SHARED AUTONOMOUS VEHICLES FOR EFFICIENT EVACUATION OF VULNERABLE POPULATIONS

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Word Count: 10,519 words

Under review for publication in *Transportation Research Part C: Emerging Technologies*.

ABSTRACT

This paper demonstrated the first-mile connection of a shared autonomous vehicle (SAV) fleet using dynamic ride-sharing (DRS) to a special evacuation bus targeted to evacuate the no-vehicles-available population. The bus is operated in both fixed and demand responsive manners to dynamically respond to the changing evacuation demand. Three scenarios for the number of seats per SAV, six different fleet sizes, and two different rerouting strategies are simulated. The simulation results suggest that large fleet size results in shorter SAV waiting time since more SAVs become available to the agents, but increased SAV travel time due to more time spent on rerouting for ride-sharing. The number of seats did not have as much impact as the fleet size on waiting and travel times, but having more seats promoted DRS with higher SAV occupancy and percentage of shared vehicle-miles traveled (VMT). Nonetheless, the non-idle time share analysis suggests that the cost-efficiency becomes low with a large fleet and more seats per SAV, so 5-seat vehicles are recommended, with 1 SAV per 14 people. The bus coordination strategy coordinates the SAVs' DRS option with the departure schedule of the bus, so DRS is restricted with shorter bus headways to speed up the transportation of passengers in high-demand situations and DRS is promoted with longer bus headways in low-demand situations. The coordination scenario's result shows that when more than 800 SAVs are in the network (1 SAV per 10 people) the SAV waiting time rises, while SAV travel time falls. Since the bus departure and bus arrival did not show significant difference between coordination and uncoordinated scenarios, coordination can be an effective evacuation strategy in which evacuees will stay at home longer while waiting for an SAV. Nonetheless, a smaller SAV fleet size did not show evacuation performance improvements with the coordination strategy. The evacuees' behavioral change of willingness-to-share and panic departure shows that when more agents are not willing to share their ride with others, SAV waiting time increased and poor evacuation performance was observed. However, the bus arrival time of 100% panic is not much different to the 0% panic base case, implying that SAV DRS can manage evacuees' panic at certain level.

KEYWORDS

Shared Autonomous Vehicle; Dynamic Ride-sharing; Evacuation; Vehicle Ownership; First-mile

Connection

BACKGROUND

Hurricanes are one of the costliest and deadliest natural disasters in the United States. Hurricane Katrina caused $125 billion in property damages (2005 USD) and 1,836 deaths in 2005 (Knabb et al., 2005), and Hurricane Harvey caused $125 billion in property damages (2017 USD) and was responsible for 68 deaths of Texas residents in 2017 (Blake & Zelinsky, 2018). Increase in greenhouse gasses, global warming, and climate change have contributed to increasing ocean's temperature and may induce more frequent landfall of major hurricanes (Levin & Murakami, 2019), which can cause more severe damages. Hurricanes are categorized by the Saffir-Simpson Hurricane Wind Scale from 1 to 5 determined by the hurricane's sustained surface wind speed, where Category 5 is the most catastrophic (National Hurricane Center and Central Pacific Hurricane Center, 2021). Although Category 1 and 2 hurricanes are still dangerous, Category 3 and higher storms are considered major hurricanes, and evacuation should always be considered during the landfall of such storms.

Privately-owned vehicles are the most preferred method of transportation during an evacuation (Yin et al., 2014), but evacuees having no privately-owned vehicles, or having an insufficient number of private vehicles to evacuate every household member must rely on non-household transportation modes to evacuate. In this paper, shared self-driving or autonomous vehicles (SAVs) are considered one of the non-household transportation modes to evacuate the population that does not own a private vehicle, or has an insufficient number of vehicles to evacuate every household member. These evacuees will be defined as the no-vehicles-available population hereafter. This paper focuses on an evacuation from Houston, Texas, and about 4% of the evacuees in this region are estimated to be part of the no-vehicles-available population. Shared mobility, regardless of self-driving or human-driven, has been considered as a potential mode to be used to evacuate people during disasters. Shared mobility helps to achieve more efficient evacuation by reducing the number of small trips (e.g., to pick-up family members), and reporting the locations of vulnerable evacuees to emergency management agencies efficiently via communication devices (Li et al., 2018). As the reduction in vehicle ownership is significantly associated with the increase in frequency and probability to use ride-sharing services (Zhang & Zhang, 2018), the no-vehicles-available population studied in this paper would already be comfortable with using the shared mobility system during their evacuation.

An SAV system, which adds vehicle autonomy to shared mobility, is more promising than traditional shared mobility to facilitate the evacuation process with its self-driving features. SAVs are more cost-effective as they reduce labor costs by eliminating the need for a human driver (Shen et al., 2018). This is especially effective for evacuation purposes because a human driver is not put at risk during a disaster. The seat that would have been occupied by a driver in a traditional shared mobility system can instead be used to transport an evacuee. Persons with a disability or without a driver's license will have increased mobility opportunities (Kröger et al., 2019) to fulfill their evacuation. SAVs' high performance computing power, sensing equipment, and communication devices can contribute to fast 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. The application of autonomous vehicle (AV) technology to evacuation problems is mainly conducted via computer simulations since AV technique is immature and evacuations are rare. AV technology can be combined with reservation-based intersection control techniques or public transit signal prioritization policies to increase travel speed while relieving safety concerns during a hurricane evacuation (Chang & Edara, 2018). When combined with strategic departure time scheduling, AV evacuation can lower the evacuation cost, network clearance time, and derive less uncertainties to the evacuation (Lee & Kockelman, 2021).

However, an SAV system may not always be the most desirable when it cannot satisfy high trip demand, has excessively long user wait time, and results in increased empty driving. The user must call an SAV to start their trip, thereby the SAV system is demand-responsive, and more SAVs will be required to serve higher demand, although dynamic ride-sharing (DRS) can manage the demand to some extent (Fagnant & Kockelman, 2018). Nonetheless, employing a larger SAV fleet size to meet the high demand will increase roadway density and may contribute to an increase in traffic congestion. When other conditions are fixed, a larger SAV fleet size will be needed to achieve shorter user wait time (Wang et al., 2019), implying that fleet size is a key variable in the SAV system's performance. Empty driving, defined as the state when a vehicle is driving without any rider, may increase congestion if the empty vehicle-miles traveled (eVMT) increases (Levin et al., 2019). As evacuation trips tend to be long-distance trips to find a safe place to stay (Bian et al., 2019; DeYoung et al., 2018; Do, 2019), increasing eVMT may lower the performance of SAV operation. In evacuation cases, an asymmetric traffic pattern with only a few destinations (e.g., endpoints) from widespread origins (e.g., evacuees' home locations) may weaken the SAV performance with greater eVMT and SAV waiting time caused by the SAV traveling a long-distance back-and-forth.

In this sense, a special evacuation bus operation combined with SAV fleet operation is proposed in this paper to evacuate the no-vehicles-available population in a symmetric traffic pattern. A special evacuation bus is a bus line that is not operated regularly and transports the evacuees to a destination that will be temporarily operated during the evacuation (e.g., public shelter), and it has been identified as one of the favorable non-household transportation mode for evacuees (Sadri et al., 2014). The first-mile connection of the no-vehicles-available population from their origin to the special evacuation bus is still required, which can be achieved by the SAV fleet operation or by walking if the distance is short enough. With this strategy, the geographical fence of SAV operation will be limited to the areas where the evacuation is ongoing, and eVMT can be minimized. Unlike the no-vehicles-available population, those having sufficient household vehicles will use their own vehicle to evacuate from their origin to final destination. Thus, this paper presents a holistic multimodal approach to facilitate timely and efficient evacuation.

TRANSPORTATION NETWORK AND FLOW ASSUMPTIONS

This section describes Houston, Texas' transportation network and likely evacuation demands by neighborhood. All evacuees are assumed to head to the endpoint that is located close to their origin. Each household is modeled as a single agent, with all members evacuating together, in a privately owned vehicle (if they have one). Agents who do not own any private vehicles are assumed to walk or ride in an SAV to the closest designated stations to evacuate with (conventional) buses to designated endpoints.

Transportation Network

Houston's roadway network has 36,124 links across 5,217 traffic analysis zones (TAZs). Roughly 20 percent (1,035) of these TAZs are likely to be threatened by hurricane landfall (categories 1 through 5). These TAZs are classified as hurricane risk zone 1 to 5 by the Texas Natural Resources Information Service (Texas Natural Resources Information Service (TNRIS), 2004), where hurricane risk zone 1 is threatened by any category hurricane, so these are the most vulnerable zones to be in. Risk zone 5 is threatened only by Category 5 hurricane, which is the strongest hurricane among the 5 categories. Sections of Brazoria, Chambers, Galveston, Harris, and Liberty counties are included in these 1 through 5 hurricane risk zones, and about 895,000 residents (12.4%) of Houston's population of 7.2 million is generally asked to evacuate (in a Category 5 storm). Persons living outside these TAZs are assumed to stay in place and not evacuate, but will still load the traffic network, at about 50% of daily weekday volumes (across 4 distinct times of day). The simulation uses 30 minutes of warm start (from 5:30 to 6 am) to fill in the empty network with this background traffic. Due to the computational limits, only 20% of the population, regardless of whether they are evacuating or not, will be sampled for the simulation. This paper does not assume an imminent or no-notice disaster but assumes that a few more days are left until the hurricane makes landfall. Figure 1 shows the network used, with at-risk TAZs in yellow to red colors and the suggested evacuation route defined by the local metropolitan planning organization (MPO).

Accessibility measure (A_i) is used to determine the evacuation-bus station locations. This access measure is simply the number of estimated persons reachable with a given distance, time, or travel cost. This paper assumes that given a TAZ's population data, the population of a link within that TAZ is proportional to the percentage of its centerline length. This method allows for the selection of the bus station that is most accessible among other locations, which enhances the efficiency of the evacuation. Eq. (1) describes the calculation of accessibility measure used in this paper with the value of the parameter (-0.054) obtained from (Papa, 2020). For each county, the link that has the maximum A_i is chosen as the location of the special evacuation bus station for that county. For Galveston County, 2 stations are chosen, one for the inland area and the other for Galveston Island since the bridge connecting the inland and island is a major bottleneck that hinders the residents from the island when trying to reach the station located in the inland area. Figure 1 shows the location of the six bus stations, five for each county and one additional bus station for Galveston Island.

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

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

Evacuation Demand

Based on the TAZ's population, the agent's origin, which is the home location of the evacuating household, is randomly chosen as a link within that TAZ. The evacuation destination is assumed to be one of the 8 endpoints in the transportation network. The exit point with shorter free-flow travel time is more likely to be chosen using Eq. (2). As agents tend to choose the destination closest to their origin, this paper assumes that the agent would evacuate to the destination that has the shortest travel time from the origin under free-flow traffic conditions. Once the agent arrives at the destination, this paper assumes that the evacuation is completed, and further activities are not tracked. Figure 1 shows the location of the eight destinations assumed in this paper.

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

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

To minimize the number of bus lines, some destinations are aggregated if they are located close together. In this case, the bus travels to the destination closest to the station first, unloads agents whose destination is at that location, and travels to the next closest destination to unload the remaining agents onboard. Figure 1 shows the destination aggregation results making up five different bus destinations for the special evacuation bus. All six bus stations operate bus lines for the five aggregated bus destinations, making up a total of 30 different bus lines in the network.

The evacuation is achieved at the household level in this paper, so the basic unit of the agent is in household. For each household, all members in that household evacuate together as a single agent. The number of households per TAZ for model year 2019 is obtained from the local MPO (Houston-Galveston Area Council (H-GAC), 2018), and the number of households with respect to the number of household members for each county are obtained from US Census Bureau (US Census Bureau, 2019b). The number of vehicles owned by each household with respect to its household size (number of household members) is obtained at the county level (US Census Bureau, 2019a). The number of household members and vehicles owned by each household in a TAZ is generated by randomly sampling the values from the dataset. This paper assumes that each household member weighs 150 lbs. and carries 50 lbs. of luggage that occupies 1/3 seat (e.g., for a household with 3 members, one seat would be occupied just by luggage, requiring a total of 4 seats). From this sampling approach, households having no privately-owned vehicles at all can be identified. Assuming a privately-owned vehicle has 5 seats, the number of household members left behind due to the household owning an insufficient number of vehicles to transport every member of the household can be identified as well. These two groups comprise the no-vehicles-available agents (4% of the evacuees), who should evacuate using the special evacuation bus.

The departure time of agents is assumed to follow a staged random distribution within the 6-hour duration from 6 AM to 12 PM on a typical weekday. The agents from the TAZs that are the closest to the coastline, categorized as hurricane risk zone 1, will depart from the origin at a random time within the first fifth of the 6-hour duration. The agents from the TAZs that are the second closest to the coastline, categorized as hurricane risk zone 2, will depart at a random time within the second fifth of the 6-hour duration. According to this rule, the agents in hurricane risk zone 5 will evacuate at a random time within the 6-hour duration. This departure time assumption applies to every agent in the corresponding risk zone regardless of mode (HV, SAV, or walk). If the agent uses an HV or walks to the bus station, they will depart from the origin immediately at the designated departure time, but if the agent uses an SAV, they will call for an SAV ride to the closest bus station at the designated departure time and wait until the SAV picks them up.

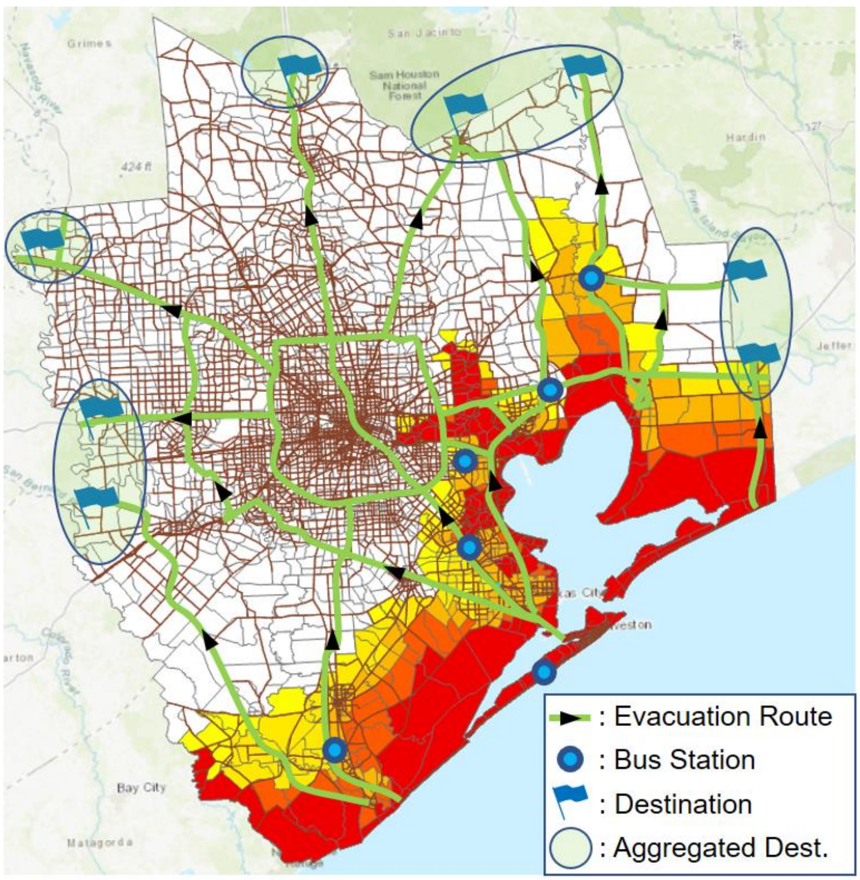


Figure 1. Evacuation Map of Houston, TX

METHODOLOGIES

This section describes 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. Due to the difficulties in demonstrating evacuation traffic in real-world scenario, a computer simulation via SUMO will be used with various dynamic ride-sharing options, SAV sizes, and fleet operations to facilitate SAVs. Due to the computational limits, only 20% of the population, regardless of whether they are evacuating or not, will be sampled for the simulation.

Traffic Simulation

SUMO is an open source traffic simulation package designed to handle large networks (Lopez et al., 2018). The time unit of the simulation is in seconds, and SUMO can track each vehicle's movement separately second-by-second, which will be used to extract specifications including average vehicle occupancy, travel time, and SAV waiting time. After 30 minutes of warm start to fill in the empty network, the evacuation departure will start at 6 AM on a typical weekday. The simulation will be terminated once all the agents arrive at their final destination. Four different transportation modes exist in the simulation including privately-owned human-driven vehicles (HVs), special evacuation bus, SAVs, and walk. The route of all vehicles in the network, except the background traffic, will be rerouted every 10 minutes to adapt to the traffic conditions and changes in the network.

Among these transportation modes, HV and special evacuation bus are the two major modes to evacuate, meanwhile the special evacuation bus can be accessed by SAV or by walking. The agents with sufficient HVs will evacuate directly from their origin to their destination by driving their HV manually. An SAV fleet will transport the no-vehicles-available population from their home location to the bus station, where the agents can transfer from SAV to the bus and evacuate to their final destination. No-vehicles-available agents will have the option to choose between SAV and walk based on the time needed to complete the travel, where mode choice is determined by Eq. (3) using the travel cost of the two modes. This paper assumes \$15/hr. for the value of travel time (VOTT), while the costs of walk time and SAV waiting time are assumed to be twice the in-vehicle travel time in an SAV. For the walk mode, 1.2 m/s (3.94 ft/s) is assumed for the walking speed following the shortest travel route.

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

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

The special evacuation bus will be operated on a fixed time schedule, but also in a demand-responsive manner. Every bus will depart when one of the following two options is achieved first: 1) 30 minutes after the last bus departure that belongs to the same bus line (fixed time schedule), or 2) whenever the bus has reached capacity (demand-responsive). The agent arriving at the bus station will sit and wait on the bus he/she should ride until the bus departs. All buses are assumed to have 37 seats for agents and 1 seat for a human driver.

A fixed-size SAV fleet that does not change during the simulation will be operated to support the no-vehicles-available population in reaching the closest bus station. In the beginning of the simulation, SAVs will be randomly distributed across the hurricane risk zones to serve travel from origins to the bus station. Three different sizes of SAVs are assumed, namely sedans with 5 seats, 3rd-row sports-utility vehicles (SUVs) with 7 seats, and vans with 12 seats. DRS can be implemented with various sharing options, so that the agents can share their ride with strangers if the sharing conditions are satisfied. Table 1 shows the specifications of the vehicles used in this paper with the values defined as SUMO default value except the number of seats is modified to demonstrate driverless SAVs and evacuation bus operations. The main difference between HVs and the various types of SAVs is in the number of seats available and the existence of a driver, but the vehicles' specifications (e.g., acceleration) do not show difference to focus the analysis on shared mobility and self-driving features.

Table 1. 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)	4.3 m	4.3	4.3	4.7	12.0
Width (m)	1.8 m	1.8	1.8	1.9	2.5
Height (m)	1.5 m	1.5	1.5	1.73	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)				
Lane Change Model	LC2013 (SUMO Default)				

Shared Autonomous Vehicle with Dynamic Ride-sharing

With the DRS option, agents can share their trips with strangers when they are traveling in an SAV. This paper suggests a rule-based DRS algorithm. The trips of different agents can be shared when all agents' travel characteristics satisfy the DRS rules, who are scheduled for a pick-up or drop-off in an SAV, already riding in an SAV or requesting a new SAV ride. SAVs have two different states: 'idle' and 'drive'. Idle is the default state of an SAV, when it does not have any trips assigned for pick-up or drop-off. In this case, the SAV stops at the position where it is located and waits there until a new travel request is received. Drive is the state when an SAV is moving to a different location, and it can be empty-driving or non-empty driving with at least 1 agent onboard. Empty driving is when the SAV is moving without any passenger onboard thanks to its self-driving feature. Non-empty driving can be further categorized as solo driving and shared driving. Solo driving is when only 1 agent (with its household members) is onboard, and shared driving is when 2 or more agents are onboard.

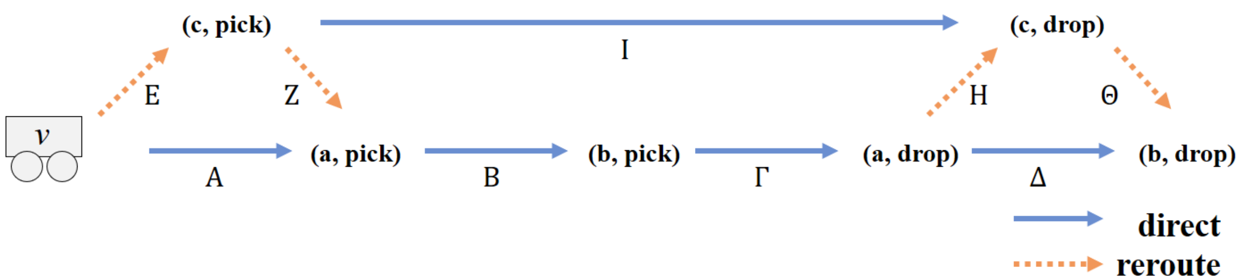
For a given SAV, v, the agent who is calling for a new SAV pick-up ride at its designated departure time is defined as p, and the agents scheduled for a pick-up and drop-off or already onboard the SAV v are defined as v_r. The SAV v should have sufficient seats left at the time when the agent p requests a pick-up to be a feasible SAV for checking DRS conditions. For the agent v_r, the direct arrival time at its SAV destination (bus station) following the current trip schedule of SAV v is defined as $D_{(v_r)}$. For the agent p, the direct arrival time at its bus station, assuming that p departs instantly after an empty SAV picks him/her, 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 $R_{(k)}$.

The SAVs are rank-ordered by the number of trips they are currently assigned, so the SAVs with fewer trip assignments are searched before the SAVs that have more trip assignments. Next, an SAV currently located in the same county as the agent will have priority to serve the trip. Due to the computational limits, 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 under any restrictions. With the variables above, Eq. (4) should be satisfied for the agent p and SAV v to be matched using DRS service. The maximum reroute-time, RT, is the variable that determines whether a new pick-up call 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 depicts how the DRS algorithm described above is implemented with a pseudo-code, where the SAV already has two agents, agents a and b, scheduled for pick-up and drop-off and it is trying to consider a new pick-up call from agent c. The Greek letters in this figure represent the travel time between the two locations. The pick-up order of the new agent, (c, pick), is always fixed to the first place due to computational limits, while its drop-off order, (c, drop), can be at any place that satisfies Eq. (4). This paper does not attempt to optimize the DRS service by finding the optimal agent, SAV, and trip assignment combination out of all possible options. If any combination of agent p and SAV v searched first under the prioritization rule satisfies the DRS rule, they are matched together. If no SAV can be matched for the agent p, this agent is appended to a set named 'unassignedAgents'. The unassignedAgents set rank-orders the agents by initial SAV call time and prioritizes the agent having the earliest initial SAV call time. Their SAV DRS match will be searched every 10 minutes, or whenever an idling SAV appears that has no trips scheduled.



if:
$(\mathrm{E} + \mathrm{Z} + \mathrm{B} + \Gamma) - (\mathrm{A} + \mathrm{B} + \Gamma) \leq RT$ (agent a)
$(\mathrm{E} + \mathrm{Z} + \mathrm{B} + \Gamma + \mathrm{H} + \Theta) - (\mathrm{A} + \mathrm{B} + \Gamma + \Delta) \leq RT$ (agent b)
$(\mathrm{Z} + \mathrm{B} + \Gamma + \mathrm{H}) - (\mathrm{I}) \leq RT$ (agent c)

then:
update SAV v's trip assignment:
from (a, pick) - (b, pick) - (a, drop) - (b, drop)
to (c, pick) - (a, pick) - (b, pick) - (a, drop) - (c, drop) - (b, drop)

Figure 2. DRS Example

The maximum reroute-time, RT, is the variable that determines the DRS performance, so a strategic assignment can be expected when this variable is coordinated with the variables that govern the evacuation performance thanks to the communication devices of SAVs. This paper suggests a method of coordinating the maximum reroute-time with the departure time headway of the special evacuation bus and the expected time an agent would arrive at the bus station, so that a dynamic reroute-time can be implemented. Whether the agent has arrived at the bus station early or not, he/she has to wait at the bus station until the bus departs. If this time can be used for the SAV to pick additional agents, while ensuring that the agents would not miss the bus, more agents may be served by SAVs to improve the evacuation performance. However, if the expected time difference for an onboard agent's arrival to the station and the departure of bus is short, the SAV would prioritize delivering the onboard agent directly to the station rather than rerouting to pick-up additional agents.

A comparable coordination method is suggested by (Huang et al., 2021) where the SAV maximum reroute-time and train's departure time headway are coordinated, but it is targeted for ordinary travel situations with a fixed time headway of the train. In this paper, the departure time headway of the special evacuation bus changes depending on the evacuation demand, since it will depart in a demand-responsive manner whenever the bus is full, or every 30 minutes. Thus, the maximum reroute-time will be dynamic and demand-responsive depending on the agent, the bus line to be used, and the time when the agent makes its SAV call by changing Eq. (4) to Eq. (5).

When the evacuation demand is low, the bus is likely to operate on a relatively longer time schedule including the 30 minutes of fixed time schedule, so an SAV may serve more DRS trips with a longer maximum reroute-time. If the evacuation demand is high, the bus is likely to operate on a relatively shorter time schedule, so SAVs should focus on transporting the agents already onboard and withhold excessive DRS service. As each agent's bus schedule differs by the time and the location of bus station and destination, every agent k, whether onboard or requesting a new SAV ride, should satisfy Eq. (5) for a new SAV ride being matched.

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

s.t.

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

where, $RT^{ijt}_{(k)}$= 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, $RT^{ijt}_{(k)}$, assumes that the departure time headway of the bus an agent k will use, would not change, and will remain the same until the agent arrives at the bus station. This bus headway value can be the demand-responsive value, which is shorter than the 30-minute fixed schedule, or the 30-minute fixed schedule due to low bus demand. Under this assumption, the expected departure time of the next available bus that agent k should ride can be estimated. Agent k's expected arrival time at that bus station is estimated with the trip schedule of the SAV v this agent is onboard (e.g., agents a and b from Figure 2) or from a new SAV's trip schedule he/she is requesting for a new ride (e.g., agent c from Figure 2). The difference between agent k's expected departure time of the bus and the expected arrival time at the station is the maximum reroute-time that agent k can allow for rerouting. Since it is not clear whether the bus will be operated in fixed schedule or in demand-responsive manner, the minimum of the two rerouting times derived from 1) 30-minute fixed headway and 2) demand-responsive headway is assumed to be the time the agent k can use for rerouting. This is the amount of time that agent k will spend on the bus before it departs, the time that could instead be used for the SAV to pick-up another agent with DRS. To ensure that the agent will not miss their bus, a safety buffer of 25% is assumed, so that only 75% of the calculated bus departure time – agent arrival time difference can be used for rerouting. Thus, the maximum reroute-time, $RT^{ijt}_{(k)}$, changes dynamically by agents, bus lines, and SAVs. Figure 3 shows the concept of SAV rerouting coordinated with bus schedule proposed in this paper, and Algorithm 1 shows the pseudo-code of the SAV DRS method including the bus coordination strategy.

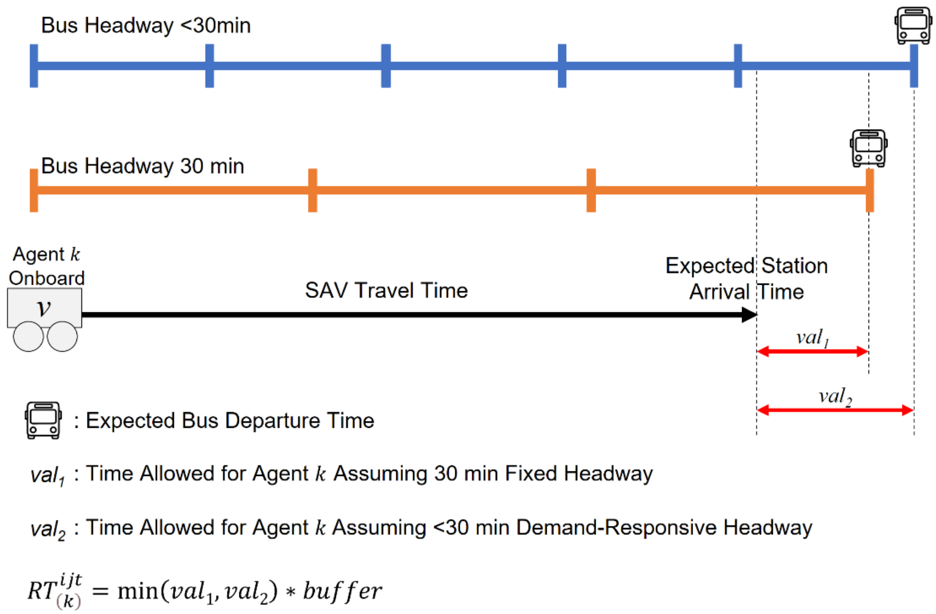


Figure 3. SAV Rerouting Coordinated with Bus Schedule

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 ∪ $\{p\}$

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

Scenario analyses performed in this paper include scenarios of different SAV fleet sizes, evacuee behavior, and panic levels. As this paper proposes 3 different types of SAVs that differ by number of seats available, different SAV specifications will be included in the scenario analyses. The coordination strategy of dynamic maximum reroute-time depending on the departure time of the special evacuation bus will be included in the end to evaluate a more strategic application of SAV fleet operation.

The evacuee behavior scenario analyses will evaluate the impact of agents' willingness to share their rides during evacuation. As the default sharing behavior is every agent being willing to share their ride in an SAV with a given maximum reroute-time, scenario analyses will add agents who are not willing to share their rides at all. In this case, their maximum reroute-time will be set to 0, so no ride-sharing will be implemented for them.

For the evacuees' panic level analysis, the departure time scenarios will be modified to incorporate different panic levels of agents. The default departure time distribution follows a staged random distribution based on the agent's hurricane risk zone. This assumption will be relaxed by inducing a certain portion of agents to be in panic. If the agent is in panic, he/she is assumed to depart at a random time within the first fifth of the 6-hour departure time duration regardless of his/her hurricane risk zone. With different departure time distributions, the proposed evacuation method's performance on a moderate to severe panic level will be evaluated.

To summarize the proposed method, the agents are moving in household level, and they will use their HV if it is available. If no HV is available, the agents can choose between Walk-bus or SAV-bus based on the expected travel cost from their home to the bus station. The bus departs from the bus station every 30 minutes or whenever it is full. Algorithm 2 is the pseudo-code to summarize the evacuation method proposed in this paper.

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 analyzes the simulation results of operating SAVs as the first-mile mode of transportation to evacuate the no-vehicles-available population with evacuation buses. Various SAV specifications, sizes, and evacuation scenarios are simulated to evaluate the sensitivity of SAV technology on evacuation performances. Each scenario is simulated 10 times and the average value is presented.

Sensitivity Analyses of Various SAV Fleets

All simulations performed for the sensitivity analyses of various SAV fleets assume the staged random departure time distribution described earlier in this paper, so that agents from hurricane risk zone 1 are more likely to depart earlier than agents from hurricane risk zone 5. However, each SAV fleet scenario has a different fleet size and number of seats per SAV. 6 different SAV fleet sizes are simulated including a small fleet size (200, 400 SAVs), medium fleet size (600, 800 SAVs), and large fleet size (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. 3 different vehicle sizes are simulated with 5-seat, 7-seat, and 12-seat SAVs. Therefore, a total of 18 different SAV fleet scenarios are simulated by the combination of SAV fleet size and number of seats per SAV. For the 18 SAV fleet scenarios, 2 different maximum reroute-times are tested, where the maximum reroute-time is fixed to 15-minutes for all agents ($RT = 15min$) or a dynamic maximum reroute-time with bus coordination ($RT_{(k)}^{ijt}$) strategy is applied. If not specified, all simulation results are based on the 15-minute maximum reroute-time assumption. The combination of 18 fleet scenarios and 2 reroute-time scenarios results in a total of 36 different SAV scenarios, and each scenario is simulated 10 times to present its average value. A microscopic SUMO simulation is performed to operate the SAV fleet and track each agent's evacuation.

Figure 4 shows the SAV mode share of the no-vehicles-available agents (4% of the total evacuees), who can choose between SAV and walk modes for the first-mile connection to the bus station. The SAV share increases when the SAV fleet size is large and when more seats are 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 does not change much after more than 600 SAVs are in the network, suggesting that an excessively large fleet would be not required. This is presumably because of the inefficiency of SAV operation, where some SAVs are idling and not serving the pick-up and drop-off requests efficiently in large fleet size scenarios, which will be analyzed in the later part of this section.

More seats result in higher SAV mode share in all scenarios. However, when the fleet size is small, the agents would not have greater opportunity to ride in an SAV, so the advantage of a large vehicle with more seats cannot be expected as in other larger fleet size scenarios. Nonetheless, the difference in mode share between 12-seat SAVs and other smaller SAVs decreases with respect to an increase in fleet size. If more seats are available in an SAV, it can take more evacuees onboard and has a higher opportunity to serve DRS trips than SAVs with fewer seats available, so the SAV mode share is larger with respect to an increase in the capacity of the SAV. However, the advantage of having more seats diminishes with larger fleet size as the SAV becomes more accessible to the agents.

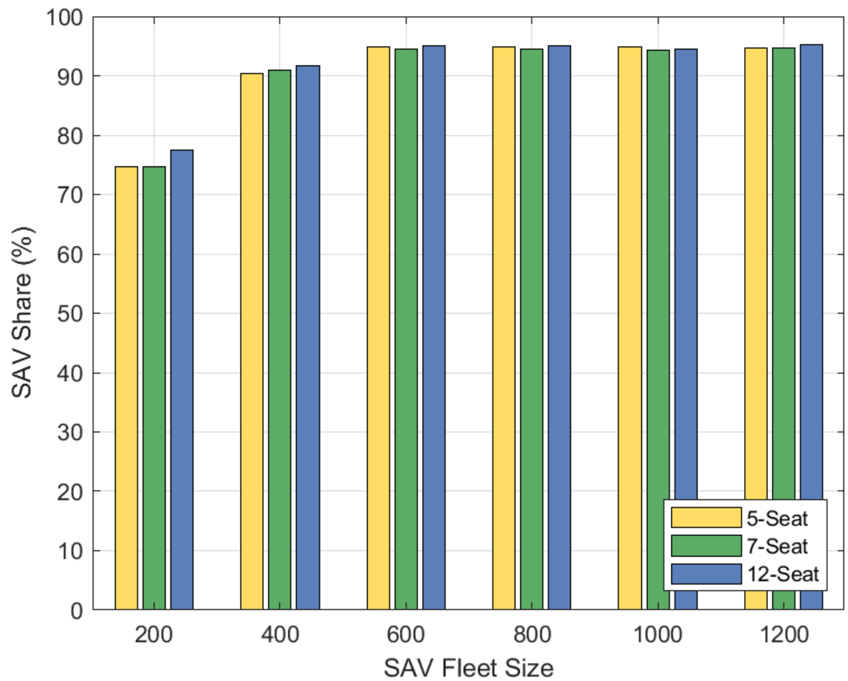
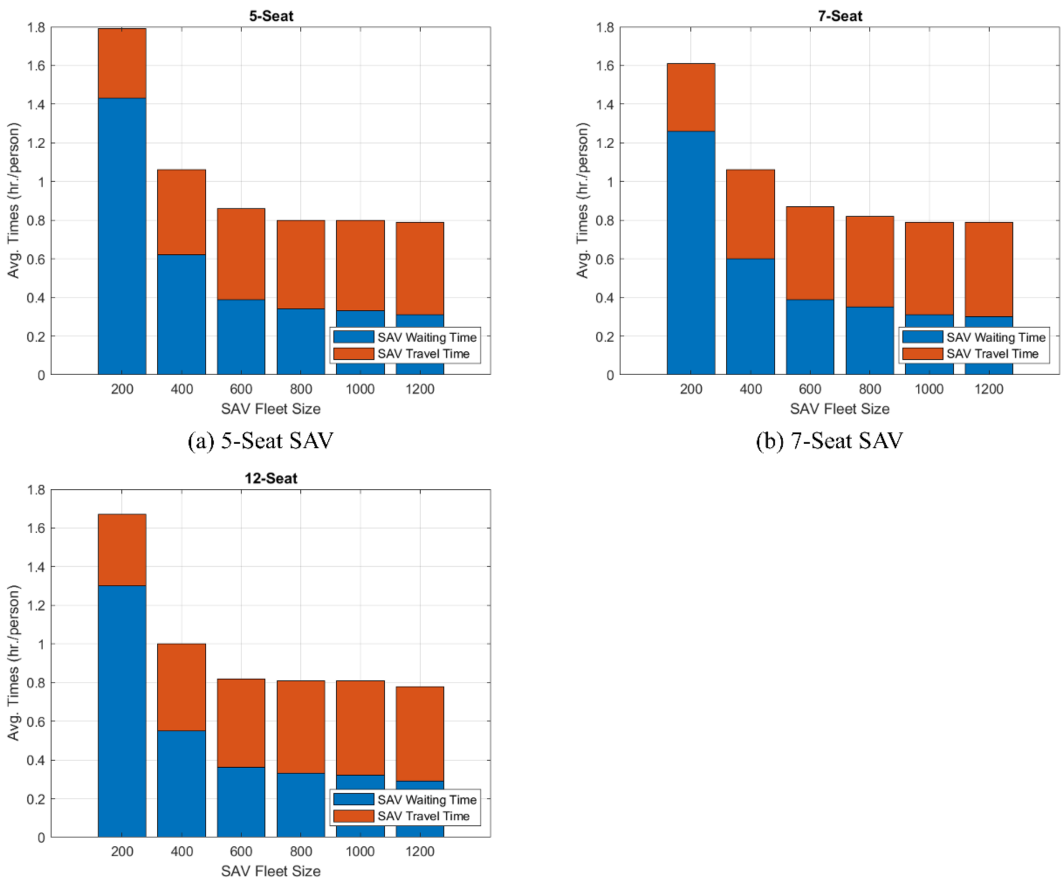


Figure 4. Mode Share of SAVs by SAV Scenario

Figure 5 shows the times spent per person waiting an SAV and traveling in an SAV. For the fleet size scenarios, the major contributing factor to reduce the total travel time is the decrease in SAV waiting time. The SAV waiting time decreases with more SAVs available in the fleet, but this impact diminishes when more than 600 SAVs are in the network. As the mode-share-increase also diminished after more than 600 SAVs are available, the change in mode share would have been caused mainly by the change in SAV waiting time. As more SAVs become available, agents have more opportunities to ride in an SAV, which reduced the waiting time. However, the SAV travel time increases with more SAVs available in the fleet. This is presumably due to the time spent for rerouting to achieve DRS increases with larger fleet size. Nonetheless, even though the SAV travel time increases with larger fleet size, the decrease of SAV waiting time offset this increase and results in reduced total time spent in an SAV. The impact of the number of seats is not expected to be as large as the impact of the fleet size on changes in SAV waiting time and SAV travel time, except in the 200 SAVs scenario.



(a) 5-Seat SAV

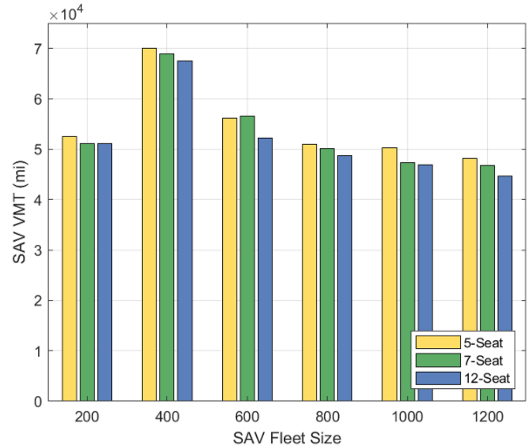
(b) 7-Seat SAV

(c) 12-Seat SAV

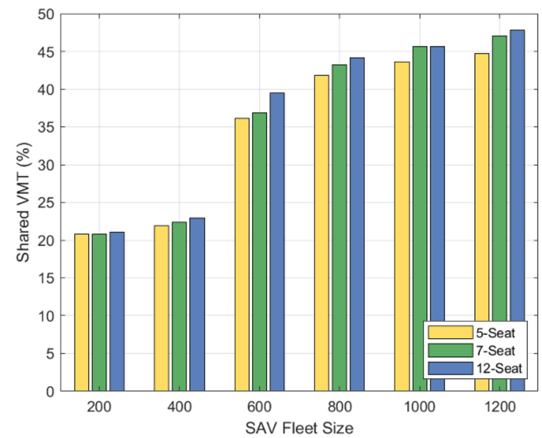
Figure 5. SAV Wait and Travel Time by Scenario

Instead of travel time improvements, larger SAVs with more seats lead to evacuation performance improvements by presenting more opportunities for DRS. Figure 6 shows the total VMT (Figure 6a), percentage of shared VMT (Figure 6b), and percentage of empty VMT (eVMT, Figure 6c) by SAV scenario. In Figure 6a, total VMT decreases as the number of seats per SAV increases, except in the 200 SAVs scenario. This means that a 12-seat SAV traveled a shorter distance on average, compared to a 5- or 7-seat SAV, to serve the same number of agents. This is possible as more agents are presumably sharing rides in a 12-seat SAV than in a 5- or 7-seat SAV. In Figure 6b, with more seats per SAV, the percentage of VMT being shared by 2 or more agents increases, as was presumed above. Additionally, Figure 6c shows that eVMT decreases with respect to the increase of the number of seats per SAV. Having more seats increases the likelihood of having at least 1 seat occupied by an evacuee at any given point in time (due to DRS). Thus, the analyses on shared VMT and eVMT clearly show that having more seats in an SAV is advantageous to facilitate DRS more efficiently.

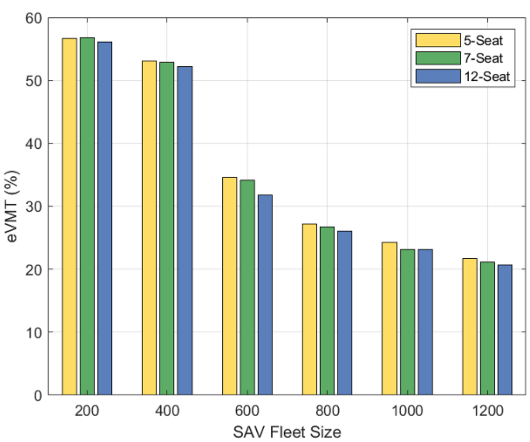
Coming back to Figure 6a again, the total VMT decreases with respect to the increase in fleet size. This is due to the more opportunities for ride-sharing (Figure 6b) and lower eVMT (Figure 6c) to operate the SAV fleet more efficiently. In Figure 6b, the percentage of shared VMT increases with respect to the increase in SAV fleet size, since the agents will have greater DRS opportunity with more SAVs in the network. Therefore, the result in Figure 6b explains why the travel time increased with larger fleet size in Figure 5, due to the increased time spent on rerouting for DRS. As shown in Figure 6c, with larger fleet size, the pick-up and drop-off of agents can be more efficiently scheduled by assigning SAVs to closer agents, so that the SAV does not have to travel empty. With the combined impact from shared VMT and eVMT, the total VMT decreases with respect to the increase in fleet size. A more efficient SAV operation with shorter evacuation time can be expected with a larger fleet size (as suggested in Figure 5) thanks to the less congested network with smaller total VMT. The 200 SAVs scenario has a smaller total VMT than the 400 SAVs scenario due to its low mode share of 75%-80% (as described in Figure 4). This scenario had to serve fewer agents than other scenarios, so small total VMT is observed in Figure 6a.



(a) Total VMT from all SAVs



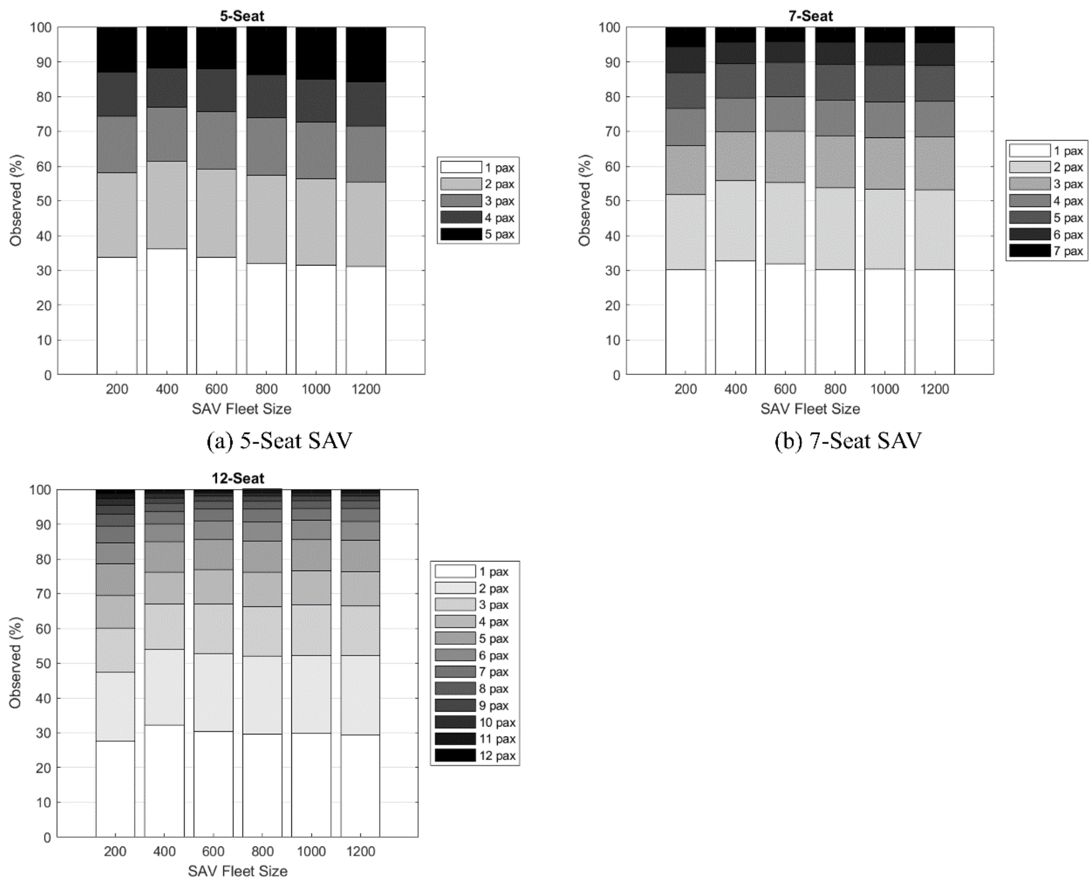
(b) Percentage of Shared VMT



(c) Percentage of eVMT

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

Greater ride-sharing opportunity from having more seats per SAV (supported by Figure 6b) impacts the occupancy of SAVs. Figure 7 shows the occupancy configuration by the percentage of each number of passengers (PAX) onboard by fleet size and number of seats. The average household size of the no-vehicles-available agent is 1.73 persons, including both households without any private vehicles, or those part of a household who were left behind due to having an insufficient number of private vehicles, so SAVs with occupancy higher than 2 PAX are shared rides with two or more agents. Figure 7 shows that on average, 42%, 46%, and 48% of the occupancy observations are made with more than 2 PAX, for 5, 7, and 12 seated scenarios, respectively. This result supports that having more seats per SAV promotes DRS and reduces total VMT. However, within each of the number of seats scenarios, the fleet size did not show much influence on occupancy configuration.



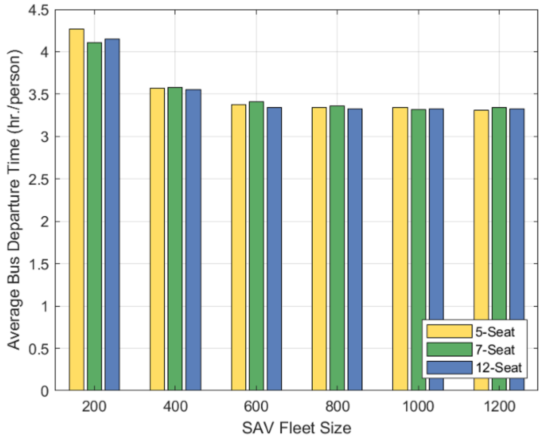
(a) 5-Seat SAV

(b) 7-Seat SAV

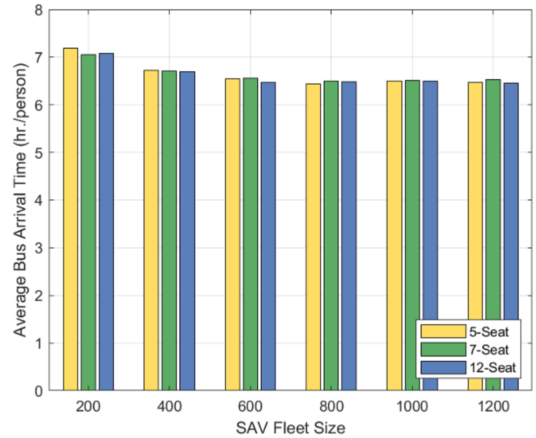
(c) 12-Seat SAV

Figure 7. SAV Occupancy Configuration by SAV Scenario

The evacuation performance of an SAV fleet can be measured by the time of bus departure and bus arrival, where early departure and arrival of the bus represents a more efficient evacuation. Figure 8 shows the average bus departure time and arrival time for each SAV scenario. Since the SAV travel time is not sensitive to the number of seats per SAV, the bus departure and arrival time did not show significant differences over the various number of seats scenarios. Thus, having more seats in SAVs helps to facilitate the systematic operation of an SAV fleet by having lower total VMT and eVMT (from Figure 6), and providing more ride-sharing opportunities (from Figure 7), but does not affect each individual's evacuation experience to arrive at the destination earlier. However, the SAV fleet size affects the bus departure time and arrival time, where a larger fleet size results in earlier bus departure and arrival to facilitate the evacuation. Nonetheless, this impact diminishes when more than 600 SAVs are 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, where the non-idle time share is calculated by non-idling time over total time spent until the last agent arrived at the bus station. It shows that the favorable evacuation performance of a large SAV fleet with more seats per SAV requires a low non-idle time share. Considering that travel time reduction diminishes when more than 600 SAVs are in the network, and more seats per SAV results in a low non-idle time share, this paper proposes 600 SAVs (1 SAV per 14 people) with 5-seat vehicles as the base case scenario to result in cost-efficient evacuation.

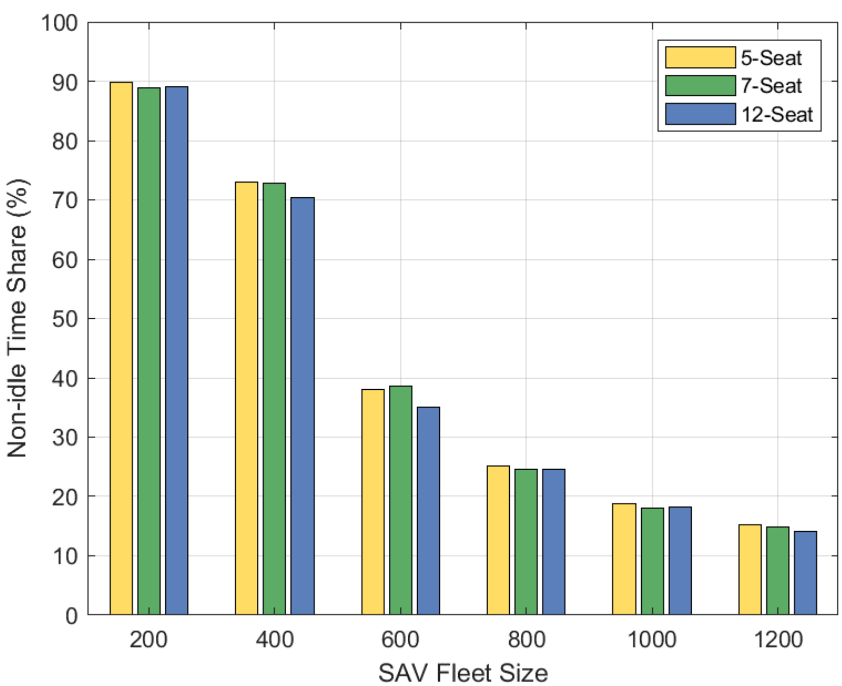


Figure 9. SAV Non-idle Time Share by SAV Scenario

SAV - Bus Coordination Strategy

A scenario analysis to adopt bus-coordinated maximum reroute time, as proposed in Figure 3, is performed to evaluate the impact of maximum reroute time and SAV fleet operation after DRS is coordinated with the special evacuation bus schedule. When bus coordination is applied, each agent has distinct maximum reroute time calculated by considering their expected arrival time and expected bus departure time, so the maximum reroute time is dynamic and demand-responsive to the traffic conditions. Table 2 shows the SAV fleet performance with bus coordination compared to the base case where the maximum reroute time is fixed to 15 minutes for all agents, given that all other conditions are equal.

The mode share result of the bus coordination scenario does not show much difference compared to the base case of the 15-minute fixed reroute time scenario. However, the total VMT shows a significant increase in the bus coordination scenario, ranging from a 6% to 45% increase, while the percentage of shared VMT decreased from 3 percent point (%p) to 18%p than the base case scenario. This suggests that fewer agents can share rides with others and DRS is not utilized in the bus coordination scenario as much as in the base case scenario. It is presumed that the maximum reroute time with bus coordination must be shorter than 15 minutes for most agents to arrive on time for their evacuation bus, so ride-sharing is not preferred in coordination scenario compared to base case scenario. Nonetheless, some agents would have been able to reroute longer than 15 minutes if they had more than 15-minutes until their bus departed.

Table 2. SAV Fleet Operation with Bus Coordination

SAV Mode Share (%)						
Fleet Size / Seats	200	400	600	800	1000	1200
5	72.91% (-1.71%p)	86.07% (-4.35%p)	93.95% (-0.86%p)	94.17% (-0.73%p)	94.39% (-0.52%p)	94.43% (-0.16%p)
7	73.96 (-0.77%p)	86.79 (-4.11%p)	93.52 (-1.05%p)	94.25 (-0.32%p)	94.75 (+0.37%p)	94.46 (+0.22%p)
12	71.75 (-5.64%p)	85.27 (-6.40%p)	93.76 (-1.31%p)	94.31 (-0.66%p)	94.3 (-0.23%p)	94.36 (-0.92%p)
Total VMT (mi.)						
Fleet Size / Seats	200	400	600	800	1000	1200
5	56,710 mi. (+7.99%)	74,488 mi. (+6.43%)	75,782 mi. (+34.82%)	64,395 mi. (+26.28%)	60,349 mi. (+20.17%)	59,262 mi. (+23.20%)
7	55,743 (+9.20%)	73,465 (+6.72%)	74,433 (+31.63%)	62,558 (+24.93%)	58,393 (+23.56%)	56,608 (+20.96%)
12	55,063 (+7.78%)	72,305 (+7.19%)	74,795 (+43.09%)	62,289 (+27.99%)	58,096 (+24.01%)	55,577 (+24.34%)
Shared VMT (%)						
Fleet Size / Seats	200	400	600	800	1000	1200
5	18.05% (-2.77%p)	17.43% (-4.44%p)	20.48% (-15.64%p)	29.71% (-12.10%p)	33.14% (-10.44%p)	34.69% (-10.06%p)
7	18.71 (-2.13%p)	18.28 (-4.13%p)	22.16 (-14.75%p)	31.82 (-11.36%p)	35.15 (-10.48%p)	36.5 (-10.60%p)

12	18.31 (-2.80%p)	18.22 (-4.74%p)	22.12 (-17.36%p)	32.27 (-11.92%p)	36.07 (-9.60%p)	37.55 (-10.29%p)

*Values in parentheses show differences from uncoordinated scenario results.

Table 3 supports the hypothesis of agents not preferring DRS in the coordination scenario, showing that SAV waiting time is longer in the coordination scenario than in the base case scenario. As agents tend to rush directly to the bus station rather than detouring to share their ride with others, SAV waiting time for the other agents increases. In coordination scenario, the SAV waiting time increases more (10-20% increase) with smaller fleet size, while the difference is negligible (less than 4% increase) when more than 1000 SAVs are in the network. However, as agents tend to travel directly to their bus station during high-demand periods instead of detouring for DRS, the travel time decreases 2% to 5%. Thus, with coordination strategy, a trade-off between increased SAV waiting time and decreased SAV travel time can be expected.

Table 3. Evacuation Performance by Bus Coordination

Avg. SAV Waiting Time (hr./person)						
Fleet Size Seats	200	400	600	800	1000	1200
5	1.62 (+13.29%)	0.74 (+19.35%)	0.46 (+17.95%)	0.38 (+11.76%)	0.33 (+0.00%)	0.32 (+3.23%)
7	1.52 (+20.63%)	0.68 (+13.33%)	0.46 (+17.95%)	0.36 (+2.86%)	0.32 (+3.23%)	0.31 (+3.33%)
12	1.44 (+10.77%)	0.67 (+21.82%)	0.46 (+27.78%)	0.36 (+9.09%)	0.32 (+0.00%)	0.30 (+3.45%)
Avg. SAV Travel Time (hr./person)						
Fleet Size Seats	200	400	600	800	1000	1200
5	0.34 **(-5.56%)**	0.41 **(-6.82%)**	0.45 **(-4.26%)**	0.46 (+0.00%)	0.46 **(-2.13%)**	0.47 **(-2.08%)**
7	0.33 **(-5.71%)**	0.41 **(-10.87%)**	0.48 (+0.00%)	0.47 (+0.00%)	0.46 **(-4.17%)**	0.47 **(-4.08%)**
12	0.35 **(-5.41%)**	0.42 **(-6.67%)**	0.48 (+4.35%)	0.48 (+0.00%)	0.47 **(-4.08%)**	0.48 **(-2.04%)**
Avg. Bus Departure Time (hr./person)						
Fleet Size Seats	200	400	600	800	1000	1200
5	4.42 (+3.51%)	3.65 (+2.24%)	3.44 (+1.78%)	3.37 (+0.90%)	3.32 **(-0.60%)**	3.32 (+0.30%)
7	4.32 (+5.11%)	3.61 (+0.84%)	3.47 (+1.76%)	3.36 (+0.00%)	3.31 **(-0.30%)**	3.31 **(-0.90%)**
12	4.27 (+2.89%)	3.59 (+1.13%)	3.47 (+3.89%)	3.37 (+1.20%)	3.33 (+0.00%)	3.30 **(-0.90%)**
Avg. Bus Arrival Time (hr./person)						
Fleet Size Seats	200	400	600	800	1000	1200

5	7.28 (+1.25%)	6.71 **(-0.15%)**	6.55 (+0.15%)	6.46 (+0.31%)	6.50 (+0.15%)	6.45 **(-0.15%)**
7	7.15 (+1.42%)	6.68 **(-0.45%)**	6.57 (+0.31%)	6.47 **(-0.46%)**	6.46 **(-0.77%)**	6.41 **(-1.69%)**
12	7.15 (+0.99%)	6.66 **(-0.45%)**	6.60 (+2.17%)	6.48 (+0.00%)	6.47 **(-0.46%)**	6.47 (+0.31%)

*Values in parentheses show differences from uncoordinated scenario results.

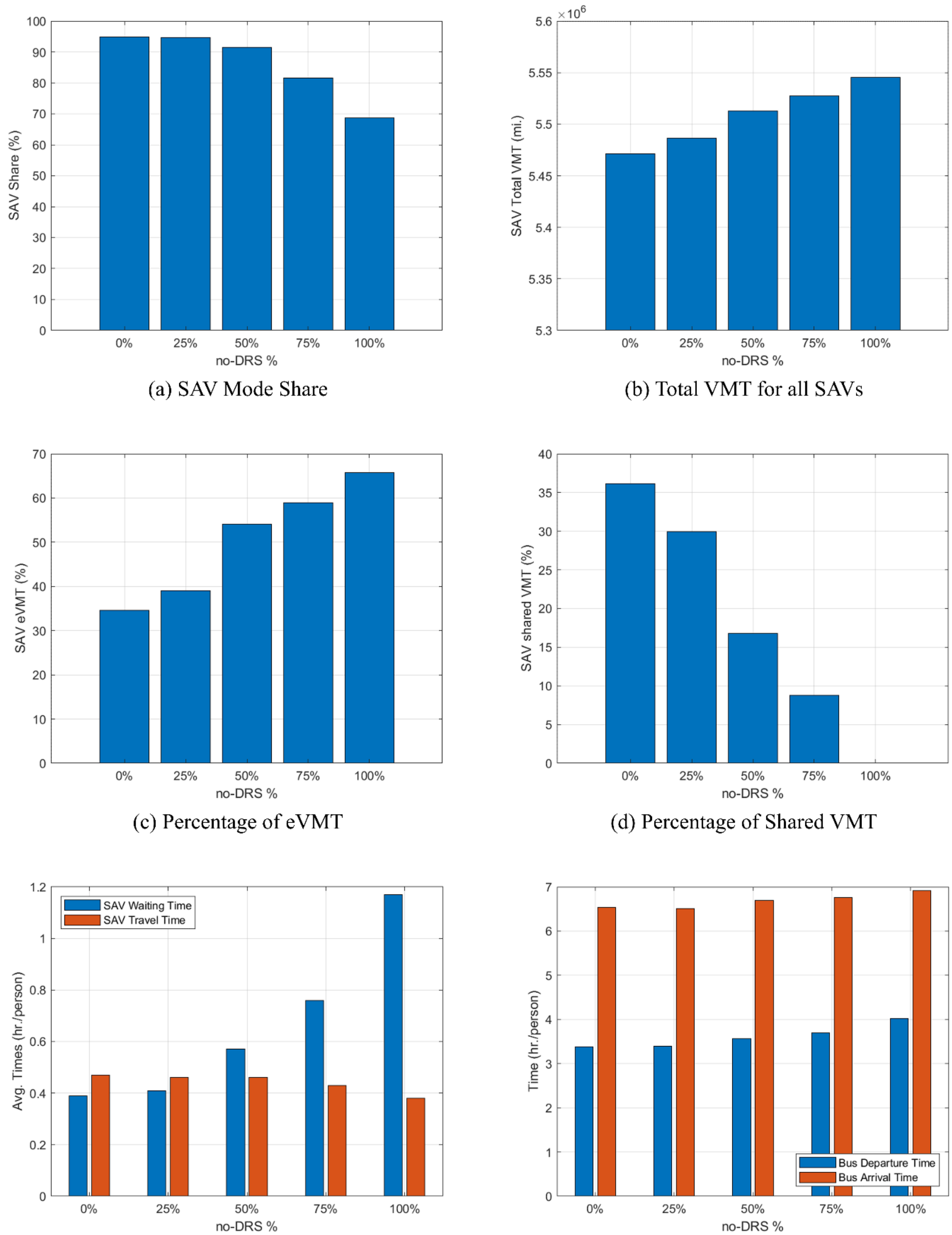
In terms of evacuation, staying safely at home (waiting for an SAV) would be a more desirable experience than traveling on the roads (riding in an SAV), if the bus that the agent will be on departs and arrives at a similar time compared to the base case scenario (as this paper assumes that the disaster is not imminent). The average bus departure time in Table 3 shows that the bus departure time is similar with more than 800 SAVs, and the worst case shows only a 5% increase. The change in average bus arrival time is less than ± 2%, suggesting that the overall evacuation performance would not change with the coordination strategy. Thus, bus coordination is an option to consider if evacuees can accept the behavioral changes expected with this strategy. Nonetheless, agents still have to make a trade-off between increased SAV waiting time and decreased SAV travel time, when coordination is applied, which could be offset with a large fleet of SAVs.

Sensitivity Analyses of Willingness-to-Share and Panic Levels

The aforementioned paragraphs focused on systematic factors of SAV fleet operation including number of SAVs, vehicle size, and rerouting strategy. Evacuee behavior is another essential aspect in an evacuation that affects the overall evacuation performance. This paper suggests two different evacuee behaviors: 1) willingness-to-share and 2) panic departure. Evacuees may refuse to share their ride during an evacuation and wish to travel directly to their destination instead. Also, they may not follow the staged evacuation departure schedule proposed in this paper and attempt to evacuate as soon as possible due to panic.

Figure 10 shows the SAV fleet operation with different percentages of no-DRS agents during evacuation, where each agent is randomly assumed to be a no-DRS agent or not, and 0% no-DRS agents is the base case used in this paper so far. The agents who refuse to share rides with others are assumed to have 0 maximum reroute time. For all no-DRS scenarios, the SAV fleet is fixed to 600 5-seat SAVs with a 15-minute maximum reroute time for DRS agents, which is analyzed to be the cost-efficient base case scenario from this paper. Figure 10a shows that the SAV mode share (vs. walk) falls from 95% to 69% when the percent of no-DRS agents increases from 0% to 100%. This result suggests that the refusal of DRS can reduce the evacuee's opportunity to ride in an SAV and affect the overall evacuation performance. Figure 10b and Figure 10c support this assumption, showing longer total VMT and a higher eVMT rate with a higher percentage of no-DRS agents. The increase of both total VMT and eVMT represents that the amount of VMT an SAV has driven empty is increasing as well. Figure 10d is the percent of shared VMT per SAV, which falls with more no-DRS agents, as expected.

Figure 10e shows that SAV waiting time increases, while SAV travel time decreases with the rise of no-DRS agents. Although a similar pattern of waiting time increase and travel time decrease is observed in the analyses of the bus coordination strategy, the average bus departure time and arrival time did not increase in the coordination scenario. However, Figure 10f shows that the average bus departure time and arrival time significantly increase with respect to the percentage of no-DRS agents, where the departure time and arrival time shows a 19% and 5% increase, respectively, when the percentage of no-DRS agents rises from 0% to 100%. This result implies that DRS affects evacuation performance, but its efficiency varies by how it is implemented.



(a) SAV Mode Share (b) Total VMT for all SAVs

(c) Percentage of eVMT (d) Percentage of Shared VMT

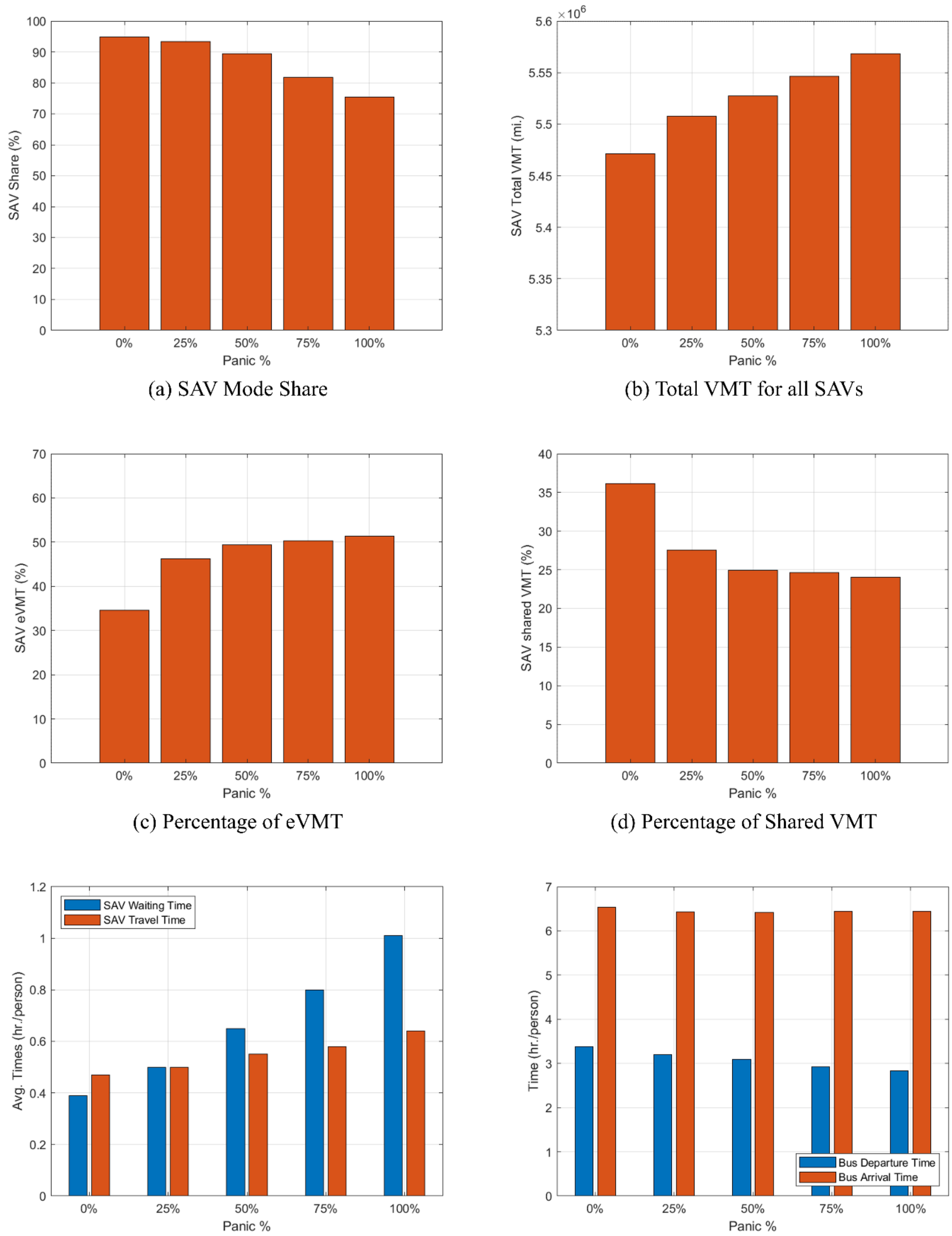
(e) SAV Wait and Travel Time (f) Avg. Bus Dept. and Arr. Time

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

Figure 11 shows the SAV fleet operation with different percentages of panic agents present during evacuation, where each agent is randomly assumed to be a panic agent or not. If an agent is in panic, he/she will refuse to follow the staged random departure time distribution and attempt to evacuate during the first fifth of the 6-hour duration. The same simulation setting of 600 5-seat SAVs with a 15-minute maximum reroute time is assumed in the panic scenarios.

Figure 11a through Figure 11c show a similar tendency of SAV mode share, total VMT, and eVMT rate as observed in the no-DRS scenario. The mode share falls, total VMT increases, and eVMT increases with respect to the percent of panic agents due to the higher evacuation demand loaded in the network. However, the eVMT increase diminishes, while shared VMT rate (as shown in Figure 11d) becomes stable around 25% when more than 50% of agents are in panic.

Figure 11e shows the SAV waiting time and SAV travel time, where both of them increase with respect to the increase in panic level. This is presumably due to the severe traffic congestion induced by loading more agents in a panic situation. Figure 11f shows that the bus departure time decreased with higher panic levels, due to the evacuees departing earlier than the base case. However, the arrival time did not show much difference, indicating that longer bus travel time is needed due to the traffic congestion in the panic situation. Contrary to Figure 10 where the increase of no-DRS agents resulted in poor evacuation performance by increasing the departure and arrival time of the bus, Figure 11f shows that the bus arrival time of the 100% panic situation is not much different to the 0% panic base case, which implies that SAV DRS can still manage the evacuation at a certain level of panic.



(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 11. SAV Fleet Operation by the Percent of Panic Agents

CONCLUSIONS

This paper demonstrated the first-mile connection of an SAV fleet using dynamic ride-sharing (DRS) to a special evacuation bus targeted to evacuate the no-vehicles-available population. The locations of the bus stations were estimated using an accessibility measure, so that the most accessible location can be chosen for evacuees. The bus was operated in both a fixed and demand responsive manner to dynamically respond to the changing evacuation demand. Three different types of SAVs that have a varying number of seats combined with 6 different fleet sizes resulted in 18 different SAV scenarios that are simulated to evaluate the impact of various SAV fleet specifications on the evacuation performance. In addition to the fleet options, SAV–bus coordination strategy was also evaluated.

The simulation results suggest that when more SAVs are in the network, SAV waiting time decreases since more SAVs become available to the agents, but SAV travel time increases due to the increased time spent on rerouting for ride-sharing. The number of seats did not have as much impact as the fleet size on waiting and travel times, but having more seats promoted DRS from the analyses on the occupancy configuration and percentage of shared VMT. When these two impacts were combined, a larger fleet size with more seats per SAV resulted in better evacuation performance. Nonetheless, the non-idle time share analysis suggests that the cost-efficiency becomes low with a large fleet with more seats per SAV, so a fleet size of 1 SAV per 14 people with 5-seat vehicles is recommended.

Since the schedule of the special evacuation bus can be fixed or demand-responsive, the bus can have a shorter time headway with high evacuation demand, while the headway will be longer when the demand is low. The bus coordination strategy coordinates the SAVs' DRS option with the departure schedule of the bus. DRS was restricted with shorter bus headways to speed up transportation of passengers in high demand situations and DRS was promoted with longer bus headways in low demand situations. The coordination scenario's result showed that when more than 800 SAVs are in the network (1 SAV per 10 people) the SAV waiting time rises, while SAV travel time falls. Since the bus departure and bus arrival from coordination scenario did not change significantly compared to the uncoordinated scenario, coordination can be an effective evacuation strategy in which evacuees will stay at home longer while waiting for an SAV. Nonetheless, a smaller SAV fleet size did not show evacuation performance improvements with the coordination strategy.

Lastly, the evacuees' behavioral change of willingness-to-share and panic departure were evaluated in addition to the aforementioned fleet operation analyses. When more agents were not willing to share their ride with others, SAV waiting time increased and resulted in poor evacuation performance compared to the base case scenario. However, the bus arrival time of 100% panic was not much different to the 0% panic base case, implying that SAV DRS can manage evacuees' panic at certain level.

This paper concludes that an SAV fleet can be accepted as an alternative mode of transportation to evacuate the population that does not have privately owned vehicles. However, the SAV application in this paper was limited to the first-mile connection from the evacuees' homes to the bus stations. Additional SAV fleet operation techniques including smart repositioning, optimal DRS matching, improved path finding algorithms, and higher market penetration of SAVs should facilitate a more efficient evacuation in the future.

ACKNOWLEDGEMENTS

The authors appreciate Jade (Maizy) Jeong for her excellent editing and administrative support. The authors acknowledge the Texas Advanced Computing Center (TACC) at The University of Texas at Austin for providing high performance computing resources that have contributed to the research results reported within this paper.

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