Leveraging Shared Autonomous Vehicles for Vulnerable Populations during Pre-Disaster Evacuation

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ABSTRACT

Increasing incidences of hurricanes along the Houston, Texas coast necessitate innovative evacuation strategies, particularly for vulnerable populations lacking private vehicle access. This study investigates the role of shared autonomous vehicles (SAVs) in enhancing evacuation efficiency, focusing on the crucial first-mile connection to bus stations for these vulnerable populations. Through microsimulation of various evacuation scenarios, this paper explores the potential of SAV fleets with different seating capacities, fleet sizes, shared-ride acceptance levels, and coordination with bus departure schedules. The findings advocate for smaller, 5-seater SAVs, operated at a ratio of 1 SAV per 14 evacuees, to optimize cost and efficiency within the Houston context. The research underscores the importance of SAV-to-bus coordination, demonstrating that strategic ride-sharing and scheduling can significantly reduce evacuee wait times and vehicle operational costs while maintaining timely bus arrivals at safe shelters. This study contributes to the emergent field of emergency management by showcasing the practical implications of integrating SAV technology with existing public transit systems to improve disaster resilience for carless populations.

KEYWORDS

Shared Autonomous Vehicle; Dynamic Ride-sharing; Evacuation Strategies; Non-Vehicle-Ownership Populations; First-mile Connection

INTRODUCTION

Hurricanes, as one of the most devastating and expensive natural disasters in the United States, incur immense damage. In 2005, Hurricane Katrina caused $125 billion in property damages (2005 USD) and 1,836 deaths (Knabb et al., 2005), and Hurricane Harvey led to equivalent property damages and claimed the lives of 68 Texas residents in 2017 (Blake & Zelinsky, 2018). Contributing factors such as rising greenhouse gas levels, global warming, and climate change have increased ocean temperatures, potentially leading to more frequent and severe hurricanes (Levin & Murakami, 2019). The Saffir-Simpson Hurricane Wind Scale categorizes hurricanes from 1 to 5 based on sustained surface wind speed, with Category 5 being the most catastrophic (National Hurricane Center and Central Pacific Hurricane Center, 2021). While Category 1 and 2 hurricanes pose risks, storms of Category 3 and above are considered major hurricanes and necessitate consideration for evacuation.

Historically, hurricane evacuations, such as those from Hurricane Floyd in 1999 and Hurricane Georges in 1998, have utilized contraflow operation, wherein inbound freeway lanes are repurposed for outbound evacuation, thereby increasing outbound network capacity (Wolshon, 2001). However, this approach predominantly serves the needs of vehicle-owning evacuees, leaving transit-dependent residents insufficiently accommodated. For example, during Hurricane Katrina, many transit-dependent residents were directed to local shelters rather than evacuated, a decision made without proper comprehension of the hurricane's severity (Litman, 2006). Moreover, during Hurricane Rita, contraflow operation in the Houston area was abandoned to allow inbound transportation of resources, highlighting the need for more comprehensive and adaptable evacuation strategies (Litman, 2006).

Following the discussion of traditional evacuation strategies and their limitations, a comprehensive examination of alternative evacuation methods and the challenges they face is crucial. These alternatives have ranged from reliance on public transit systems (Teichmann et al., 2021) to temporary housing solutions (Johnson, 2007) and government-orchestrated evacuations (Teo et al., 2015). Despite their intent to provide broader coverage, many of these strategies still fall short, particularly in serving the most vulnerable populations effectively.

For instance, public transit, while offering a potential lifeline for those without private vehicles, often lacks the capacity and route flexibility needed in widespread emergency situations (Hou et al., 2020). Temporary shelters, on the other hand, while critical, can become overwhelmed quickly, raising concerns about accessibility, safety, and resource availability (Zhao et al., 2017). Government-coordinated evacuations, though well-intentioned, can be hampered by disparities in access to information and communication technologies among vulnerable groups, leading to inefficiencies and confusion among evacuees (Howard et al., 2017). These challenges underscore the necessity for innovative solutions that address the diverse needs of all population segments during evacuations.

To address the identified challenges in current evacuation methods, a novel approach is essential, one that enhances the reach and efficiency of evacuation efforts while minimizing the strain on existing resources. An innovative solution should ideally offer door-to-door service (Gray-Graves et al., 2011), ensuring accessibility for all individuals, especially the most vulnerable who might lack personal transportation options. This approach would alleviate the pressure on temporary shelters by providing more direct routes to safety, thus better managing the surge in demand these shelters often face during emergencies.

Moreover, overcoming the common bureaucratic and coordination challenges requires a system that can be seamlessly integrated into the current emergency management framework, ensuring swift and effective responses. Utilizing cutting-edge technology could significantly enhance route optimization (Wang et al., 2023), reduce congestion (Ibrahim et al., 2023), and improve overall safety, making the evacuation process faster and more reliable. Such a system would not only cater to individual needs but also ensure a coordinated and efficient use of resources, addressing the capacity limitations of traditional public transit systems (Hou et al., 2020) and making a substantial difference in emergency response strategies.

Additionally, saving lives and preserving properties necessitates a resilient transportation infrastructure that accommodates varying individual circumstances. The resilience of transportation infrastructure impacts not only the network's performance during evacuation onset but also post-disaster response time (Donovan & Work, 2017). Although private vehicles are the preferred evacuation mode (Yin et al., 2014), those without such vehicles or with insufficient vehicle numbers must turn to non-household transportation modes. These evacuees will be defined as the no-vehicles-available population hereafter. This study considers shared autonomous vehicles (SAVs) as a potential mode for evacuating this no-vehicles-available population, which constitutes an estimated 4% of the evacuees in Houston, Texas.

Shared mobility, whether self-driven or human-driven, can enhance evacuation efficiency by reducing the number of small trips and providing accurate evacuee location data via communication devices (Li et al., 2018). The decline in vehicle ownership corresponds to increased ride-sharing usage (Zhang & Zhang, 2018), suggesting that the no-vehicles-available population may be comfortable using shared mobility for evacuation.

SAVs, adding vehicle autonomy to shared mobility, show greater promise for evacuation processes. They offer cost-effectiveness by eliminating labor costs and avoiding human risk in disaster situations (Shen et al., 2018). The driver's seat can instead accommodate an evacuee, providing greater mobility opportunities for those with disabilities or without a driver’s license (Kröger et al., 2019). High-performance computing power, sensing equipment, and communication devices of SAVs facilitate rapid route-searching (Al-Hasan & Vachtsevanos, 2002), safe driving and crash reduction (Moody et al., 2020), and may reduce traffic congestion (Wang et al., 2017) to achieve faster evacuation. As autonomous vehicle (AV) technology remains immature and evacuations are infrequent, its application to evacuation problems has primarily been simulated. Incorporating AV technology with reservation-based intersection control techniques or public transit signal prioritization policies can increase travel speed and safety during hurricane evacuations (Chang & Edara, 2018). Combined with strategic departure time scheduling, AV evacuation can lower costs, reduce network clearance time, and bring certainty to the evacuation process (Lee & Kockelman, 2021).

However, SAV systems may not always be the optimal choice due to limitations such as inability to satisfy high trip demands, extended user wait times, and increased periods of empty driving. SAV systems operate on demand-responsive principles, meaning that as demand escalates, the need for more SAVs rises, although dynamic ride-sharing (DRS) can somewhat manage this increased demand (Fagnant & Kockelman, 2018). Nevertheless, deploying a larger SAV fleet to meet this high demand escalates roadway density, potentially exacerbating traffic congestion. Under fixed conditions, a larger SAV fleet is necessary to ensure shorter user wait times (Wang et al., 2019), indicating that fleet size is crucial to the SAV system's performance. Empty driving, where a vehicle is on the road without passengers, can also contribute to traffic congestion if empty vehicle-miles traveled (eVMT) increase (Levin et al., 2019). Given that evacuation trips are often long-distance (Bian et al., 2019; DeYoung et al., 2018; Do, 2019), an increase in eVMT may hinder the efficiency of SAV operation. The asymmetric traffic pattern during evacuations, with numerous widespread origins and few destinations, may further strain SAV performance due to increased eVMT and SAV wait times.

To address the operational challenges highlighted, research on SAVs in emergency evacuations must delve deeper into their real-world applicability and scalability. This involves scrutinizing how SAV fleets can be rapidly deployed to meet the urgent demands of mass evacuations and how they adapt to the complex traffic conditions typical of disasters. Additionally, understanding the acceptance of SAVs among vulnerable populations and overcoming logistical hurdles, such as fleet management and coordination with emergency services, are crucial areas needing focused exploration to truly gauge the viability of SAVs in enhancing emergency responses. This paper contributes to overcoming some limitations of current emergency management practices by introducing an SAV-based evacuation strategy.

Recognizing these operational challenges underscores the importance of addressing the broader context of SAV deployment, including technological readiness, regulatory frameworks, and societal acceptance. Despite significant advancements, SAVs are still navigating through technological limitations, regulatory hurdles, and questions of societal acceptance. For instance, the operational reliability of SAVs under diverse and extreme weather conditions, typical of hurricane scenarios, remains an area requiring further research and validation (Zhang et al., 2023). Regulatory frameworks for SAVs are also evolving, with ongoing discussions on safety standards, liability, and ethical considerations, alongside research on user needs and social acceptance, crucial for their integration into roadways and emergency systems (Paddeu et al., 2020). Moreover, societal acceptance is pivotal; building trust in SAVs' capability to safely and efficiently transport evacuees is essential for their future deployment in disaster situations (Miller et al., 2022). Current pilot programs and case studies, such as those exploring SAV applications in controlled environments and simulated disaster scenarios (Dia & Javanshour, 2017), offer valuable insights into their potential and limitations. These efforts contribute to a growing body of knowledge, paving the way for SAVs to become a viable component of a holistic and resilient emergency management framework, capable of addressing the unique challenges of disaster evacuations. Acknowledging the challenges facing SAV technology, this paper also explores potential advancements that promise to enhance SAV reliability and integration into future emergency evacuation frameworks.

In response to the outlined challenges, this paper pioneers an integrative evacuation strategy that synergizes special evacuation bus operations with a SAV fleet, specifically targeting the no-vehicles-available population. A special evacuation bus is a non-regularly operated line that transports evacuees to temporary destinations such as public shelters during evacuations, and has been identified as a favorable mode of non-household transportation for evacuees (Sadri et al., 2014). This novel approach introduces a dual-mode evacuation model, where special evacuation buses serve as the backbone for mass transit to safe locations, while SAVs provide critical first-mile connectivity, ensuring no individual is left behind due to lack of personal transportation. This paper's innovation lies in its detailed exploration of SAV deployment within defined evacuation zones, optimizing routes and minimizing eVMT, a key concern in previous models.

Furthermore, this research delves into the dynamics of vulnerable populations during evacuations, offering new insights into how SAV technology can be tailored to meet their specific needs, thereby enhancing inclusivity and accessibility in disaster response. By constraining SAV operations to targeted evacuation zones, this paper introduces a scalable and efficient framework that significantly reduces logistical complexities and operational inefficiencies observed in traditional evacuation strategies.

This comprehensive multimodal approach not only marks a significant advancement in the application of SAV technology to emergency management but also sets a new precedent for evacuation models, seamlessly blending automated mobility solutions with conventional mass transit systems to achieve a more effective and timely evacuation process. This paper contributes novel perspectives and practical solutions to the evolving discourse on leveraging technology for disaster resilience, particularly in addressing the critical first-mile challenge for vulnerable populations. To contextualize this paper within the broader field of disaster management and SAV applications, Table 1 provides a summary of key literature that informs this paper’s approach, delineating the evolution of evacuation strategies, the emerging role of SAVs, and their potential to address the unique challenges of disaster scenarios.

Table 1. Summary of Literature on Evacuation Strategies and AV Applications

Research Area	Literature	Summary
Hurricane Damages and Impact	(Knabb et al., 2005)	Property damages and fatalities caused by Hurricane Katrina.
	(Blake & Zelinsky, 2018)	Property damages and fatalities caused by Hurricane Harvey.
	(Levin & Murakami, 2019)	The relationship between climate change factors and the severity and frequency of hurricanes.
Hurricane Evacuation Strategies	(Wolshon, 2001)	Contraflow operation in hurricane evacuations.
	(Teichmann et al., 2021)	Public-transit-based evacuations.
	(Johnson, 2007)	Temporary housing solutions utilized during evacuations.
	(Gray-Graves et al., 2011)	Door-to-door strategy for evacuations.
Autonomous Vehicles for Evacuation	(Al-Hasan & Vachtsevanos, 2002) (Moody et al., 2020)	Capabilities of AVs for evacuations, including route-searching, enhanced safety, and congestion reduction.

	(Wang et al., 2017)	
	(Lee & Kockelman, 2021)	AVs with strategic departure scheduling for evacuations.
	(Zhang et al., 2023)	Further validation needed for SAV reliability under diverse weather conditions for use in evacuations.
	(Paddeu et al., 2020)	Regulatory frameworks required for the use of AVs.
	(Miller et al., 2022)	Social acceptance necessary for widespread adoption of AVs.

TRANSPORTATION NETWORK AND FLOW ASSUMPTIONS

In preparation for an in-depth exploration of Houston's transportation network and the foundational assumptions regarding evacuation flows, it is essential to first articulate the primary challenges this section intends to examine. The analysis centers on the evacuation dynamics within Houston, Texas, with a particular focus on accommodating the varied needs of the evacuees in the face of hurricane threats. The objectives are multifaceted, encompassing the estimation of evacuation demands, elucidation of evacuation resource distribution and accessibility, and the evaluation of the integration of various transportation modes — notably SAVs and special evacuation buses — to facilitate an effective evacuation process for all inhabitants, including those without private vehicle access. Subsequent discussions will elaborate on the capacity of the transportation infrastructure to manage evacuation traffic, the strategic location allocation of bus stations for enhanced accessibility, and the operational assumptions that inform the simulation of evacuation scenarios. Therefore, this section provides an overview of the transportation network in Houston, Texas, and estimates evacuation demands per neighborhood. It is assumed that all evacuees will proceed towards the nearest endpoint from their origins. Each household is represented as a single entity with all members evacuating together using a privately-owned vehicle, if available. Those without personal vehicles are assumed to travel on foot or utilize SAVs to the nearest designated stations, where conventional buses will transport them to designated endpoints.

Transportation Network

Houston, TX has a large and complex network of roads, with 36,124 links spread across 5,217 areas, known as traffic analysis zones (TAZs). Out of these, 1,035 zones are in areas that are highly likely to be hit by hurricanes, ranging from Category 1 to the most severe Category 5. These zones are ranked by their risk levels, from 1 to 5, based on how vulnerable they are to hurricanes, with the information provided by the Texas Natural Resources Information Service (Texas Natural Resources Information Service (TNRIS), 2004). The riskiest areas include parts of Brazoria, Chambers, Galveston, Harris, and Liberty counties. During a major Category 5 hurricane, an estimated 900,000 residents, which constitutes around 12.4% of the Houston area's population of 7.2 million, are likely to receive evacuation orders.

In this paper, residents living outside the designated high-risk zones are generally expected to remain in place, yet their activities are assumed to contribute to approximately 50% of the typical daily traffic volume, distributed across various times throughout the day. This assumption of halved traffic flow during a hurricane event in Houston is informed by a case study in Hiroshima, Japan by (Safitri & Chikaraishi, 2022), where road usage decreased by half due to heavy rainfall. Although the contexts of Houston and Hiroshima differ, this paper adopts the 50% reduction as a reasonable proxy to model potential changes in Houston's road use during hurricane conditions. This comprehensive mapping of Houston's transportation network, particularly the high-risk zones, lays the foundation for addressing the critical challenge of efficiently coordinating large-scale evacuations under the threat of severe hurricanes.

To navigate these challenges, this paper leverages the SUMO (Simulation of Urban MObility, (Lopez et al., 2018)) traffic simulator, which is a tool to assess traffic congestion and network capacities. This study models pre-disaster evacuation scenarios, predicated on the assumption of advance notice, with a lead time of several days before the hurricane's landfall. Therefore, the simulation process involves a preparatory 30-minute warm-up period (from 5:30 to 6 am) to populate the network with background traffic. Due to computational limitations, only 20% of the population, regardless of their evacuation status, will be sampled for the simulation. The use of SUMO traffic simulator effectively models pre-disaster evacuation scenarios, ensuring a balanced reflection of traffic congestion characteristics essential for scenario analysis. Also, this methodology allows for a direct examination of the congestion and logistical challenges inherent in mass evacuations, aiming to provide data-driven insights for optimizing evacuation routes and timings. Figure 1 shows the utilized network, with at-risk TAZs marked in yellow to red and the recommended evacuation route defined by the local metropolitan planning organization (MPO).

A cornerstone of the methodological framework is the adoption of an accessibility measure (A_i) instrumental in pinpointing optimal locations for special evacuation bus stations. The population of a link within a TAZ is assumed to be proportionate to the percentage of its centerline length, given the TAZ's population data. This measure, articulated in Eq. (1) with the value of the parameter (-0.054) obtained from (Papa, 2020), evaluates the potential reachability of individuals within a defined parameter, thereby informing the strategic placement of bus stations to maximize evacuation efficiency. The selection process for these stations considers the geographic distribution of the population and the inherent bottlenecks within the network, such as the critical bridge connecting Galveston Island to the mainland. Figure 1 shows the location of the six bus stations: one for each county and an additional station for Galveston Island.

$$A_i = \sum_{j=1}^{J} D_i exp(-0.054\ FFTT_{ij}) \tag{1}$$

where, J= set of destinations, D_i= population of i, $FFTT_{ij}$= free-flow travel time from *i* to *j*.

The methodologies employed, including traffic simulation and accessibility analysis for bus station placement, provide practical strategies to improve evacuation efficiency in Houston. These approaches facilitate the development of more adaptable and resilient evacuation plans in response to hurricane threats.

Evacuation Demand

In the face of hurricane threats in Houston, accurately gauging evacuation demand becomes essential. This section delves into the methodology employed to assess how households within various TAZs respond to evacuation orders, highlighting the intricate dynamics of evacuation processes. For each TAZ, a household's evacuation starting point is algorithmically determined based on the population distribution within that zone. The model assumes that households will aim for one of eight predefined evacuation endpoints, with a preference for those requiring the least travel time, as denoted in Eq. (2). This assumption aligns with the rationale that evacuees are likely to opt for the nearest feasible exit route. Upon reaching the designated endpoint, the model considers the evacuation for that household complete and ceases further tracking. The locations of these eight endpoints are illustrated in Figure 1.

$$Pr(j) = \frac{exp(-FFTT_{ij})}{\sum_{d=1}^{J} exp(-FFTT_{id})} \tag{2}$$

where, $Pr(j)$= probability to choose destination *j*, $FFTT_{ij}$= free-flow travel time from *i* to *j*, J= set of destinations.

To streamline the evacuation process and reduce the number of required bus routes, the model groups nearby evacuation endpoints. Buses will first journey to the closest endpoint relative to their station, disembarking passengers whose intended destination matches, before moving on to sequentially unload individuals at subsequent proximate endpoints. This strategic destination aggregation is depicted in Figure 1, which results in the identification of five distinct bus destinations for the evacuation. Consequently, each of the six bus stations manages routes to these five aggregated destinations, collectively operating a network of 30 distinct bus routes.

At the core of this paper's evacuation demand analysis lies the household-level approach, accounting for the distribution of households across TAZs and their vehicular resources. This granular perspective ensures a realistic representation of evacuation capabilities and constraints, particularly spotlighting those households devoid of private transportation means. In this model, each household is considered a unified entity for evacuation purposes, with all members evacuating as a collective unit. Data regarding household composition within each TAZ for the 2019 model year was obtained from the local MPO (Houston-Galveston Area Council (H-GAC), 2018), while demographic information regarding household size by county was acquired from the US Census Bureau (US Census Bureau, 2019b). Vehicle ownership statistics, correlated to household size, were also obtained at the county level from the U.S. Census Bureau (US Census Bureau, 2019a), with specific household and vehicle allocations within TAZs established through random sampling from these data sources.

The analysis incorporates an assumption of an average weight of 150 lbs. per household member, plus an additional 50 lbs. for luggage, equating to one-third of a seat per person (e.g., a three-member household would necessitate four seats to accommodate luggage). This methodology, assuming a standard five-seater capacity for privately-owned vehicles, facilitates the identification of households lacking access to private vehicles, as well as those with an inadequate number of vehicles to transport all members, categorizing them as no-vehicles-available agents. These individuals, constituting approximately 4% of the evacuating population, are modeled to utilize special evacuation buses for their departure.

Finally, evacuees' departure times are scheduled within a defined six-hour window from 6 AM to 12 PM, reflecting the structure of a real evacuation order, such as the one issued for Hurricane Laura in Galveston, Texas on August 25, 2020 (Mayor Pro Tem of The City of Galveston, 2020). This six-hour evacuation window is designated specifically for pre-disaster scenarios, ensuring that the evacuation process is completed well before the expected arrival of the hurricane, as exemplified by the evacuation order issued for Hurricane Laura. Departure timings for residents in the most at-risk coastal areas, identified as hurricane risk zone 1, are distributed randomly within the initial segment of this timeframe. This staggered departure pattern extends to those in subsequent risk zones, with each zone allocated a successive portion of the six-hour window for departures. This methodology ensures a systematic and staggered evacuation flow, with those in the most critical zones leaving earliest. Thus, agents representing households will initiate their evacuation at these assigned times, using either personal vehicles or, for those without access to private transportation, seeking SAVs for transit to designated bus stations, thus ensuring a coordinated and orderly evacuation process.

The analysis of evacuation demand and the implementation of a strategic departure schedule are key elements discussed in this section. By analyzing household-level evacuation needs and optimizing departure timings, the study seeks to mitigate congestion and enhance the efficacy of Houston's evacuation protocol during hurricane events, ensuring a more organized and safer process for all residents.

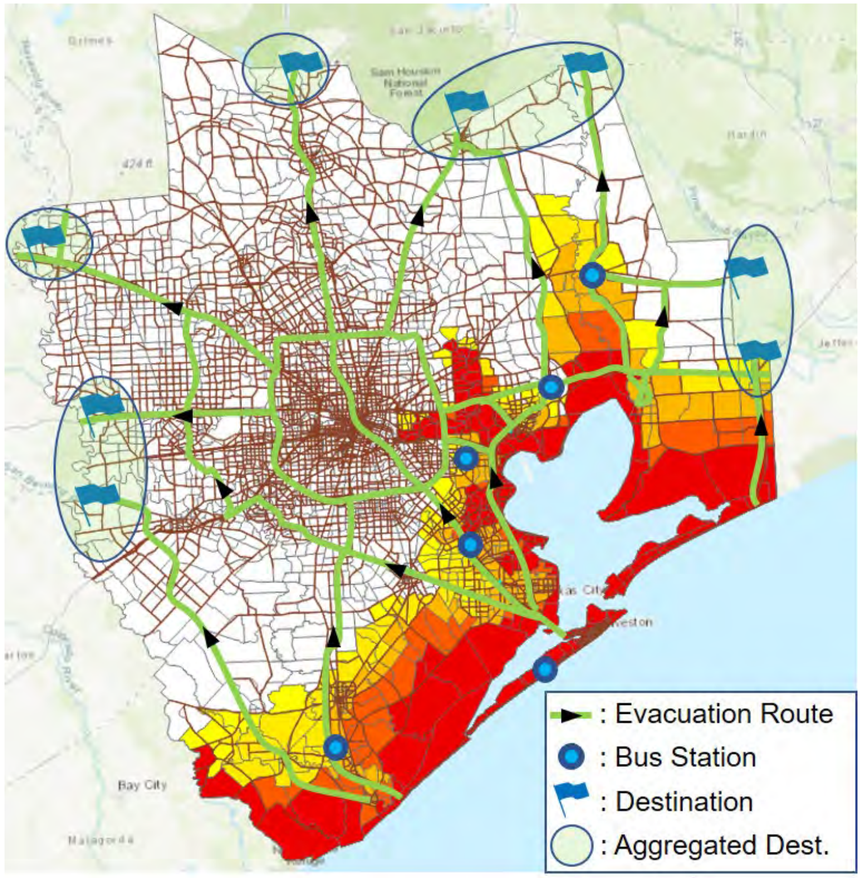


Figure 1. Evacuation Map of Houston, TX

METHODOLOGIES

This section outlines the traffic simulation software SUMO (Simulation of Urban MObility), the SAV fleet operation using dynamic ride-sharing (DRS), and the scenarios assumed in this paper. Because of the challenges associated with recreating evacuation traffic in real-world scenarios, a computer simulation through SUMO will be employed, incorporating various dynamic ride-sharing options, SAV sizes, and fleet operations to support SAVs. Due to computational constraints, only 20% of the population, regardless of their evacuation status, will be sampled for the simulation.

Traffic Simulation

SUMO is an open-source traffic simulation tool designed to handle extensive networks (Lopez et al., 2018). The time unit for the simulation is in seconds, and SUMO can track each vehicle's movement separately on a second-by-second basis. This capability will be used to derive metrics including average vehicle occupancy, travel time, and SAV waiting time. Within the SUMO simulation, vehicle interactions, including those involving SAVs and HVs, are governed by an underlying car-following model, which dynamically adjusts vehicle speeds and inter-vehicle distances based on real-time traffic conditions and vehicle behaviors. For SAVs, specifically, the simulation employs the Intelligent Driver Model (IDM, (Treiber et al., 2000)) to emulate their autonomous driving behavior, allowing for more sophisticated and adaptive decision-making in terms of speed adjustments and vehicle spacing. The use of IDM for SAVs is instrumental in showcasing their autonomy by simulating realistic self-driving characteristics such as smoother acceleration and deceleration patterns, and the ability to maintain optimal distances from other vehicles, thereby enhancing safety and efficiency within the mixed traffic flow. Moreover, SAVs are assumed to have real-time route optimization capabilities, finding the shortest path every second, thereby displaying superior route-choice abilities compared to human drivers, who are assumed to have re-routing intervals of 10 minutes. Lastly, SAVs are programmed to prioritize residents more intensely affected by flooding during Hurricane Harvey in 2017.

Following a 30-minute warm-up period to populate the empty network, the evacuation will commence at 6 AM on a typical weekday. The simulation will terminate once all agents reach their final destination. The simulation accommodates four different transportation modes: human-driven vehicles (HVs), special evacuation buses, SAVs, and walking. The route of all human-driven vehicles and buses in the network, except the background traffic, will be rerouted every 10 minutes to adapt to network changes and traffic conditions.

SAVs' self-driving features are demonstrated by rerouting every second to prioritize residents who experienced severe flooding during Hurricane Harvey's landfall in 2017. This 1-second rerouting feature is used to demonstrate SAVs' real-time communication and route-choice ability. Prioritizing residents who experienced severe flooding leverages SAVs as a form of emergency rescue vehicle, ensuring those at risk are picked up first. Flood records at the TAZ level were sourced from the 2017 Hurricane Harvey flood map (Federal Emergency Management Administration (FEMA), 2018; United States Geological Survey (USGS), 2020). Readers can refer to (Lee & Kockelman, 2021) for a detailed explanation of the modeling method for link-level flood depth.

Among the transportation modes, HVs and special evacuation buses are the primary means of evacuation. Meanwhile, the special evacuation bus can be accessed by SAV or on foot. Agents with sufficient HVs will evacuate directly from their origin to their destination by manually driving their HVs. An SAV fleet will transport the no-vehicles-available population from their homes to the bus station, where agents can transfer from the SAV to the bus and proceed to their final destination. No-vehicles-available agents have the choice between SAV and walking based on the time required to complete the evacuation. Mode choice is determined by Eq. (3) which takes into account the travel costs of the two modes. This paper assumes a value of travel time (VOTT) of $15/hr., with the costs of walking time and SAV waiting time assumed to be twice that of in-vehicle travel time in an SAV. For the walking mode, a speed of 1.2 m/s (3.94 ft/s) is assumed, following the shortest travel route. This speed is commonly used by the US Highway Capacity Manual (Highway Capacity Manual, 2010).

$$Pr(Walk) = \frac{exp(-2WalkCost)}{exp(-2WalkCost) + exp(-(SAVTravelCost + 2\,SAVWaitingCost))} \tag{3}$$

$$Pr(SAV) = 1 - Pr(Walk)$$

The special evacuation bus will operate on a fixed time schedule as well as in a demand-responsive manner. Each bus will depart when one of two conditions is met first: 1) 30 minutes after the departure of the last bus from the same line (fixed time schedule), or 2) when the bus reaches full capacity (demand-responsive). An agent arriving at the bus station will wait on the appropriate bus until it departs. All buses are assumed to have 37 seats for passengers and 1 seat for a human driver. The 37-seater MB-917 bus made by Mercedes Benz serves as the model for the evacuation bus in this paper.

A fixed-size SAV fleet, consistent throughout the simulation, will be operated to assist the no-vehicles-available population in reaching the nearest bus station. At the start of the simulation, SAVs will be randomly distributed across hurricane risk zones to facilitate travel from the origin to the bus station. Three different sizes of SAVs are assumed: sedans with 5 seats, third-row sports-utility vehicles (SUVs) with 7 seats, and vans with 12 seats. DRS can be implemented with various sharing options, allowing passengers to share rides with strangers if sharing conditions are met. Table 2 presents the specifications of the vehicles used in this paper, with values defined as per SUMO default, except the number of seats, which has been modified to reflect driverless SAVs and evacuation bus operations. The main difference between HVs and various types of SAVs is the number of available seats and the presence of a driver. Other vehicle specifications (e.g., acceleration) are kept constant to focus the analysis on shared mobility and self-driving features.

Table 2. Vehicle Specifications by Type

Specifications \ Vehicle Type	HV	SAV			Special Evacuation Bus
		Seat 5	Seat 7	Seat 12	
Seats (Agent + Driver)	4+1 seats	5+0	7+0	12+0	37+1
Length (m) Width (m) Height (m)	4.3 m 1.8 m 1.5 m	4.3 1.8 1.5	4.3 1.8 1.5	4.7 1.9 1.73	12.0 2.5 3.4
Minimum Gap (m)	2.5 m	2.5	2.5	2.5	2.5
Maximum Acceleration (m/s^2)	2.9 m/s^2	2.9	2.9	2.9	1.2
Maximum Deceleration (m/s^2)	9.0 m/s^2	9.0	9.0	9.0	7.0
Deceleration (m/s^2)	7.5 m/s^2	7.5	7.5	7.5	4.0
Car Following Model	Krauss (SUMO Default)	Intelligent Driver Model (IDM)			Krauss (SUMO Default)
Lane Change Model	LC2013 (SUMO Default)				

Shared Autonomous Vehicle with Dynamic Ride-sharing

With the DRS option, agents can share their rides with strangers when travelling in an SAV. This paper suggests a rule-based DRS algorithm. Different agents' trips can be shared when all agents' travel characteristics satisfy the DRS rules. These agents may be scheduled for pickup or drop-off in an SAV, already riding in an SAV, or requesting a new SAV ride. SAVs operate in two states: 'idle' and 'drive'. The 'idle' state is the default, in which the SAV, without any assigned trips for pick-up or drop-off, stays at its current location awaiting a new travel request. The 'drive' state occurs when an SAV is moving to a different location, which can be 'empty driving' (no agent on board) or 'non-empty driving' (at least one agent on board). Non-empty driving can be further classified as 'solo driving' (only one agent onboard) and 'shared driving' (two or more agents onboard).

In this scenario, let's define SAV as v, agent requesting a new SAV pick-up as p, and passengers scheduled for pick-up, drop-off or already onboard the SAV v as v_r. The SAV v must have enough seats available when agent p requests a pick-up to be a feasible SAV for DRS conditions. For each agent v_r, their direct arrival time at their SAV destination (bus station) based on the current trip schedule of SAV v is defined as $D_{(v_r)}$. For the agent p, the direct arrival time at their bus station, assuming p departs immediately after an empty SAV picks them up, is defined as $D_{(p)}$. The new arrival time of an agent k, due to the rerouting of the SAV v because of an DRS request, is defined as $R_{(k)}$.

SAVs are ordered by the number of trips they are currently assigned, meaning SAVs with fewer trip assignments are considered before those with more. Also, an SAV located in the same county as the passenger will be given priority to serve the trip. Due to computational limitations, this paper assumes that a new pickup request by agent p should be prioritized over other trip assignments that SAV v is scheduled for, while the drop-off order of the agent p is not restricted. Lastly, the agent p who experienced more intense flooding from Hurricane Harvey will be prioritized over other passengers. Given these variables, Eq. (4) must be satisfied for the agent p and SAV v to be matched using DRS service. The maximum reroute-time, RT, is a variable that determines whether a new pick-up request can be assigned to the SAV or not.

$$R_{(k)} - D_{(k)} \leq RT, \ \ \forall k \in \{p, v_r\} \tag{4}$$

s.t.

$$Seat_{(v)} \geq HH_p$$

where, RT= maximum reroute-time, $Seat_{(v)}$= number of seats left in v at the time when p requests a pick-up, HH_p= number of persons in household p.

Figure 2 shows the implementation of the described DRS algorithm using pseudo-code. This is an example of multiple drop-offs to show how rerouting works if SAVs are to drop passengers at different county's bus stations. It is a generalization to showcase the algorithm's capability to manage rerouting efficiently if multiple drop-off locations were plausible within the evacuation strategy. The SAV already has two agents, agents a and b, scheduled for pick-up and drop-off and considers the inclusion of a new pick-up request from agent c. In this context, Greek letters represent the travel time between two locations. Due to computational constraints, the pick-up order for a new agent, denoted as (c, pick) always assumes the initial position, while its drop-off order, (c, drop), can be anywhere that satisfies Eq. (4). While this paper employs a rule-based algorithm to dynamically match agents with SAVs for efficient ride-sharing, it acknowledges the inherent computational and practical constraints by not exhaustively searching for the absolute optimal agent, SAV, and trip assignment combinations. Instead, it focuses on a feasible and adaptive pairing approach that aligns with real-world operational scenarios and available resources, ensuring a balanced and pragmatic application of DRS services during evacuations. If a searched pair of agent p and SAV v adheres to the DRS rule under the priority sequence, they are paired together. If no SAV can be matched to agent p, this agent is added to a set titled ‘unassignedAgents’, ordered by the initial SAV call time. The unassignedAgents set favors the agent who made the earliest initial SAV request. An attempt to match them with an SAV DRS takes place every 10 minutes or when an idle SAV with no scheduled trips becomes available.

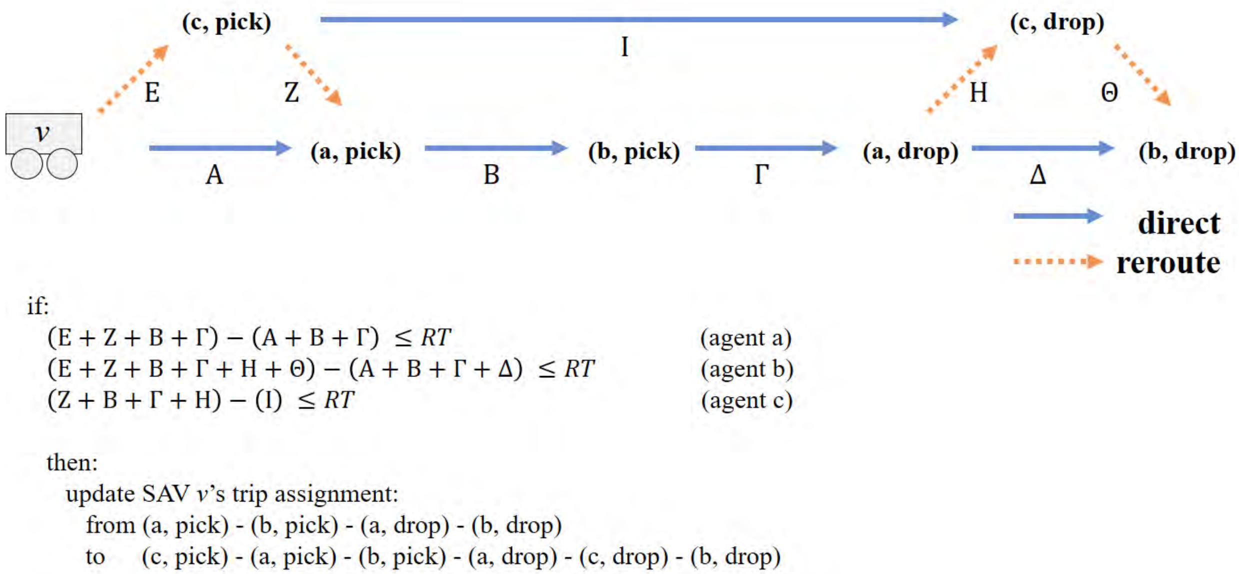


Figure 2. DRS Example

The key variable influencing DRS performance is the maximum reroute-time, RT. Strategic assignment is plausible when this variable coordinates with the variables dictating evacuation performance, courtesy of SAV's communication devices. This paper proposes a technique to synchronize the maximum reroute-time with the departure time headway of a special evacuation bus and the predicted time an agent would reach the bus station, allowing the establishment of a dynamic reroute-time. Regardless of the agent's early arrival at the bus station, he/she must await bus departure. If this waiting time can be utilized for the SAV to accommodate more agents—provided the agents do not miss the bus—the number of agents served by SAVs can be increased, thereby enhancing evacuation performance. Conversely, if the time difference between an onboard agent's expected station arrival and bus departure is minimal, the SAV will prioritize delivering the onboard agent straight to the station rather than detouring to pick up more agents.

A similar coordination method is proposed by (Huang et al., 2021), which coordinates the SAV maximum reroute-time and the train's departure time headway. However, this is intended for regular travel situations with a fixed train time headway. In contrast, this paper accommodates the changing departure time headway of the special evacuation bus based on evacuation demand. It departs either when the bus is full or every 30 minutes, in a demand-responsive manner. Consequently, the maximum reroute-time is both dynamic and demand-responsive, varying according to the agent, bus line to be used, and when the agent places the SAV request—amending Eq. (4) to Eq. (5).

During periods of low evacuation demand, the bus is likely to operate on an extended schedule, including the fixed 30-minute timeframe, allowing an SAV to undertake more DRS trips via a prolonged maximum reroute-time. When evacuation demand is high, the bus tends to operate on a shorter schedule, obliging SAVs to concentrate on transporting already onboard agents and restrict excessive DRS service. As each agent's bus schedule varies by time and location of the bus station and destination, every agent k, whether onboard or requesting a new SAV ride, must satisfy Eq. (5) for a new SAV ride to be matched.

$$R_{(k)} - D_{(k)} \leq RT_{(k)}^{ijt}, \quad \forall k \in \{p, v_r\} \tag{5}$$

$s.t.$

$$Seat_{(v)} \geq HH_p$$

where, $RT_{(k)}^{ijt}$= dynamic reroute-time for agent k departing from i to j at time t, $Seat_{(v)}$= seats left in v

at the time when p requests for a pick-up, HH_p= household size of agent p.

The dynamic maximum reroute-time, $RT_{(k)}^{ijt}$, assumes that the departure time headway of the bus, agent k intends to use, will remain constant until the agent reaches the bus station. This headway value could either be a demand-responsive value, shorter than the 30-minute fixed schedule, or the 30-minute fixed schedule resulting from low bus demand. Under this assumption, the expected departure time of the next available bus for agent k can be estimated. Agent k's expected bus station arrival time is deduced from the trip schedule of the SAV v, whether the agent is onboard or requesting a new ride. The time difference between agent k's expected bus departure time and the predicted arrival time at the station represents the maximum reroute-time agent k can allow for rerouting. Given the ambiguity surrounding the bus operation schedule—whether fixed or demand-responsive—the minimum of two rerouting times derived from 1) the 30-minute fixed headway, and 2) the demand-responsive headway is assumed as the rerouting time for agent k. This time corresponds to the duration agent k would spend on the bus before it departs—a duration that could alternatively be used by the SAV to pick up another agent via DRS. A safety buffer of 25% is employed to ensure the agent does not miss the bus, meaning only 75% of the calculated difference between bus departure time and agent arrival time can be used for rerouting. Consequently, the maximum reroute-time, $RT_{(k)}^{ijt}$, varies dynamically according to agents, bus lines, and SAVs. Figure 3 the proposed concept of SAV rerouting synchronized with the bus schedule, while Algorithm 1 shows the pseudo-code of the SAV DRS method, inclusive of the bus coordination strategy.

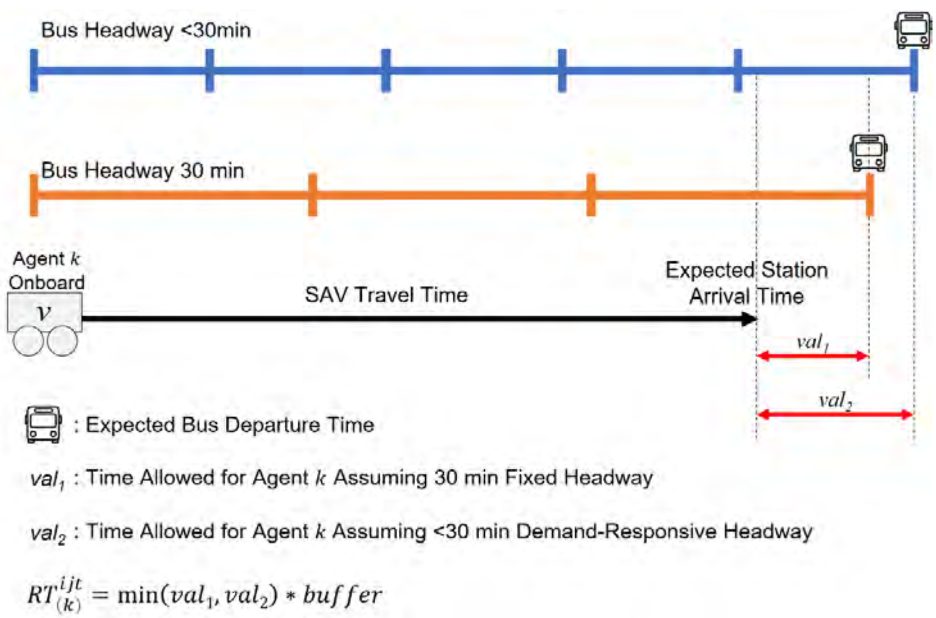


Figure 3. SAV Rerouting Coordinated with Bus Schedule

Algorithm 1. SAV DRS Matching Method

for agent p:
  if (t=t_p) or (p ∈unassignedAgents and t%10=0) or (p ∈unassignedAgents and idleSAV≠∅)
    for SAV v:
      if coordinated:
        if $R_{(k)} - D_{(k)} \leq RT_{(k)}^{ijt}$:
          $p - v$ matched
          break

else:
if $R_{(k)} - D_{(k)} \leq RT$:
$p - v$ matched
break
if $p - v$ not matched:
unassignedAgents = unassignedAgents $\cup$ $\{p\}$

where
t= current time (min)
t_p= initial SAV call time for agent p
$t\%10$= the remainder after division of t by 10
idleSAV= set of idling SAVs

Scenarios and Model Summary

This paper conducts scenario analyses encompassing different SAV fleet sizes, evacuee behaviors, and non-compliance levels. Given that three distinct types of SAVs are proposed, differentiated by the number of seats available, these variations will be incorporated into the scenario analyses. Moreover, this paper integrates the dynamic maximum reroute-time coordination strategy dependent on the special evacuation bus's departure time to evaluate a more strategic SAV fleet operation application.

This paper examines evacuee behavior through analyzing the impact of agents' willingness to share their rides during an evacuation. The baseline sharing behavior assumes that all agents are amenable to ride-sharing in an SAV, given a predetermined maximum reroute-time. However, scenarios will incorporate agents who are unwilling to participate in ride-sharing. For these individuals, their maximum reroute-time will be set to zero, thus preventing any ride-sharing implementation.

This paper also assesses evacuee non-compliance levels by adjusting departure time scenarios to account for varying agent non-compliance degrees. The baseline departure time distribution is a staged random distribution based on the agent's hurricane risk zone. This assumption will be relaxed by prompting a portion of agents to ignore the staged evacuation strategy. If an agent chooses to disregard the strategy, they are assumed to depart randomly within the first fifth of the six-hour departure time duration, regardless of their hurricane risk zone. This adjustment allows for an evaluation of the proposed evacuation method's performance under moderate to severe non-compliance levels.

In summary, the proposed method considers agents moving at a household level, using their HVs if available. If HVs are not available, agents can choose between the Walk-bus or SAV-bus, depending on the expected travel cost from home to the bus station. Buses depart from the bus station every 30 minutes or when full. Algorithm 2 summarizes the proposed evacuation method.

Algorithm 2. Summary of Proposed Method

while every agent arrived at destination *j*
for agent k:
if t=t_k:
if HV available:
evacuate from origin *i* to destination *j*
else:
if Walk:
walk from origin *i* to closest bus station *s*
when arrived at *s*, wait until bus departs to destination *j*
else:
Perform Algorithm 1 to ride a SAV from origin *i* to closest bus station *s*

```
            when arrived at s, wait until bus departs to destination j

    for Bus Station s:
        for Bus b traveling from s to j:
            if (Bus b is full) or (in every 30 minutes):
                Bus b evacuates from s to j

    if t%10:
        reroute HV, SAV, and Bus

    t= t+1

where
t= current time
t_k= departure time of the agent k
    (equivalent to initial SAV call time t_p if the agent uses SAV)
t%10= the remainder after division of t by 10
```

EVACUATION SIMULATION

This section evaluates the simulation results of using SAVs as the primary mode of transportation for evacuating populations without available vehicles, using evacuation buses. The paper explores various SAV specifications, sizes, and evacuation scenarios to determine SAV technology's influence on evacuation performances. Each scenario is simulated ten times, and the average value is presented.

Sensitivity Analyses of Various SAV Fleets

The sensitivity analyses of various SAV fleets all presuppose the staged random departure time distribution discussed earlier, with agents from hurricane risk zone 1 more likely to depart earlier than those from hurricane risk zone 5. However, each SAV fleet scenario varies by fleet size and seats per SAV. Six distinct SAV fleet sizes are simulated: small (200, 400 SAVs), medium (600, 800 SAVs), and large (1000, 1200 SAVs). 200, 400, 600, 800, 1000, and 1200 SAVs in the network corresponds to 1 SAV per 40, 20, 14, 10, 8, and 7 people, respectively. This paper also examines three vehicle sizes with 5-seat, 7-seat, and 12-seat SAVs. Consequently, a total of 18 unique SAV fleet scenarios are simulated by combining fleet size and seats per SAV.

In addition, for the 18 SAV fleet scenarios, two different maximum reroute-times are tested. In one scenario, the maximum reroute-time is fixed to 15 minutes for all agents ($RT = 15min$) and in the other, a dynamic maximum reroute-time with bus coordination ($RT_{(k)}^{ijt}$) strategy is implemented. The assumption of 15-minutes maximum reroute-time was obtained from the research results by (Gurumurthy & Kockelman, 2018). Unless specified otherwise, all simulation results are based on the 15-minute maximum reroute-time assumption. The combination of 18 fleet scenarios and two reroute-time scenarios results in a total of 36 distinct SAV scenarios, each simulated ten times to produce an average value. A microscopic SUMO simulation is performed to operate the SAV fleet and track each agent's evacuation.

Figure 4 represents the SAV mode share for no-vehicles-available agents (4% of total evacuees), who can choose between SAV and walk modes for the first-mile connection to the bus station. The SAV share increases with larger fleet sizes and more seats available in each SAV. As more SAVs become available to the agents with greater fleet size, the agents will have greater opportunity to ride in an SAV to travel to the bus station. However, the SAV mode share plateaus after more than 600 SAVs are in the network, indicating that a fleet size exceeding this may not be necessary. This phenomenon is likely due to operational inefficiencies in large fleet size scenarios, where some SAVs are idling and not serving pick-up and drop-off requests effectively. This aspect will be analyzed in the subsequent sections.

In most scenarios, a higher number of seats in SAV correlates with an increased SAV mode share. However, the gap in mode share between 12-seat SAVs and smaller alternatives contracts as the fleet size expands. More seats in an SAV equates to a greater number of onboard evacuees and a heightened chance to serve DRS trips, hence the larger SAV mode share. Yet, the benefit of increased seating capacity diminishes as the fleet size grows and SAVs become more accessible.

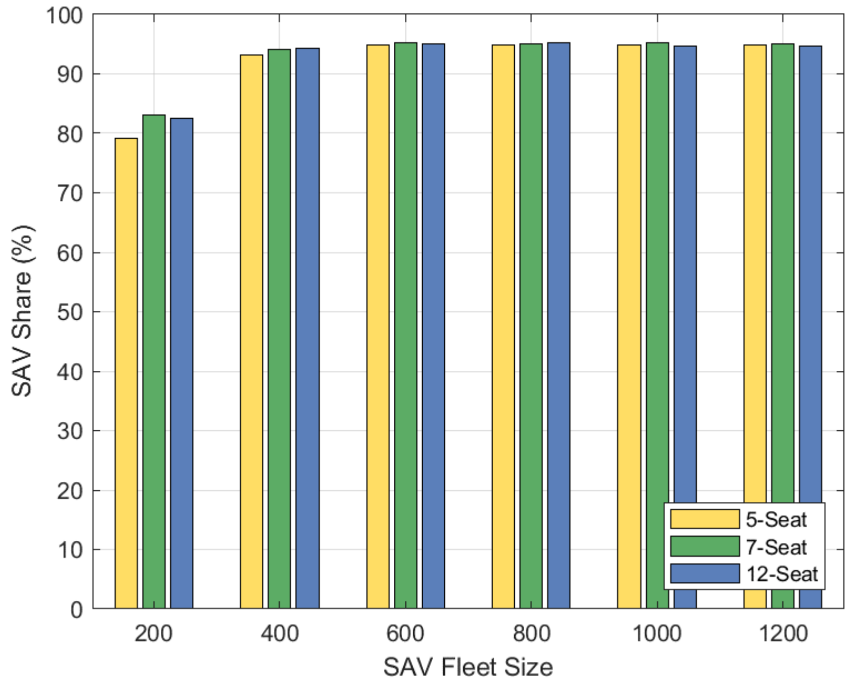
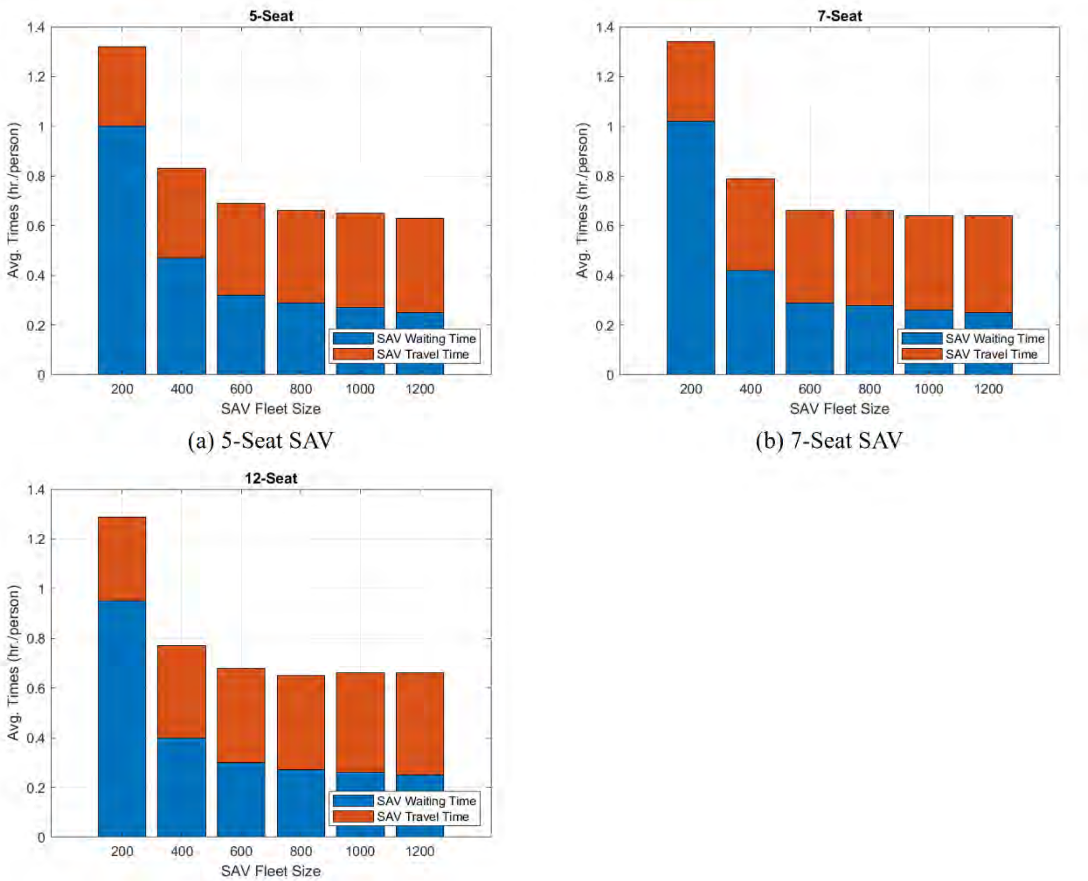


Figure 4. Mode Share of SAVs by SAV Scenario

Figure 5 presents the time each individual spends waiting for and travelling in an SAV. Within the fleet size scenarios, the significant contributor to reducing total travel time is the diminishment of SAV waiting time. An increase in available SAVs leads to a reduced wait time, although the impact lessens with more than 600 SAVs. A corresponding decline in mode share increase after the 600 SAV threshold indicates that the change in mode share is primarily triggered by the alteration in SAV waiting time. Conversely, as the number of SAVs grows, so does the travel time due to the extended time spent rerouting for DRS. Despite this, the decrease in waiting time compensates for the increased travel time, resulting in an overall reduction in total SAV time. The influence of the number of seats is less significant on changes in SAV waiting and travel time compared to the impact of fleet size.



(a) 5-Seat SAV

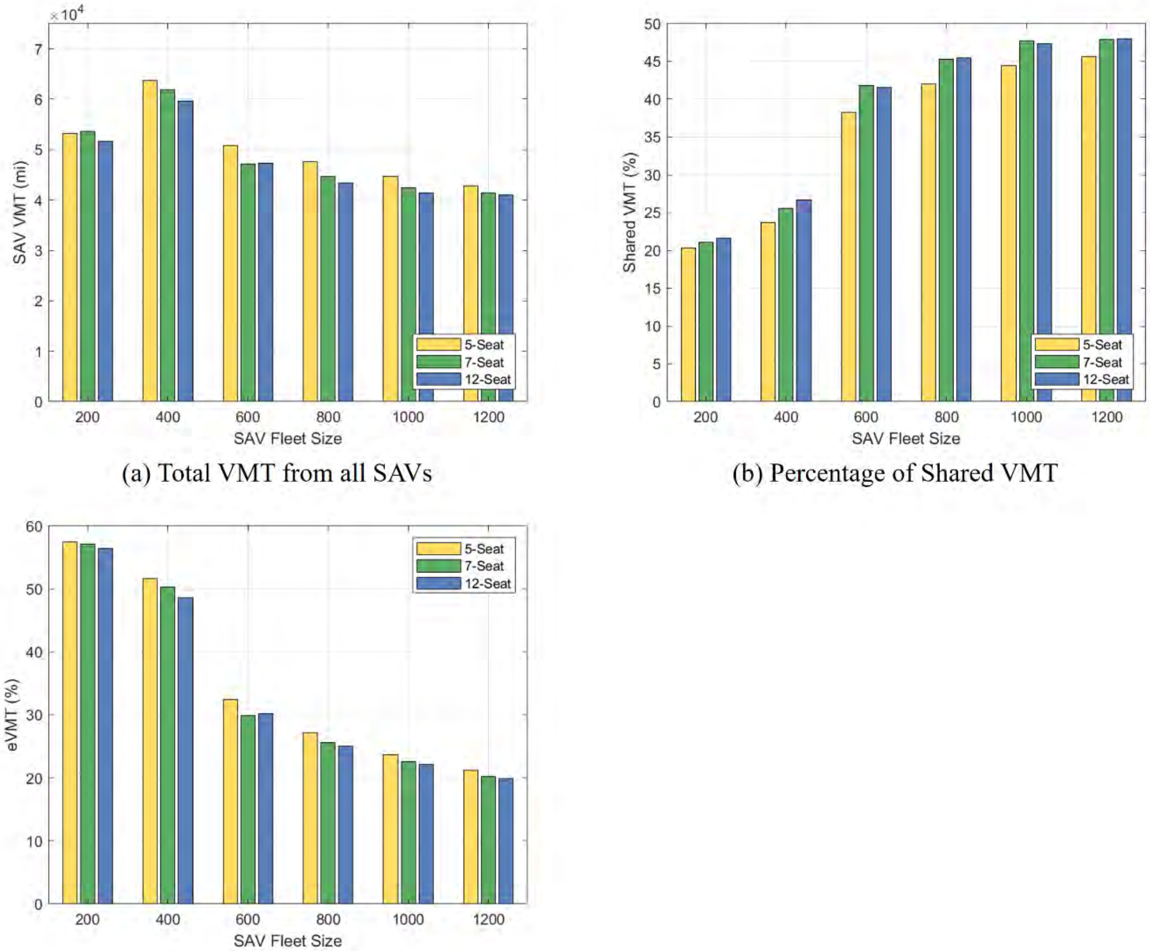
(b) 7-Seat SAV

(c) 12-Seat SAV

Figure 5. SAV Wait and Travel Time by Scenario

Larger SAVs contribute to evacuation performance enhancements by providing more opportunities for DRS rather than reducing travel times. Figure 6 shows the total VMT (Figure 6a), the percentage of shared VMT (Figure 6b), and the percentage of empty VMT (eVMT, Figure 6c) for each SAV scenario. In Figure 6a, as the number of seats per SAV increases, the total VMT decreases. This represents that a 12-seat SAV covers a shorter average distance to serve the same number of agents compared to a 5- or 7-seat SAV due to more agents likely sharing rides. This assumption is reinforced in Figure 6b, where an increase in seats corresponds to a rise in the percentage of VMT shared by two or more agents. Figure 6c further reveals that eVMT decreases as the number of SAV seats increases. This is because having more seats heighten the chances of having at least one seat occupied by an evacuee at any time due to DRS.

Revising Figure 6a, the total VMT decreases in line with an increase in fleet size, except for the 200 to 400 SAV scenario. This is due to increased ride-sharing opportunities (Figure 6b) and reduced eVMT (Figure 6c), optimizing SAV fleet operation. Figure 6b reveals that the percentage of shared VMT grows with an increasing SAV fleet size, as more SAVs provide greater DRS opportunities. The data in Figure 6b rationalizes the increased travel time with a larger fleet size noted in Figure 5, due to the increased time spent rerouting for DRS. As shown in Figure 6c, larger fleets can schedule pick-ups and drop-offs more efficiently by assigning SAVs to nearer agents, preventing the need for empty travel. With the combined effects of shared VMT and eVMT, total VMT decreases with fleet size increase. A more efficient SAV operation with reduced evacuation time can be anticipated with a larger fleet size, as suggested in Figure 5, due to less network congestion from reduced total VMT. The 200 SAVs scenario registers lower total VMT than the 400 SAVs scenario due to its low mode share of 75%-85% (as described in Figure 4). As this scenario served fewer agents than others, its total VMT is lower than the 400 SAV scenario, as observed in Figure 6a.



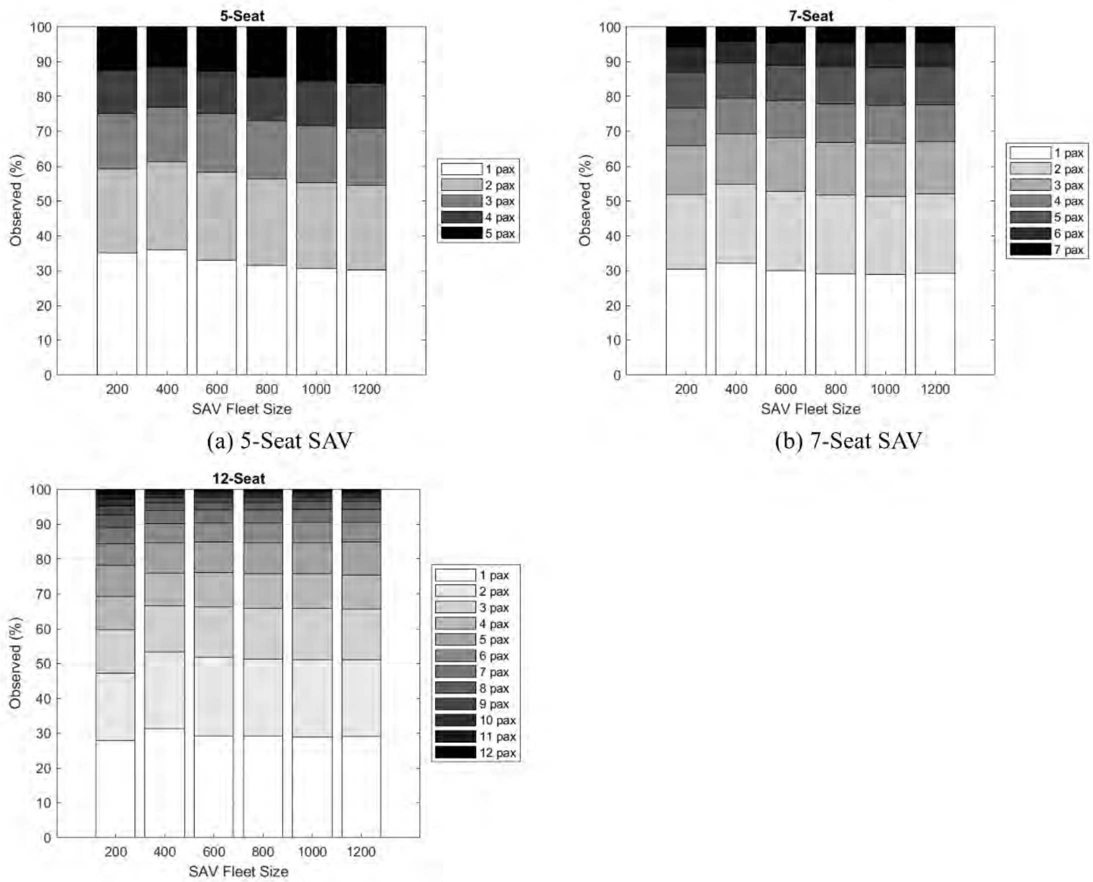
(a) Total VMT from all SAVs

(b) Percentage of Shared VMT

(c) Percentage of eVMT

Figure 6. SAV VMT and Shared VMT Percentage by SAV Scenario

Increased ride-sharing opportunities from more SAV seats (supported by Figure 6b) affect SAV occupancy. Figure 7 depicts the occupancy configuration by the percentage of each number of passengers (PAX) onboard per fleet size and number of seats. The average household size of the no-vehicles-available agent is 1.73 persons, which includes both households without private vehicles and those left behind due to a shortage of such vehicles. Therefore, SAVs with occupancies over 2 PAX are shared rides catering to two or more agents. Figure 7 shows that on average, 43%, 48%, and 49% of the occupancy observations are made with over 2 PAX for the 5, 7, and 12 seat scenarios respectively. This indicates that increased SAV seating promotes DRS and decreases total VMT. However, within each seating capacity scenario, fleet size exerts minimal influence on occupancy configuration.



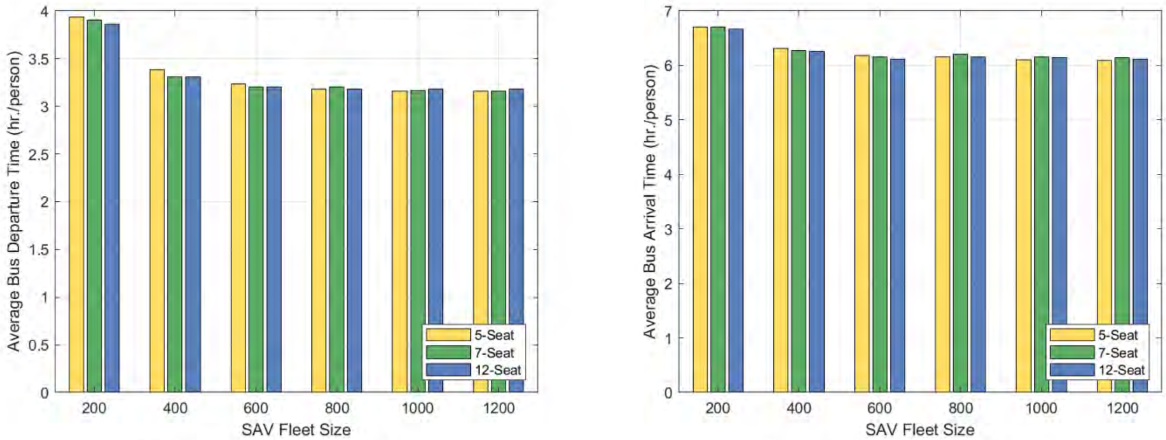
(a) 5-Seat SAV

(b) 7-Seat SAV

(c) 12-Seat SAV

Figure 7. SAV Occupancy Configuration by SAV Scenario

In assessing the efficacy of an SAV fleet for evacuation purposes, it is crucial to consider the average bus departure and bus arrival times for each scenario, as seen in Figure 8. The y-axis of Figure 8 represents how much time has elapsed per individual evacuee when the bus departed and arrived after the evacuation started at 6 AM. In this regard, earlier bus departures and arrivals signify a more efficient evacuation process. Interestingly, the totalVMT and eVMT are generally lower with larger SAVs (as per Figure 6), but the average individual evacuation experience to arrive at the destination earlier is not significantly impacted by the seating capacity of the SAVs. Conversely, the fleet size influences the bus departure and bus arrival times, with larger fleets resulting in earlier times, albeit the impact diminishes beyond 600 SAVs in the network. In conclusion, larger fleet size reduces total VMT and eVMT and increases shared VMT (from Figure 6), has no impact on occupancy configuration (from Figure 7), and reduces the total time needed to evacuate (from Figure 5 and Figure 8).



(a) Avg. Bus Departure Time (b) Avg. Bus Arrival Time

Figure 8. Avg. Bus Departure and Arrival Time by SAV Scenario

A larger the fleet size and a greater the number of seats in each SAV may result in a better evacuation experience by reducing travel time or VMT. However, it may not be cost-efficient to operate large SAV fleets with more seats per SAV. Figure 9 shows the non-idle time share by scenario, calculated as non-idling time over total time until the final agent arrives at the bus station. This demonstrates that the impressive evacuation performance of a large SAV fleet, particularly one with more seats per SAV, is contingent upon a low non-idle time share. Thus, this strategy is less efficient overall. Taking into consideration that travel time reduction plateaus with more than 600 SAVs and the lower non-idle time share of SAVs with more seats, this paper proposes a base case scenario of 600 5-seat SAVs, approximating to one SAV per 14 people for cost-efficient evacuation. While these findings are derived from this paper's specific settings and are scientifically grounded, they are subject to change with different conditions or parameters.

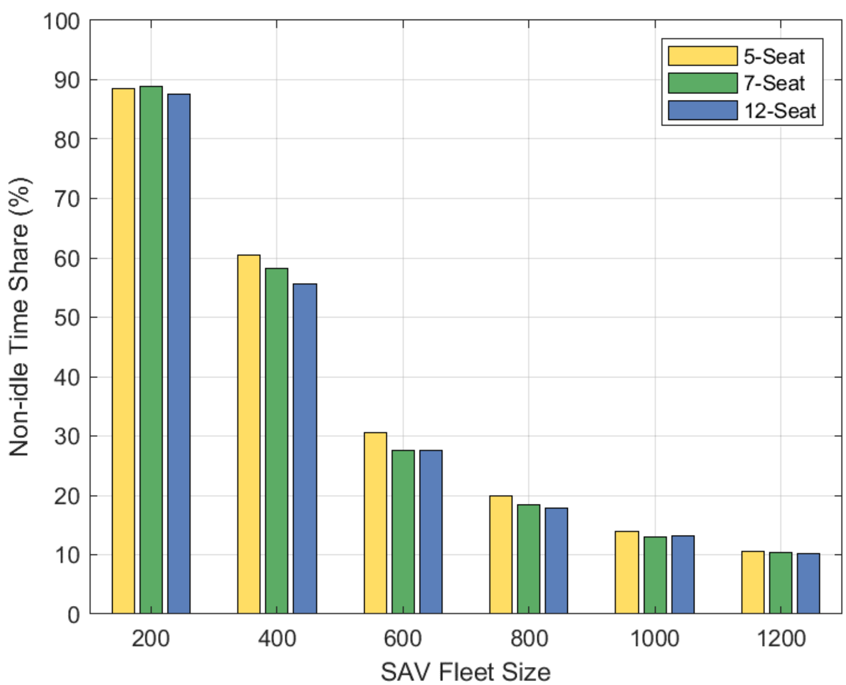


Figure 9. SAV Non-idle Time Share by SAV Scenario

Impact of Vehicle Autonomy

Analyzing the impact of vehicle autonomy is also integral to understanding the evacuation with SAVs. This paper assumed that SAVs employ AV communication technology, car-following behavior derived from intelligent driver model, and real-time route optimization to find the shortest path every second, thus displaying superior route-choice ability compared to human drivers (who are assumed to reroute in every 10 minutes). Additionally, SAVs are programmed to prioritize residents more intensely affected by flooding during Hurricane Harvey in 2017. The impact of these AV features can be measured by analyzing the results without these vehicle autonomy features, which can be considered as simple DRS operation conducted by human drivers (with Krauss SUMO default car-following model), such as Uber and Lyft. The simulation was achieved on 600 5-seat SAVs, which was defined as the base case scenario in the previous section.

The results in Table 3, derived from this paper's simulation settings, highlight that both waiting and travel times for shared vehicles and buses amplify when SAVs are substituted with shared human-operated vehicles. This outcome suggests a less efficient evacuation scenario in the absence of vehicle autonomy. Although there is an increase in the non-idle time share when vehicle autonomy is eliminated, there is also a noticeable rise in both empty VMT share and total VMT per vehicle, accompanied by a decrease in shared VMT. These findings suggest that the human-driven shared vehicle conduct DRS operations less efficiently, taking more time than SAVs. Consequently, these outcomes affirm that vehicle autonomy can facilitate a more effective evacuation of residents than human-driven vehicles.

The findings regarding increased waiting and travel times when substituting SAVs with human-operated shared vehicles are based on the simulation's assumptions, where autonomous systems are presumed to process information and adjust routes more rapidly and accurately. This assumption underlines the potential for more efficient vehicle utilization during evacuations with full autonomy. The comparison is intended to demonstrate the benefits of autonomous vehicles in evacuation scenarios, without diminishing the potential of human drivers knowledgeable in DRS operation strategies.

Table 3. Vehicle Autonomy and First-mile Connection

	Shared Autonomous Vehicle + Bus	**Shared Human-driven Vehicle + Bus**
Shared Vehicle Wait Time (hr./person)	0.32	0.39 (+21.9%)
Shared Vehicle Travel Time (hr./person)	0.37	0.47 (+27.0%)
Bus Wait Time (hr./person)	0.17	0.17 (+0.0%)
Bus Travel Time (hr./person)	2.95	3.15 (+6.8%)
Total Time (hr./person)	3.82	4.18 (+9.4%)
Non-idle Time Share (%/vehicle)	30.53	38.07 (+24.7%)
eVMT (%/vehicle)	32.46	34.55 (+6.4%)
Shared VMT (%)	38.25	36.12 (-5.6%)
VMT per vehicle (mi.)	86.54	95.03 (+9.8%)

* Values in parentheses show differences from SAV + Bus scenario.
** All simulations performed 600 5-seat SAVs, and the average values after repeating each scenario 10 times are shown.

SAV - Bus Coordination Strategy

A scenario analysis was also conducted to evaluate the effect of a maximum reroute time in SAV fleet operation, coordinated with the special evacuation bus schedule, as shown in Figure 3. In this scenario, each agent is assigned a unique, dynamic maximum reroute time, calculated based on their expected arrival time and bus departure time. Table 4 contrasts the SAV fleet performance in this scenario with the base case scenario where the maximum reroute time is set to 15 minutes for all agents.

The mode share in the bus coordination scenario does not vary significantly from the base case of the 15-minute fixed reroute time scenario. However, total VMT sees a considerable increase, ranging between 8% to 33%, while the shared VMT percentage drops by 3 to 17 percent points (%p) from the base case. To help readers who are not familiar with the unit "percent point", it is the arithmetic difference of two percentages (e.g., 34% is 4%p larger than 30%). It can be inferred that ride-sharing and DRS utilization in the bus coordination scenario is lower than in the base case. This is likely due to the maximum reroute time with bus coordination being shorter than 15 minutes for most agents, in order to ensure timely arrival for their evacuation bus. This would result in less opportunity for ride-sharing compared to the base case scenario. However, agents with more than 15 minutes until their bus departure could potentially reroute for longer than 15 minutes.

Table 4. SAV Fleet Operation with Bus Coordination

SAV Mode Share (%)						
Fleet Size / Seats	200	400	600	800	1000	1200
5	80.82% (+1.59%p)	90.37% (-2.76%p)	94.27% (-0.54%p)	94.38% (-0.55%p)	94.41% (-0.36%p)	94.37% (-0.45%p)
7	79.56% (-3.45%p)	90.88% (-3.23%p)	94.35% (-0.82%p)	94.25% (-0.79%p)	94.47% (-0.73%p)	95.11% (+0.12%p)
12	79.88% (-2.64%p)	90.24% (-3.99%p)	94.58% (-0.40%p)	94.45% (-0.76%p)	94.53% (-0.18%p)	94.99% (+0.26%p)
Total VMT (mi.)						
Fleet Size / Seats	200	400	600	800	1000	1200
5	58,833 mi. (+10.53%)	72,947 mi. (+14.48%)	63,207 mi. (+24.36%)	56,822 mi. (+19.23%)	54,172 mi. (+21.24%)	51,439 mi. (+20.15%)
7	58,470 mi. (+8.90%)	70,000 mi. (+13.16%)	62,637 mi. (+32.96%)	54,901 mi. (+22.84%)	53,081 mi. (+25.17%)	49,103 mi. (+18.58%)
12	57,229 mi. (+10.82%)	69,778 mi. (+16.98%)	62,787 mi. (+32.85%)	54,131 mi. (+24.68%)	51,541 mi. (+24.29%)	49,107 mi. (+19.82%)
Shared VMT (%)						
Fleet Size / Seats	200	400	600	800	1000	1200
5	18.59% (-1.71%p)	17.84% (-5.88%p)	25.21% (-13.04%p)	31.18% (-10.82%p)	34.00% (-10.40%p)	35.40% (-10.29%p)

7	18.42% (-2.62%p)	19.13% (-6.40%p)	25.44% (-16.39%p)	33.58% (-11.70%p)	36.54% (-11.17%p)	38.12% (-9.80%p)
12	18.97% (-2.69%p)	18.83% (-7.85%p)	25.88% (-15.68%p)	34.16% (-11.34%p)	37.13% (-10.17%p)	38.78% (-9.19%p)

*Values in parentheses show differences from uncoordinated scenario results.

Table 5 lends support to the hypothesis that agents demonstrate a lower preference for DRS in the coordination scenario, leading to prolonged SAV waiting times relative to the base case scenario. As agents are more prone to head directly to the bus station rather than diverting to share a ride, this leads to increased waiting times for other SAV passengers. Notably, the waiting time in the coordination scenario rises more significantly (a 15-35% increase) with a smaller fleet size, while the difference is relatively insignificant (a less than 8% increase) when the network contains more than 800 SAVs. However, due to agents opting to travel directly to the bus station during peak demand periods rather than diverting for DRS, travel time reduces between 2% and 10%. Therefore, the coordination strategy presents a trade-off between extended SAV waiting times and reduced SAV travel times. The scenarios with 1200 SAVs, each with either 7 or 12 seats, show a decrease in both SAV waiting and travel times with bus coordination. This is presumably due to the surplus of SAV resources in these scenarios, suggesting that the benefits of bus coordination can be fully realized only with a substantial market share of SAVs.

Table 5. Evacuation Performance by Bus Coordination

Avg. SAV Waiting Time (hr./person)						
Fleet Size / Seats	200	400	600	800	1000	1200
5	1.33 (+33.00%)	0.58 (+23.40%)	0.35 (+9.38%)	0.31 (+6.90%)	0.28 (+3.70%)	0.26 (+4.00%)
7	1.19 (+16.67%)	0.51 (+21.43%)	0.35 (+20.69%)	0.29 (+3.57%)	0.27 (+3.85%)	0.23 **(-8.00%)**
12	1.18 (+24.21%)	0.51 (+27.50%)	0.34 (+13.33%)	0.29 (+7.41%)	0.27 (+0.00%)	0.24 **(-4.00%)**
Avg. SAV Travel Time (hr./person)						
Fleet Size / Seats	200	400	600	800	1000	1200
5	0.30 **(-6.25%)**	0.34 **(-5.56%)**	0.35 **(-5.41%)**	0.37 (+0.00%)	0.35 **(-7.89%)**	0.35 **(-7.89%)**
7	0.30 **(-6.25%)**	0.34 **(-8.11%)**	0.36 **(-2.70%)**	0.37 **(-5.26%)**	0.37 **(-2.63%)**	0.36 **(-7.69%)**
12	0.31 **(-8.82%)**	0.35 **(-5.41%)**	0.37 **(-2.63%)**	0.37 **(-2.63%)**	0.37 **(-7.50%)**	0.37 **(-9.76%)**
Avg. Bus Departure Time (hr./person)						
Fleet Size / Seats	200	400	600	800	1000	1200
5	4.19 (+6.35%)	3.46 (+2.37%)	3.23 (+0.00%)	3.19 (+0.31%)	3.15 **(-0.32%)**	3.15 **(-0.32%)**
7	4.09 (+4.60%)	3.40 (+2.72%)	3.25 (+1.56%)	3.17 **(-0.94%)**	3.16 **(-0.32%)**	3.12 **(-1.27%)**

12	4.07 (+5.44%)	3.40 (+2.72%)	3.23 (+0.94%)	3.21 (+0.94%)	3.18 (+0.00%)	3.13 **(-1.57%)**
Avg. Bus Arrival Time (hr./person)						
Fleet Size / Seats	200	400	600	800	1000	1200
5	6.88 (+2.69%)	6.34 (+0.48%)	6.15 **(-0.49%)**	6.14 **(-0.32%)**	6.13 (+0.33%)	6.09 (+0.00%)
7	6.83 (+1.94%)	6.29 (+0.32%)	6.21 (+0.81%)	6.09 **(-1.93%)**	6.13 **(-0.33%)**	6.11 **(-0.49%)**
12	6.84 (+2.55%)	6.31 (+0.80%)	6.20 (+1.31%)	6.17 (+0.16%)	6.16 (+0.33%)	6.10 **(-0.33%)**

*Values in parentheses show differences from uncoordinated scenario results.

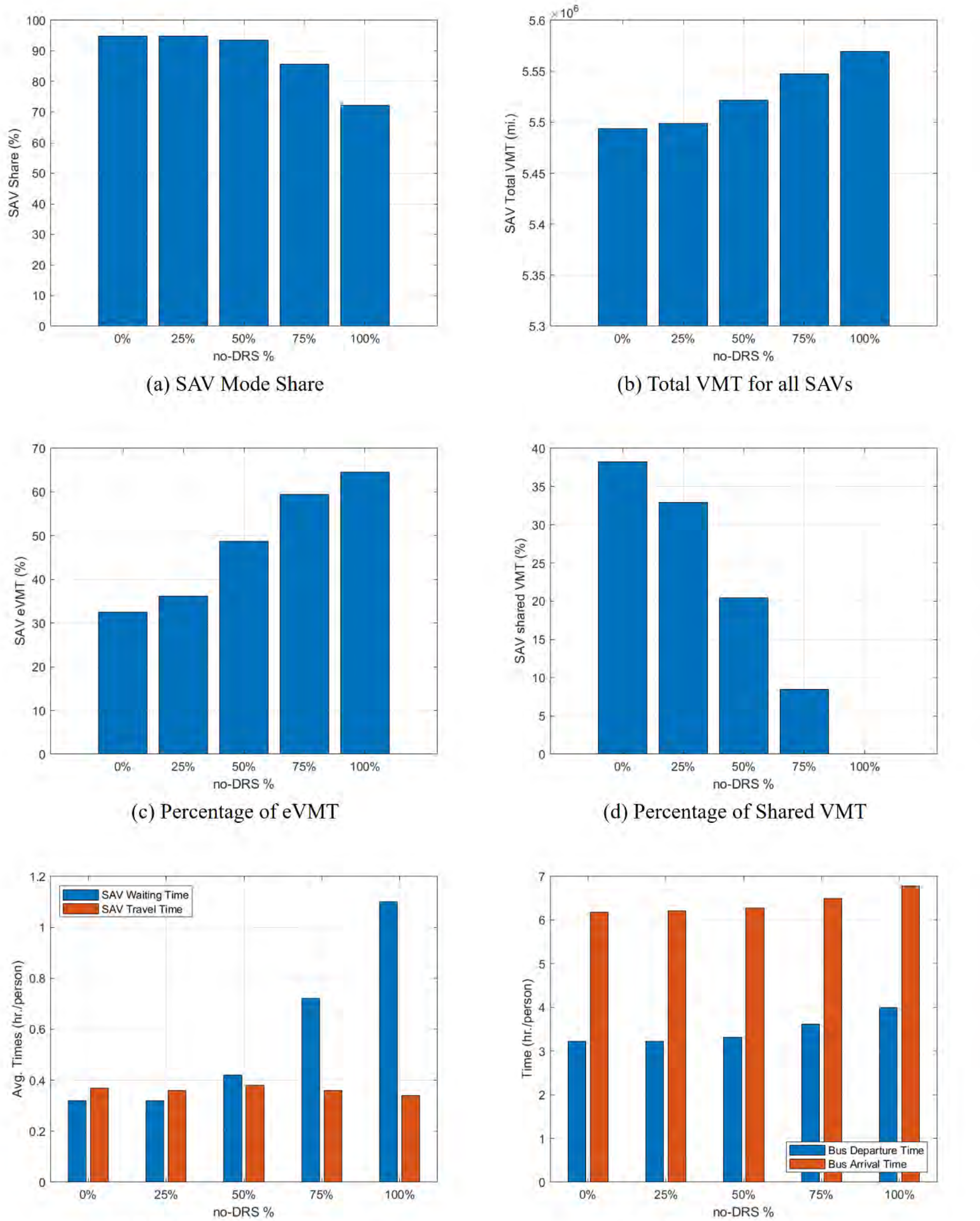
In the context of evacuation, remaining safely at home (awaiting an SAV) is considered a more favorable experience than traveling on the roads (riding in an SAV), if the bus departure and arrival times are comparable to the base case scenario. This is assuming that the disaster is not imminent. According to Table 4 , the average bus departure time with more than 800 SAVs is similar, with the worst-case scenario from all the scenarios showing a mere 7% increase (200 5-seat SAVs). The change in average bus arrival time is less than ±3%, suggesting that the overall evacuation performance would not vary significantly with the coordination strategy. Thus, bus coordination could be a viable option if evacuees are willing to adapt to the expected behavioral changes. However, a trade-off between extended SAV waiting times and reduced SAV travel times must still be considered when implementing coordination, which can be balanced with a substantial fleet of SAVs.

Sensitivity Analyses of Willingness-to-Share and Non-compliance Levels

The paragraphs above have primarily focused on systematic factors of SAV fleet operation including the number of SAVs, vehicle size, and rerouting strategy. Evacuee behavior, another critical factor, also influences the overall evacuation performance. This paper introduces two different evacuee behaviors: 1) willingness-to-share, and 2) compliance with the staged evacuation strategy. Evacuees might resist sharing their ride during an evacuation, preferring instead to travel directly to their destination. They might also choose not to adhere to the staged evacuation departure schedule proposed in this paper, opting to evacuate as soon as possible.

Figure 10 presents the SAV fleet operation with varying percentages of no-DRS agents during evacuation, with each agent randomly designated as a no-DRS agent or not. In this context, 0% no-DRS agents is considered the base case. Agents who refuse to share rides are assumed to have a maximum reroute time of zero. For all no-DRS scenarios, the SAV fleet is fixed to 600 5-seat SAVs with a maximum reroute time of 15 minutes for DRS agents. This is established as the cost-efficient base case scenario as determined by this paper. Figure 10a indicates that the SAV mode share (vs. walking) drops from 95% to 71% as the percentage of no-DRS agents increases from 0% to 100%. This suggests that refusal of DRS can limit an evacuee's chance to ride in an SAV, impacting the overall evacuation performance. This hypothesis is supported by Figure 10b and Figure 10c, which show longer total VMT and a higher eVMT rate with a larger percentage of no-DRS agents. The increase in both total VMT and eVMT implies an accompanying increase in empty SAV travel. As expected, Figure 10d shows a decline in the percentage of shared VMT per SAV as the number of no-DRS agents grows.

Figure 10e reveals an increase in SAV waiting time and a decrease in SAV travel time with an increasing percentage of no-DRS agents. This pattern of waiting time increase and travel time decrease is similar to the trend observed in the analyses of the bus coordination strategy. However, in contrast to the coordination scenario, Figure 10f demonstrates a significant increase in both average bus departure time and arrival time with respect to the percentage of no-DRS agents. Specifically, the departure time and arrival time rise by 24% and 10% respectively when the percentage of no-DRS agents grows from 0% to 100%. These results imply that while DRS does impact evacuation performance, its efficiency varies depending on the implementation.



(a) SAV Mode Share

(b) Total VMT for all SAVs

(c) Percentage of eVMT

(d) Percentage of Shared VMT

(e) SAV Wait and Travel Time

(f) Avg. Bus Dept. and Arr. Time

Figure 10. SAV Fleet Operation by the Percent of no-DRS Agents

Figure 11 shows the operation of the SAV fleet with varying levels of non-compliance during evacuation, wherein each agent is randomly determined to either follow or disregard the staged evacuation strategy. Should an agent opt not to adhere to the strategy, they will bypass the scheduled departure times and aim to evacuate within the initial fifth of the 6-hour window. The settings used for these non-compliance scenarios are consistent with those used previously: 600 5-seat SAVs with a maximum rerouting time of 15 minutes.

Figure 11a through Figure 11c present similar trends as seen in the no-DRS scenario regarding SAV mode share, total VMT, and eVMT rate. As the percentage of non-compliance agents rises, mode share declines, total VMT escalates, and the eVMT rate increases due to heightened evacuation demand. However, the increase in eVMT slows, while the shared VMT rate decreases (as shown in Figure 11d) when more than 50% of agents disregard the staged strategy.

Figure 11e shows both SAV waiting and travel times, which increase in response to higher levels of non-compliance. This is presumably due to exacerbated traffic congestion caused by the premature departure of agents in non-compliance scenarios. Figure 11f indicates that bus departure times decrease with higher levels of non-compliance, as evacuees depart earlier than in the base case. Yet, the arrival times show little variance, suggesting that longer bus travel times are necessitated by the resultant congestion. Unlike Figure 10, where an increase in no-DRS agents compromised evacuation performance, Figure 11f demonstrates that the bus arrival time in the 100% non-compliance scenario is comparable to the 0% base case, indicating that SAV DRS can somewhat handle non-compliant evacuations.

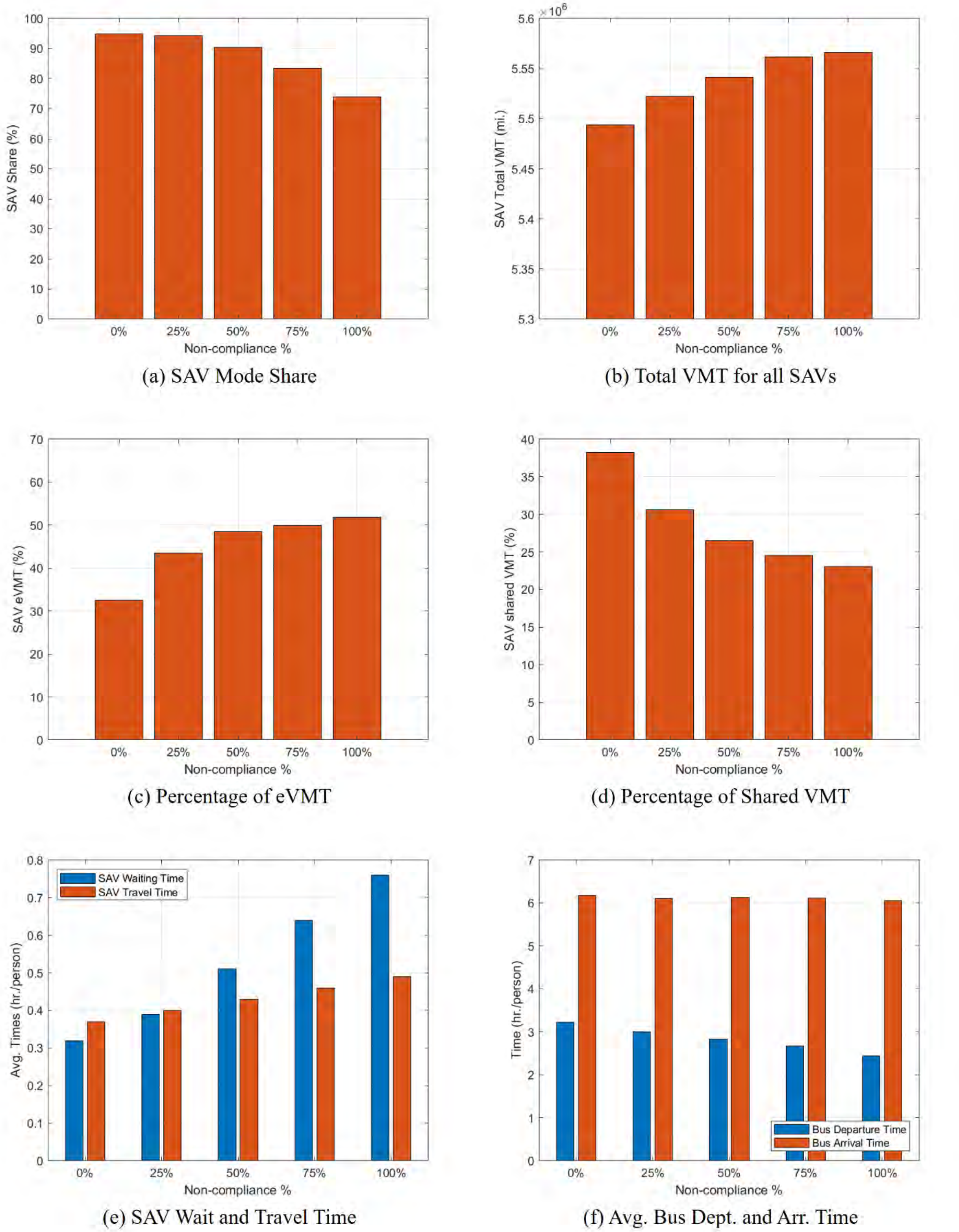


Figure 11. SAV Fleet Operation by the Percent of Non-compliance Agents

DISCUSSIONS AND LIMITATIONS

This paper provides valuable insights into the strategic deployment of SAVs to enhance evacuation efficiency in anticipation of natural disasters. Moreover, the rule-based DRS algorithm showcases the potential of real-time routing and ride-sharing to adapt to dynamic evacuation demands, enhancing the overall efficiency of the evacuation process.

Nonetheless, several limitations must be acknowledged as follows. The operational dynamics of SAVs, the behavioral responses of individuals to evacuation directives, and the evolving traffic conditions during an evacuation are modeled based on a series of assumptions. These assumptions are instrumental in structuring the simulation but might not encompass the multifaceted nature of disaster response, which is characterized by significant uncertainty and variability. Also, this paper's primary focus on pre-disaster evacuation conditions inherently limits its applicability to the immediate onset of a disaster. This temporal boundary excludes the post-disaster phase, which is often marked by chaotic environmental changes, infrastructural breakdowns, and unpredictable human behaviors, all of which are critical to understanding the full spectrum of evacuation dynamics. Moreover, the recommendations regarding the optimal fleet size and vehicle capacity are based on simulations under specific conditions. The generalizability of these recommendations to diverse geographic locations, disaster types, and urban layouts may be limited. Lastly, this paper assumes the availability and seamless operation of SAVs and DRS technology, which may not currently be widespread. The transition from theoretical models to practical application involves numerous logistical, regulatory, and societal hurdles that were not addressed in this study.

However, the insights and methodologies presented in this paper remain valuable for several reasons. Firstly, they provide a structured framework for evaluating the role of emerging technologies, such as SAVs and DRS systems, in pre-disaster response scenarios. This framework can serve as a foundation for future research, enabling more nuanced studies that can build upon and refine the initial assumptions made in this paper. Secondly, the simulation results, even within their specific context, offer a significant insight into how autonomous mobility solutions can potentially transform evacuation logistics, making them more adaptable and responsive to real-time conditions. Thirdly, by highlighting the limitations and potential areas for further exploration, this study underscores the importance of interdisciplinary collaboration in disaster management, bridging the gap between transportation engineering, urban planning, and emergency response strategies. Lastly, this paper's exploration of pre-disaster evacuation strategies contributes to the broader discourse on disaster preparedness, emphasizing the need for proactive planning and the integration of innovative mobility solutions in emergency management frameworks.

CONCLUSIONS

This paper pioneered the exploration of utilizing an SAV fleet, employing dynamic ride-sharing (DRS), to facilitate the first-mile connection of evacuations for those without personal vehicles. Bus station locations were determined based on accessibility measures, ensuring the most convenient locations were selected for evacuees. These special evacuation buses operated under fixed and demand-responsive mechanisms, reacting dynamically to changing evacuation needs. A variety of SAVs with different seating capacities, along with six varying fleet sizes, constituted 18 unique SAV scenarios simulated to evaluate the influence of diverse fleet specifications on evacuation performance. Beyond fleet variations, SAV-bus coordination strategies were also examined.

Simulation outcomes suggest that with more SAVs in the network, waiting times reduce due to increased vehicle availability, but travel times increase due to extended rerouting times for ride-sharing. The number of seats had a lesser impact than fleet size on waiting and travel times, but larger seating capacity encouraged DRS, as seen in the analysis of occupancy configuration and shared VMT percentage. A combination of larger fleet sizes and increased seats per SAV enhanced evacuation performance. However, the non-idle time share analysis indicates a decline in cost-efficiency with larger fleets and more seats per SAV; therefore, a fleet size of 1 SAV per 14 people with 5-seat vehicles is proposed.

Evacuation buses can operate with a flexible or demand-responsive schedule, offering shorter time headways during high evacuation demand and longer headways when demand subsides. Coordination strategies synchronize SAVs' DRS option with the bus departure schedule, restricting DRS during shorter bus headways to expedite passenger transportation during high demand situations and promoting DRS during longer headways when demand is lower. Results from the coordination scenario reveal that with more than 800 SAVs in the network (1 SAV per 10 people), SAV waiting times increase while travel times decrease. As bus departure and arrival times in the coordination scenario did not differ significantly from the uncoordinated scenario, coordination emerges as a viable evacuation strategy, allowing evacuees to wait for an SAV at home for a longer duration. However, smaller SAV fleet sizes did not demonstrate improvements in evacuation performance with the coordination strategy.

In addition to fleet operation analyses, evacuees' behavioral shifts, specifically their willingness to share and their compliance with the staged strategy, were evaluated. As more agents were unwilling to share rides, SAV waiting times extended, culminating in a poorer evacuation performance compared to the base case. However, the bus arrival time in the 100% non-compliance scenario was not significantly different from the 0% base case, indicating that SAV DRS can accommodate evacuees' non-compliance.

In conclusion, this paper asserts that SAV fleets present a viable alternative mode of transportation for evacuating populations without access to private vehicles. However, the application of SAVs in this study was limited to the first-mile connection from evacuees' homes to bus stations. Further improvements in SAV fleet operation techniques—including smart repositioning, optimal DRS matching, enhanced path finding algorithms, and a greater market penetration of SAVs—are likely to enable more efficient evacuations in the future.

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