration and deceleration rates to safely exit the impacted region from the fire, as discussed previously in the literature.



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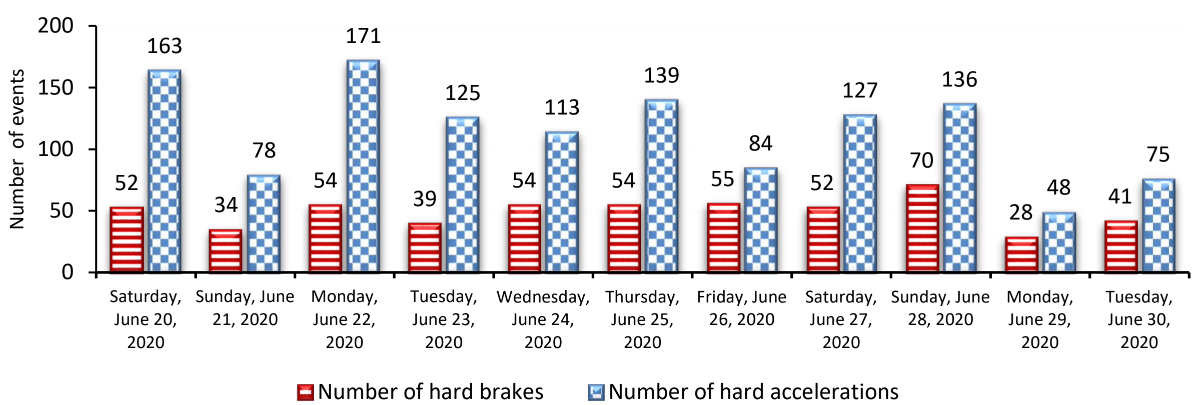


(b)

Figure 2.1 Saratoga Springs, UT, USA (a) driving-events map, (b) driving-events data

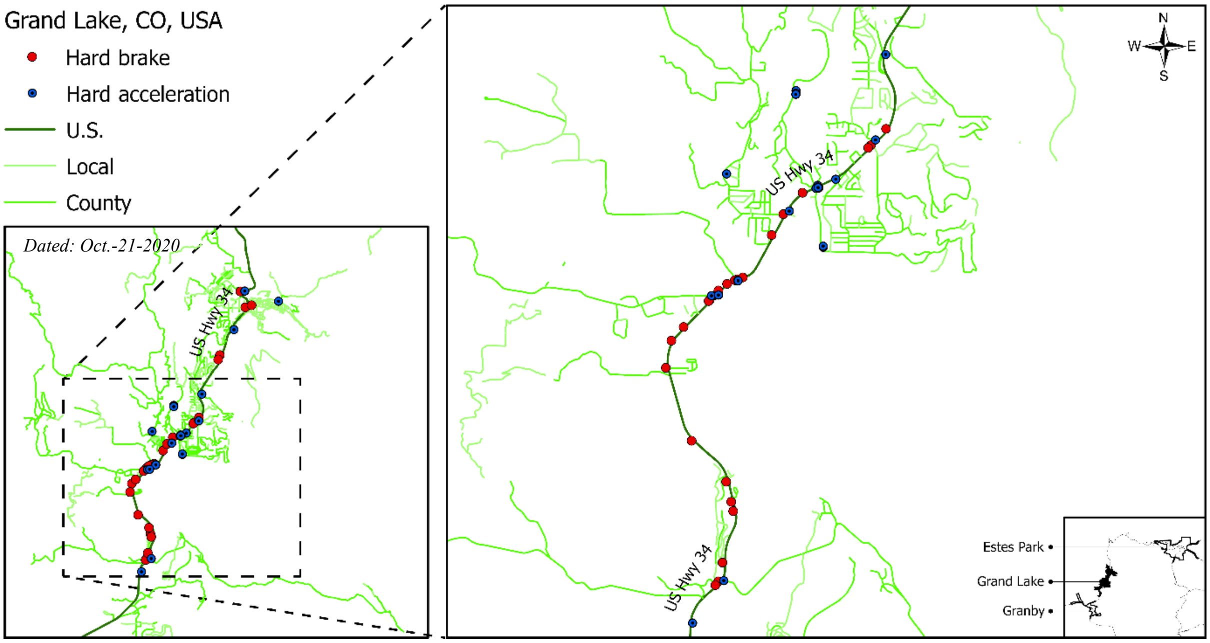
It was also observed that throughout the study period, the southern neighborhoods of the city, which were initially asked to evacuate, observed the highest number of HB and HA events on the day of evacuation, as noted in Table 2.3 and depicted in the call-out drawn in Figure 2.1(a). Additionally, the southern neighborhoods observed almost 83% of the day's HB and 73% of the day's HA events during the evacuation period (2:45 p.m. to 7:00 p.m.). This highlights the significant temporal and spatial impact of the fire and the subsequent hurried evacuation driving behavior in the affected neighborhoods. Furthermore, the data evaluation also revealed that the traffic intersections are critical congestion points where the highest number of driving events are observed. This implies that vehicles formed queues at the intersections requiring drivers to apply HB to stop the vehicle and then HA to leave the area quickly, as previously noted in the literature. The driving event data for this city demonstrate the driving behavior of people evacuating the city on very short notice out of fear for their lives, as supported by the studied case reported in the previous section.

Table 2.3 Call-out area daily driving events

Date	Number of hard brakes	Number of hard accelerations
Saturday, June 20, 2020	17	30
Sunday, June 21, 2020	11	19
Monday, June 22, 2020	8	39
Tuesday, June 23, 2020	7	28
Wednesday, June 24, 2020	10	27
Thursday, June 25, 2020	7	21
Friday, June 26, 2020	9	14
Saturday, June 27, 2020	7	18
Sunday, June 28, 2020	24	41
Monday, June 29, 2020	3	10
Tuesday, June 30, 2020	5	15

The data for the three towns in Colorado were analyzed, including the Grand Lake area consisting of neighborhoods along U.S. Highway 34 (MM 5 to 17) and the Granby area consisting of neighborhoods along U.S. Highway 40 (MM 207 to 216), U.S. Highway 34 (MM 0 to 3), and State Highway 125 (MM 0 to 3). The Estes Park area consisted of neighborhoods along U.S. Highway 34 (mile marker 54 to 70), U.S. Highway 36 (MM 1 to 7) and State Highway 7 (MM 0 to 7).

Starting with the evacuation of Grand Lake, it was observed that the majority of evacuation day driving events occurred on U.S. Highway 34 with traffic traveling south toward Granby, as reported in the previous section and illustrated in Figure 2.2(a). The increasing occurrence of HA events for vehicles traveling south in particular demonstrates the urgency of evacuees to leave the affected area. Secondly, since both lanes of U.S. Highway 34 were used to reduce congestion during the evacuation, a high increase in HB events was not observed, as detailed in Figure 2.2(b). Another reason for the lack of significant increase in driving events during evacuation might be that the town received fewer visitors because the west side of Rocky Mountain National Park toward Grand Lake was closed for visitors on the evacuation day.



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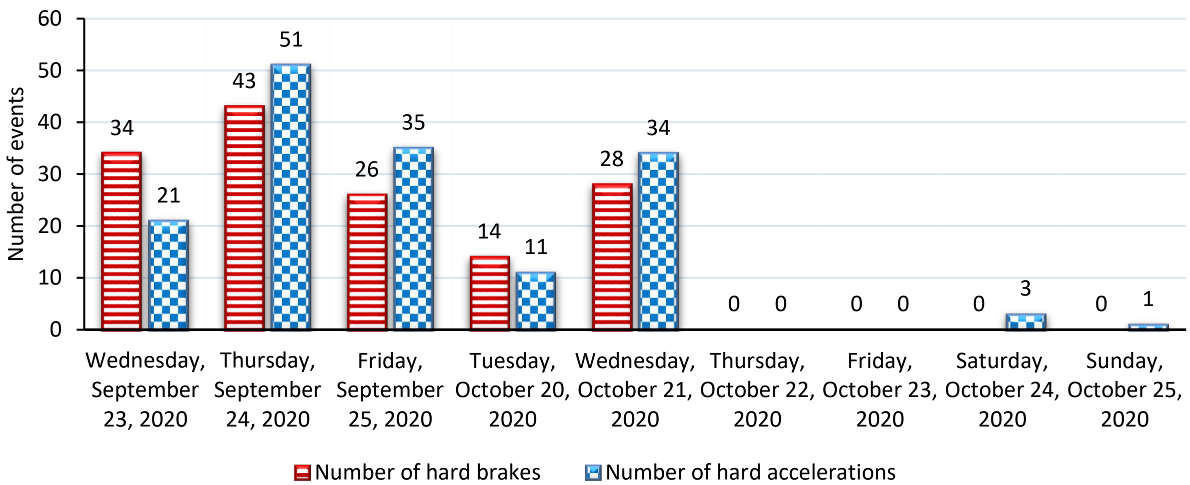
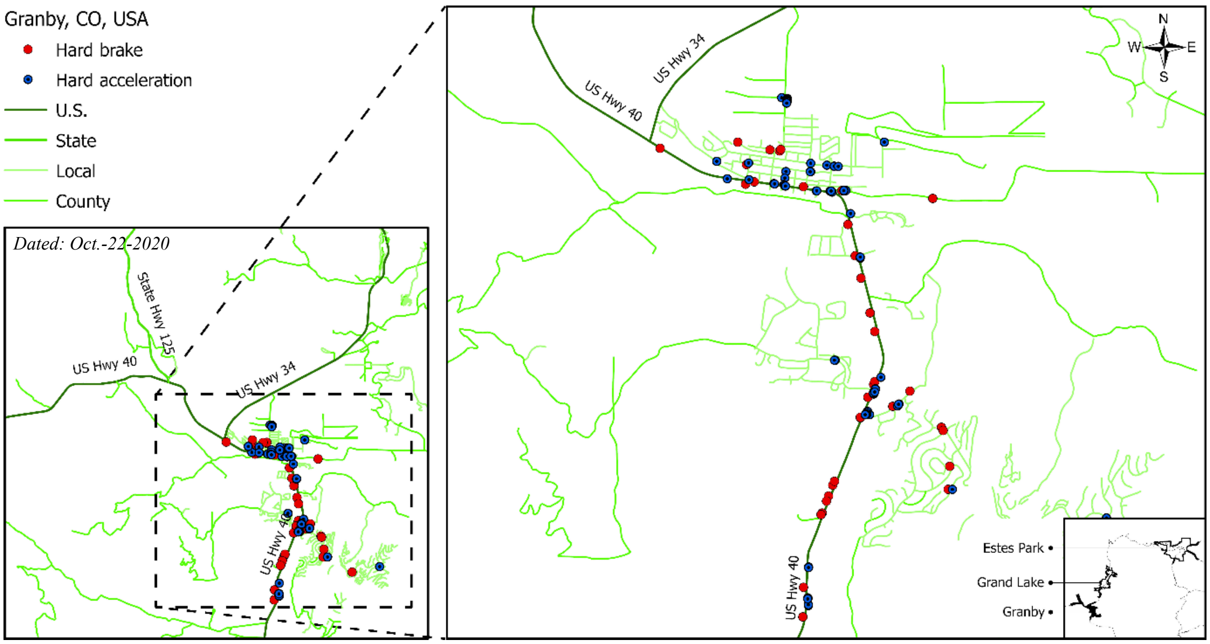


(b)

Figure 2.2 Grand Lake, CO, USA (a) driving events map, (b) driving events data

In Granby, we observed an increase in driving events on October 21 and 22, particularly HA events as depicted in Figure 2.3(b). One likely reason for the increase in such events was the rushed arrival of evacuees from Grand Lake on October 21 to shelter in Granby, as explained earlier, and later all residents of Granby and Grand Lake evacuated the town using a southbound route on October 22, which led to congestion on the exiting route. Figure 2.3(a) gives further evidence that all driving events within the town's proximity were reported either in the center of the town or in the traffic moving south on U.S. Highway 40 away from the fire-impacted paths to the north (State Highway 125 and U.S. Highway 34).



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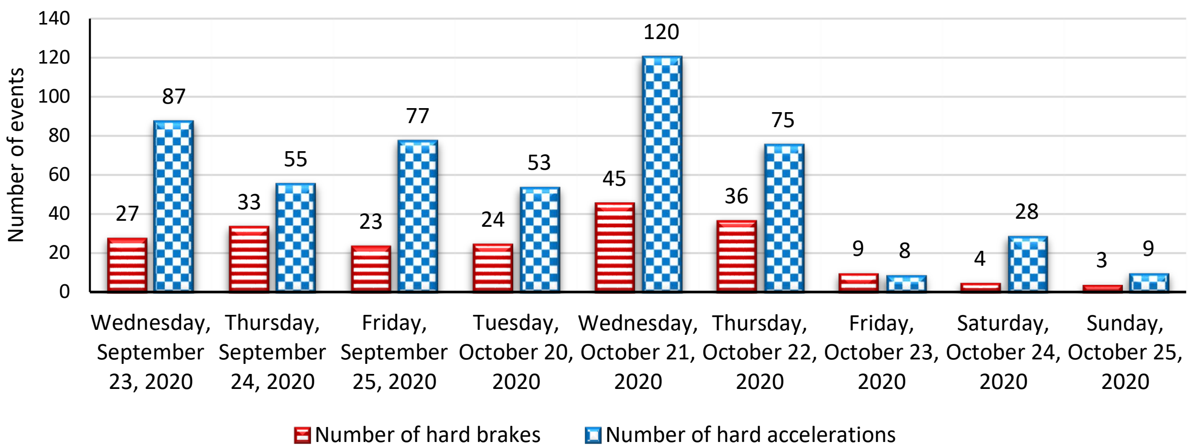
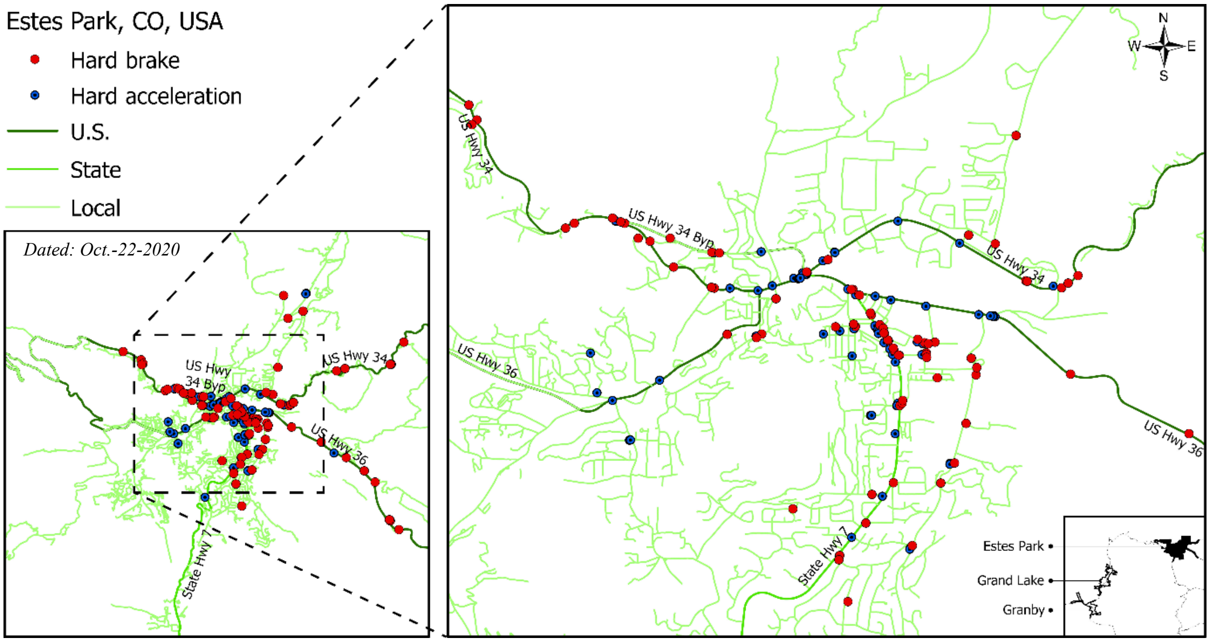


(b)

Figure 2.3 Granby, CO, USA (a) driving events map, (b) driving events data

The data analysis for Estes Park showed the formation of clusters of HA and HB events on all major exit routes, particularly U.S. Highways 34 and 36 and State Highway 7, during the evacuation period, as depicted in Figure 2.4(a). This suggests that congestion and stop-and-go traffic situations were observed at traffic intersections and junctions, as reported in the previous section. Secondly, the number of driving events reported from the study period October 20-22, 2020, as detailed in Figure 2.4(b), suggests that the town received fewer visitors due to the closure of Rocky Mountain National Park in this period, as previously reported in the literature.

Finally, the data comparison for the three Colorado towns showed the least number of driving events for many days following the evacuation day in the study period, demonstrating the state of evacuated towns as explained previously.



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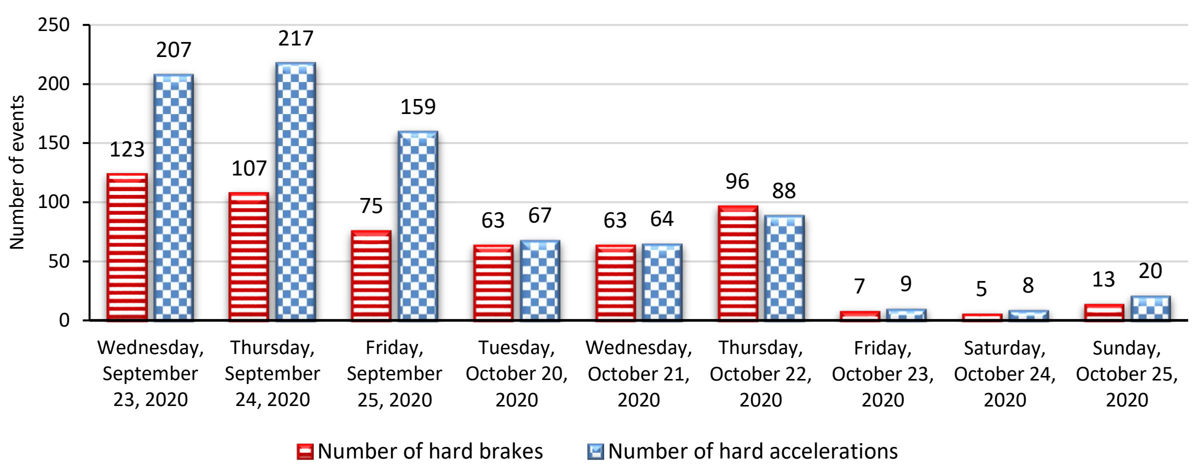


(b)

Figure 2.4 Estes Park, CO, USA (a) driving events map, (b) driving events data

2.5 Evaluation of Traffic Operation Conditions: A Case Study of Knolls Fire 2020, Utah

The fire event selected for evaluation was the 2020 Knolls Fire that occurred in Saratoga Springs, Utah, on June 28, 2020. The fire erupted between 2:00 p.m. and 2:30 p.m. east of Lake Mountain and south of Saratoga Springs and spread quickly toward the city driven by 60 mph gusting winds [105]. Saratoga Springs is one of the fastest-growing cities in Utah, with a population density of around 1,625 people/sq. mi. [106]. The city is surrounded by Utah Lake on the eastern border and Lake Mountain on the western border with State Route 68 (SR-68), also called "Redwood Road," serving as the main exit corridor for the city. Following the fire's ignition, mandatory evacuation orders were issued for more than 3,100 homes or 13,000 residents, i.e., almost one-third of the population of the city [105], [107], [108]. The evacuation began at 2:45 p.m., initially in the southern neighborhoods of the city, and residents were forced to evacuate their homes with very short notice amid high winds, smoke, and dust. Later in the afternoon, all residents who lived south of Grandview Boulevard on the west side of Redwood Road were asked to evacuate their homes because of the rapid spread of the fire, as seen in Figure 2.5 [107], [109].

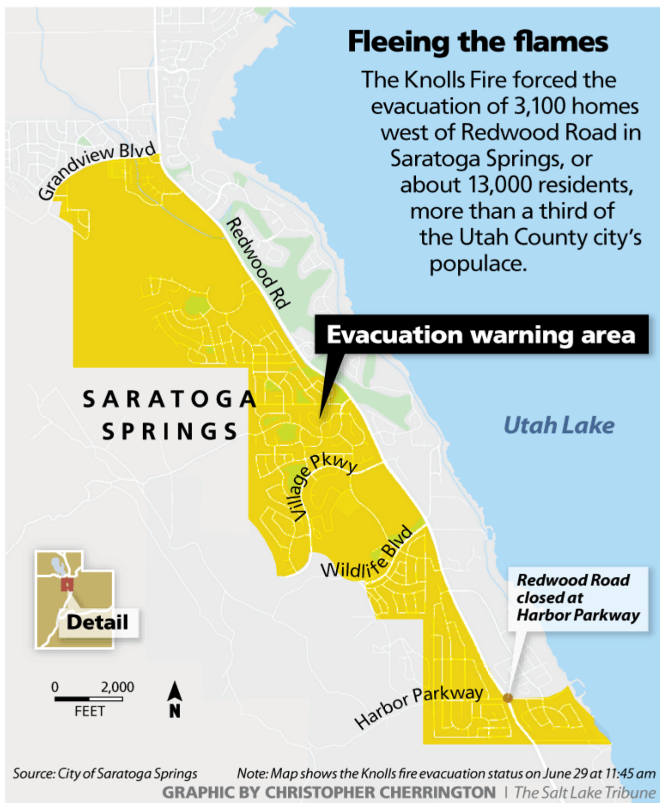


Figure 2.5 Knolls Fire 2020 evacuation area [32]

Emergency responders used Redwood Road to redirect the evacuation traffic northbound (NB) toward Westlake High School, which served as a shelter area for the affected evacuees. Additionally, due to downed powerlines near the fire perimeter, the road was closed for southbound traffic [111]. The evacuation process created heavy traffic congestion and vehicular queues on NB SR-68, especially in the evening period, as detailed in Table 2.1, which contains operator response notes on the incident obtained from the Utah Department of Transportation (UDOT).

2.5.1 Data Collection and Analysis

In this study, Wejo's vehicle trajectory data were collected for 10 days from June 20-29, 2020, to evaluate the travel time variation between evacuation and non-evacuation time frames for the selected study area. The definition of key attributes of the dataset is provided in Table 2.4.

Table 2.4 Wejo CV data attributes

S No.	Data attributes	Definitions
1	Data-point ID	Records' a unique identifier for an individual captured data-point every 3 seconds.
2	Journey ID	Records' a unique identifier for an individual vehicle's movement through an ignition of an event.
3	Timestamp	Records the time and date of each data-point along with location time zone offset.
4	Heading	Records the heading of each data-point with 0 = North moving clockwise to 359°.
5	Speed	Records the speed of vehicle at each data-point.
6	Latitude	Provides the north-south positioning of the vehicle on the Earth's surface.
7	Longitude	Provides the east-west positioning of the vehicle on the Earth's surface.

2.5.2 Temporal Coverage Assessment

In this study, the hourly average travel time for all shorter segments in the 10-day study period was calculated based on the number of Journey IDs available for the one-hour slots. It was considered that to accurately estimate travel time for each shorter segment, enough Journey IDs for the one-hour slots must be obtained. The data's temporal coverage was assessed to calculate the percentage of the uncovered one-hour slots for 24 hours of the 10-day study period. It is assumed that a one-hour slot with an average zero number of Journey IDs for the entire road segment is considered as an uncovered one-hour slot, as assumed in an earlier study [100]. Furthermore, several minimum Journey ID threshold values were also set to tighten the criteria for calculating the percentage of the uncovered one-hour slots.

2.5.3 Traffic Signal Performance Metrics

In April 2012, UDOT began implementing an automated traffic signal performance measures (ATSPM) program statewide on signalized intersections in collaboration with Purdue University, the Federal Highway Administration (FHWA), and the Indiana Department of Transportation (INDOT). The ATSPM program installed on signalized intersections contains historical and real-time information on various traffic signal performance metrics, such as approach volume, turning movement counts, and Purdue coordination diagrams, which can be used to evaluate the quality of traffic progression along corridors and identify maintenance issues that affect traffic flow on signalized intersections. This information is collected every 10 to 15 minutes with high-resolution traffic signal controllers as well as detector data associated with each equipped intersection. The system is installed at most of Utah's signalized intersections, and historical performance metrics for signalized intersections are accessible for public use via the UDOT ATSPM website.

Therefore, this system, installed at signalized intersections along the selected section of SR-68, provides an opportunity to gather historical performance metrics for the defined time frame in the study area. These performance metrics can be fed into traffic simulation platforms for historical traffic modeling. The calibrated model can then generate travel time estimates of the study area, which can be compared with CV data travel times. In this context, the PTV VISSIM microsimulation platform was adopted to develop a model of the selected study region, which is detailed in the following section.

2.6 Network Simulation in VISSIM

The study area for travel time calculation consisted of five miles of the NB SR-68 roadway between mile markers (MM) 25-30 to analyze the impact that the Knolls Fire had on SR-68 traffic conditions. This section of SR-68 consisted of several connecting roads and five traffic signals, allowing vehicular traffic to enter and exit the affected neighborhoods. The entire city dataset containing more than 11 million data-points for the studied time frame was segregated to include only data-points from the studied section of SR-68, and the heading attribute of each data-point was used to eliminate the traffic heading south.

3. MICROSIMULATION MODEL VALIDATION FOR WILDFIRE EMERGENCY EVACUATION

3.1 PTV VISSIM Modeling

For this study, historical imagery of the road network was obtained from Google Earth, and a VISSIM model that consisted of three miles of SR-68 between MM 27-30 was created. This also contained five traffic signals and several roads interconnecting the selected section of the state highway. The historical performance metrics at the five signalized traffic intersections were obtained from the UDOT ATSPM website for a two-day traffic period, i.e., June 21-22, 2020, because the data for the evacuation day event were not available on the system, possibly due to communication loss or power outage at the selected intersections, as confirmed by UDOT. The collected data consisted of approach volume, turning movement counts, and Purdue coordination diagrams, which were used to calibrate the model parameters such as traffic flow and signal phasing. The speed limits on the study corridor were 50-55 mph over the three-mile section, so the VISSIM input volumes were assigned a speed distribution based on the posted speed limit. In addition, the traffic composition was considered based on vehicle class data obtained from UDOT Performance Measurement System (PeMS).

3.2 Similarity Assessment Measures

To assess the similarity of travel time calculated using a CV dataset and VISSIM modeling for the two-day assessment period, the hourly average travel times of the shorter segments obtained from the two datasets were compared by calculating the correlation coefficients, RMSE and MAPE, to quantify their similarities and differences. The following Equations (1) to (3) were used to calculate these measures based on the two datasets with the same sample size as:

$$Correlation\ Coefficient = \frac{\sum_{t=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{t=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}} \quad \text{Equation (1)}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(x_i-y_i)^2}{n}} \quad \text{Equation (2)}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{x_i-y_i}{x_i}\right| \quad \text{Equation (3)}$$

where, x and y represent two sample groups. Each of them contains n samples, x_i and y_i represent the t-th sample in each group, and $\bar{x}$ and $\bar{y}$ represent the mean values of these two groups.

3.3 Wejo Travel Time Calculation Results

This section presents the hourly average travel time for the five-mile segment over the 10-day study period for the hours NB SR-68 was impacted by the Knolls Fire 2020, as illustrated in Figure 3.1. The comparative analysis showed that the non-evacuation days observed consistent travel time, while a significant increase in the travel time values was observed on the evacuation day.

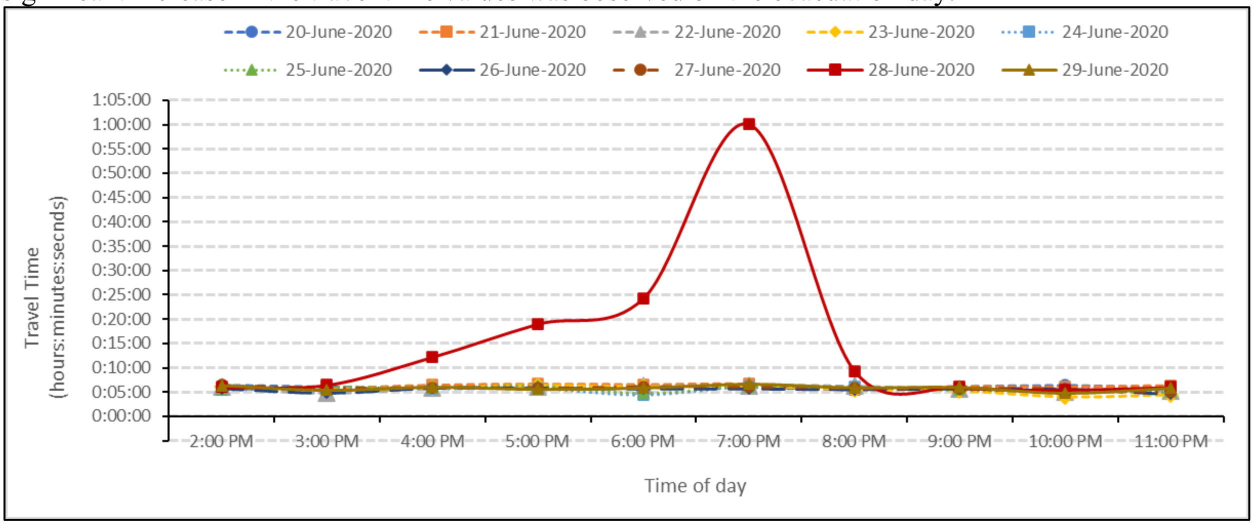


Figure 3.1 CV travel time calculation results before, during, and after the evacuation period

The highest traffic delays were seen during evening peak hours, which is further evident by the observation of slow-moving traffic between MM 26-30 after 6:00, as depicted by the speed profile illustrated in Figure 3.2. These traffic operation conditions were consistent with the operator response notes provided by UDOT on the incident, showing high traffic delays on the four-mile section of NB SR-68. This indicates that the evacuees were forced to spend a considerable amount of time stuck in traffic as their exit options were limited, putting their lives in danger.

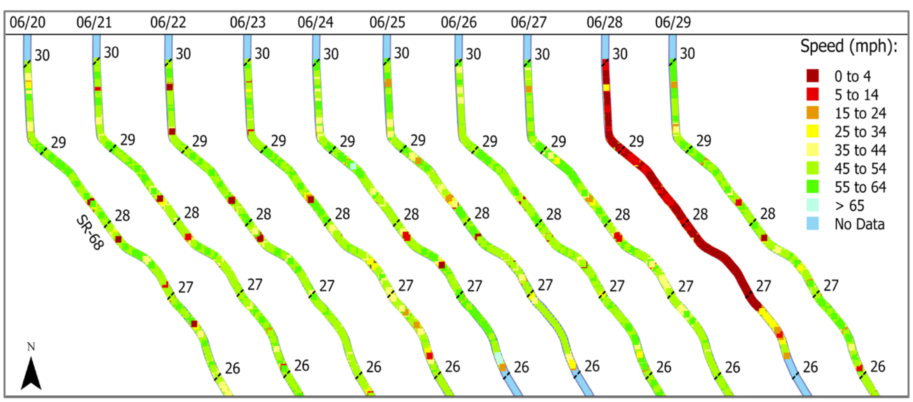


Figure 3.2 NB SR-68 MM 26-30 speed profile heatmap June 20-29, 2020 (6 PM - 7 PM)

3.4 Temporal Coverage Assessment

Considering the criterion explained earlier, a high temporal coverage rate of 90.00% was observed in the base case scenario, where only 24 out of 240 slots were marked as CV-uncovered, as detailed in Figure 3.3. These uncovered slots mostly occurred during low-volume early midnight hours. Additionally, the threshold for determining the minimum number of Journey IDs to define CV uncovered slots was increased from zero to three with an interval of one, considering that more trips can result in more accurate travel time results. Here, we observed a noticeable decrease in CV-covered slots with the increase in the minimum threshold values, i.e., 81.25% (threshold = 1), 72.50% (threshold = 2), and 67.50% (threshold = 3). Given the low penetration rate of Wejo CV data in 2020, this evaluation showed roughly 67% to 90% of the one-hour slots with enough Wejo samples to estimate travel times in the studied region. In addition, the test results showed a significant increase in CV volume on June 28, 2020, during the peak evacuation time frame when compared with the same day the week before.

Dates of June-2020

Hour of the day	06/20	06/21	06/22	06/23	06/24	06/25	06/26	06/27	06/28	06/29
0:00	0	0	0	0	0	0	0	0	0	0
1:00	1	3	2	0	0	0	1	2	1	1
2:00	0	0	0	0	0	1	1	0	0	2
3:00	2	1	1	2	1	1	1	1	1	1
4:00	1	0	1	4	1	2	2	1	0	1
5:00	3	1	11	10	9	10	4	3	2	3
6:00	7	3	19	15	17	13	13	7	0	7
7:00	8	2	10	11	15	11	14	8	2	3
8:00	9	8	15	11	7	14	10	8	3	6
9:00	11	9	11	8	11	8	11	14	7	10
10:00	18	11	6	7	11	8	11	11	11	10
11:00	15	9	8	8	12	9	11	16	11	10
12:00	15	11	11	8	8	10	8	14	13	12
13:00	14	15	8	12	14	9	9	11	7	9
14:00	20	10	8	10	8	7	11	12	15	12
15:00	16	17	8	9	5	5	6	15	28	9
16:00	8	10	12	14	13	15	15	11	25	9
17:00	19	13	15	11	12	13	13	14	20	12
18:00	11	14	12	12	8	5	13	12	11	11
19:00	10	11	8	9	8	8	5	11	12	5
20:00	4	5	7	6	7	4	6	6	4	7
21:00	10	5	6	5	4	4	5	5	2	4
22:00	4	3	2	1	2	2	3	5	3	2
23:00	3	0	2	2	2	2	3	2	4	2

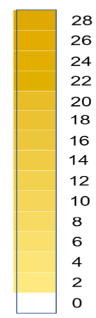
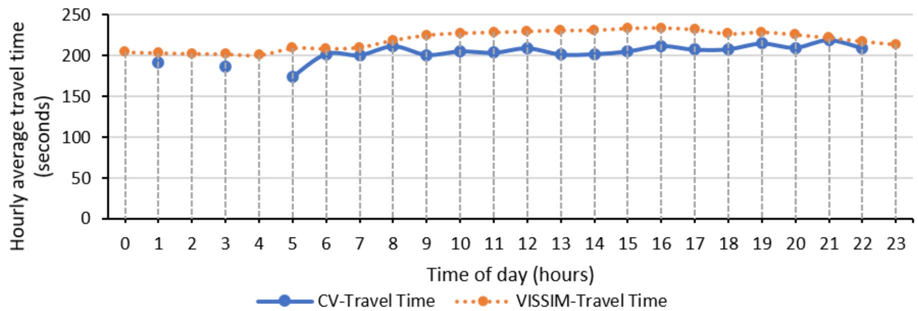


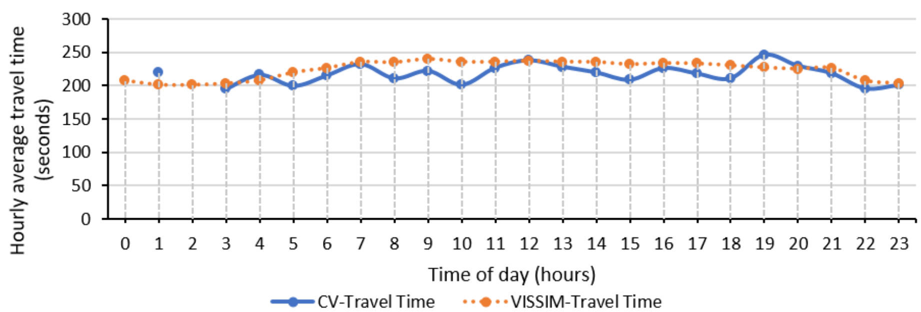
Figure 3.3 CV data temporal coverage June 20-29, 2020

3.5 Similarity Assessment

This test reports the hourly average travel time of CV and VISSIM for the selected 24-hour evaluation period of June 21 and 22, 2020. Figures 3.4(a) and (b) show that the CV and VISSIM travel times appear to be closer in estimating hourly average travel times for most hours of the day. However, considering that the low-volume midnight hours had the most CV uncovered slots, as observed in the temporal coverage analysis, the dataset lacked the needed sample size to estimate travel times for these hours.



(a)



(b)

Figure 3.4 Travel time results using CV and VISSIM modeling (a) June 21, 2020, (b) June 22, 2020

To better assess the statistical relationship between the travel times of the two datasets, the similarity assessment measures were calculated for the two-day period defined in the earlier section. Table 3.1 shows that a high correlation was observed between the travel time calculated using CV and VISSIM modeling at the base calculation threshold, which increased to a maximum of 0.99 for the weekend day and 0.97 for the weekday when tightening the calculation criteria. The RMSE and MAPE were also estimated to be relatively low at the base calculation threshold for both days, showing a strong relationship between the two calculated travel times, which further improved with the increase in minimum threshold values. This validates the earlier assumption that more trips result in more accurate travel time estimation results. Hence, the CV data were determined to be a valuable data source that could generate travel time estimates comparable to those of the VISSIM results that simulated historical ATSPM data.

Table 3.1 CV data similarity assessment June 21-22, 2020

Calculation Threshold	1	2	3	4
Sunday, June 21, 2020				
Correlation Coefficient	0.97	0.98	0.99	0.99
RMSE (in seconds)	9.85	8.75	7.95	7.54
MAPE (%)	9.63	8.61	7.67	7.08
Monday, June 22, 2020				
Correlation Coefficient	0.89	0.94	0.96	0.97
RMSE (seconds)	18.95	17.51	16.44	16.40
MAPE (%)	10.25	9.15	7.93	7.80

4. FORECASTING FUTURE EVACUATION NEEDS AND MAKING RECOMMENDATIONS

Automation advancements in the vehicle industry are a continuous process that delivers several benefits, such as reduced driver's fatigue, improved road safety, greater fuel efficiency, and smart parking options. Autonomous vehicles (AVs) are also known as self-driving cars that require little driver's assistance [1]. It is important to understand the difference among the terms AV, "connected vehicle (CV)," and "connected autonomous vehicle (CAV)." Atkins provided brief definitions for AV as "a car that is capable of fulfilling the operational functions of a traditional car (e.g., driving, lane-change, parking, etc.) without the aid of a human operator," and CV as "a car that is equipped with a technology enabling it to connect and communicate with other devices within the car, and also to other surrounding cars and external networks (e.g., internet, navigation, environment data, etc.)" [2]. Thus, a CAV is supposed to be a vehicle that can fulfill the operational functions of a traditional vehicle by itself and can communicate with nearby vehicles and infrastructures for safer driving.

4.1 Arrival of CAVs and People's Attitude

The advent of AVs will be one of the most influential changes that the transportation sector has ever experienced. Depending on the level of automation, these vehicles can control some of the entire driving operation such that, in a fully automated vehicle, there is no need for driver intervention and the vehicle can drive itself [33], [34]. It is expected that the highest level of automation will be deployed around 2030 [34]. In a study by Litman, 2045 has been suggested as the year when 50% of new vehicle sales and 40% of vehicle travel could be done by AVs, and fleet penetration has been estimated to be up to 60% by 2060 [35].

The users' perception of AVs is one of the contributing factors to the adoption and acceptance of AVs as new technology [36], [37]. In this regard, the behavioral intention of users, which stems from their attitude, plays a key role in the use of this newly introduced technology. The attitude toward a concept represents its mental assessment and comprises three elements: cognition, affect, and conation elements [38]. The cognition variables include different factors such as perceived usefulness, ease of use, risk, and trust, which are also known as psychological factors. The affect element refers to whether or not a person likes a concept, and the conative element represents a person's intention in the context, such as the intention of riding in an AV [39]. Different studies usually consider various measures to define each of the attitudinal variables. For the AVs, there are several measures for perceived usefulness or benefits, perceived risks or concerns, and for trust.

4.2 Research Gap: Reviewing Public Perceptions of CAVs

There are several shortcomings and research gaps in the study of attitudes toward AVs. First, a majority of previous research has been conducted in large U.S. states and areas, such as California [40-42] and Austin, TX [43], [44], or in other countries like Korea [37], Australia [45], Austria [46], Ireland [47], and China [41]. These studies often relied on survey data.

One significant research gap pertains to smaller U.S. metropolitan areas with substantial populations of college and university students and employees. These areas have received relatively little attention in past research. These smaller metropolitan regions have unique community characteristics, including less traffic congestion, shorter travel times, and fewer modes of transportation due to their smaller size. Furthermore, their travel patterns are influenced by the presence of colleges and universities, which can significantly affect transportation dynamics at different times of the year.

This study aimed to assess the influence of socioeconomic factors on the perceived usefulness, perceived risk, and the acceptance of AVs as a solution to enhance transportation safety during harsh winter conditions. To achieve this, a multivariate probit model system was employed to concurrently analyze these three perceptual dimensions among respondents, the majority of whom comprised college students and employees, making up 98% of the sample.

4.3 The Attitudes Toward Autonomous Vehicles in a Medium-Sized Metropolitan Area with Cold Winters

4.3.1 Fargo-Moorhead Study Area

The study focused on the population of college students and employees in Fargo-Moorhead, a medium-sized U.S. metropolitan area characterized by prolonged severe winters. The adverse weather conditions prevalent in this region could pose a significant barrier and raise concerns regarding the performance of AVs in such conditions. Consequently, this study sheds light on how these factors influence people's willingness to use or invest in AVs in the future.

4.3.2 Segmentation by Age and Student Status:

The research delved deeper into the behavior of respondents by dividing them into two age groups and distinguishing between students and non-students. This segmentation provided valuable insights into how different demographic groups perceive AVs.

4.3.3 Realistic Evaluation of Variable Contributions

The study offered a more realistic assessment of the variables contributing to the acceptance of AVs to enhance winter transportation safety. This is achieved through marginal effects (ME), revealing the impact of these variables while accounting for respondents' recognition of the benefits and risks associated with AVs.

4.3.4 Findings

The study's results provide insights into the connection between explanatory variables and attitudinal factors. This information can be of significant value to policymakers, aiding in understanding how students, faculty, and staff in medium-sized college towns with similar environmental conditions perceive the usefulness and risks of AVs. The findings suggest that certain factors, such as gender, exhibit consistent patterns in relation to perceived benefits and risks, aligning with previous research conducted in larger metropolitan areas. However, variables like commute duration or household income levels may yield different outcomes, especially when examined within various age groups or among students and non-students.

This research has practical applications for government agencies and urban planners, enabling them to make predictions specific to their communities. Additionally, it equips manufacturers and decision-makers with insights into the factors shaping public perceptions of AVs, allowing them to tailor their future guidelines and plans. For instance, manufacturers and public agencies could target individuals with boat/RV trailers or households with children under 18, emphasizing the benefits of AVs during extremely cold winters to foster a positive attitude toward them. Furthermore, the study highlights disparities in acceptance based on race, suggesting a need for planners to address these disparities in transportation planning, especially in areas with a predominant enrollment of white students.

The findings are also relevant for parking studies in the context of AVs, particularly in regions with a substantial population of college students who share characteristics with those in the Fargo-Moorhead area. Additionally, the results can inform predictions about willingness to pay, adoption rates, and mode preferences related to AVs.

4.4 Forecasting the Future Needs

Future studies could explore attitudinal variables that differentiate between privately owned and shared AVs. Moreover, given the limitations of the data collected in this study, there is room for future research to target more diverse populations in similar metropolitan areas. Altering the conditions of the ME function for various scenarios of usefulness and risk perception could reveal how explanatory variables influence the willingness to invest in or use AVs with different levels of optimism or pessimism. Furthermore, future research may introduce additional attitudinal parameters to further enhance the modeling process.

4.4.1 CAV's Role in Emergency Evacuations

Moreover, the study's focus on extreme weather conditions, such as harsh winters, is highly relevant to evacuation scenarios in regions prone to weather-related disasters. AVs equipped to navigate challenging weather conditions can be instrumental in ensuring that evacuations proceed smoothly, even in adverse environments. Understanding the public's willingness to use AVs under these conditions can help authorities allocate resources effectively.

In summary, the study's insights can inform the incorporation of autonomous vehicles into evacuation strategies by tailoring messaging, resource allocation, and service provision to align with public attitudes and preferences. This can lead to safer, more efficient, and more organized evacuations, ultimately saving lives and reducing the impact of disasters.

5. CURRICULA AND EDUCATIONAL DEVELOPMENT

This project had involved and trained 13 graduate students, including three master's students (Hafiz Usman Ahmed, Salman Ahmad, Elizabeth Arthur) and 10 Ph.D. students (Asad Ali, Babak Mirzazadeh, Xinyi Yang, Mingwei Guo, Yihao Ren, Gul Badin, Awuku Bright, Tofatun Jannat, Leonard Chia, and Yasir Mahmood). Four graduate students are from underrepresented groups. Among the 13 graduate students, three master's students (Hafiz Usman Ahmed, Salman Ahmad, Elizabeth Arthur) and two Ph.D. students (Babak Mirzazadeh and Leonard Chia) graduated with theses and dissertations acknowledging the support. Additionally, this project also provided training to three Fargo and West Fargo high school teachers as summer research teacher programs: Martha Nelson from North High, Jill Wold from West Fargo High, and Joshua Rogers from Davis High. Based on this project, the teachers developed high school course modules, which will be taught to an average of 20 high school students annually.

In addition, this project also partially supported various outreach activities for underrepresented students, such as female students, minority refugee minors, and Native American students. Specifically, there are four different outreach activities:

1) In October 2021 and 2022, this project partially supported a BrainSTEM Workshop, which was offered to more than 60 middle school students.
2) From December 2021 to January 2022, this project also partially supported the CORE Outreach Program, which collaborates with the YMCA of Cass and Clay Counties to promote engineering to young minority generations. It offered an eight-day workshop series to more than 100 underrepresented elementary school students, including low-income families, refugees, and young girls.
3) From October to December 2022, this project also partially supported the NATURE SUNDAY Academy by offering a one-day Sunday camp for Native American high school students at the five different tribal sites (Turtle Mountain Community College, Sitting Bull College, Cankdeska Cikana Community College, Nueta Hidatsa Sahnish College, and United Tribes Technical College) with an average enrollment of 20 students at each tribal site (total ~100 students each year) with fully developed new interactive and hands-on lesson plans.

6. SUMMARY AND FUTURE RESEARCH

Connected Vehicle Data for Wildfire Evacuations

The study addressed the critical need for accurate evacuation time estimates during historical wildfire events by leveraging connected vehicle (CV) data. It revealed a significant increase in traffic delays on evacuation routes during wildfire events, particularly during evening hours. This real-world data supported observations from the relevant state department of transportation, corroborating operational challenges during evacuations. The study also highlighted the significance of temporal coverage assessment and similarity assessment tests for validating travel time estimates and dataset usability. Ultimately, the findings demonstrated the suitability of CV datasets for estimating traffic delays during wildfire evacuations, offering valuable insights for emergency responders and planners despite acknowledging the need for further research to generalize the findings to different scenarios.

Driving Behavior in Wildfire Evacuations

The study also offered a unique perspective on human driving behavior during wildfire evacuations, drawing insights from CV data across different regions. It revealed the dynamic nature of driving behavior patterns as individuals encountered changing driving conditions during wildfire events. This was evidenced through shifts in hard braking (HB) and hard acceleration (HA) patterns. Moreover, the study underscored the pivotal role of evacuation warning time in shaping aggressive driving behavior. Short-notice evacuations led to increased occurrences of HA events, emphasizing the urgency of evacuees to leave fire-impacted areas. The research also identified traffic intersections and junctions as critical congestion points during evacuations, with clusters of HB events indicating vehicular queues and traffic delays. The detailed analysis differentiated between rural and urban evacuation patterns, which is essential for tailored planning strategies in diverse environments.

Autonomous Vehicles in Winter Conditions

In the exploration of autonomous vehicles (AVs) within the challenging context of inclement winter weather, this study uncovered the intricate web of influences on public perception. Factors like demographics and socioeconomic parameters play a pivotal role in shaping attitudes toward AVs. Gender patterns align with previous studies in larger metropolitan areas, but variables such as travel time to work and household income level yield distinct results, particularly when analyzed within specific age groups or student and non-student categories. These insights have far-reaching implications, guiding strategies for policymakers and AV manufacturers to enhance acceptance and adoption. Understanding that certain demographics find AVs more beneficial in extremely cold winters can inform marketing and promotion efforts. Additionally, the study highlights the importance of recognizing the unique attitudes of students and non-students, particularly in medium-sized U.S. college towns with extended periods of frigid winters.

In summary, these three studies collectively enhance our understanding of transportation safety, evacuation preparedness, and human behavior during adverse conditions. They provide valuable guidance for policymakers, manufacturers, and emergency responders, emphasizing the importance of considering demographic nuances, leveraging real-world data, and understanding the psychology of drivers during evacuations.

Future Research Directions

In the pursuit of advancing our knowledge in transportation and emergency evacuation, future research should prominently feature the exploration of diverse scenarios. The value of running various scenarios cannot be overstated. These scenarios should encompass a wide range of environmental conditions, from extreme weather and natural disasters to differing climates and regions. By examining diverse scenarios, researchers can uncover how these unique circumstances influence human behavior, vehicle performance, and the effectiveness of AVs and other transportation systems.

Furthermore, the focus of future research should extend beyond wildfire evacuations to other critical events such as hurricanes, floods, pandemics, and more. Each of these scenarios poses distinct challenges in terms of traffic management, public safety, and technology application. Understanding how transportation systems function and how people respond in these various situations is essential for developing adaptable and resilient emergency plans.

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