Improving Infrastructure and Community Resilience with Shared Autonomous Electric Vehicles (SAEV-R)

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***Abstract*—We propose using surface and aerial shared autonomous electric vehicles (SAEVs) to improve the resilience of infrastructure and communities, or SAEV-R. In disruptive events, SAEVs can be temporarily deployed to evacuate and rescue at-risk populations, provide essential supplies and services to vulnerable households, and transport repair crews and equipment. We present a modeling framework for feasibility analysis and strategic planning associated with deploying SAEVs for disaster relief. The framework guides our examination of three scenarios: a hurricane-induced power outage, a pandemic-affected vulnerable population, and earthquake-damaged infrastructure. The results demonstrate the flexibility of the proposed framework and showcase the potential and versatility of SAEV-R systems to improve resilience.**

***Keywords*— shared autonomous electric vehicles, community resilience, infrastructure recovery, disaster response**

I. INTRODUCTION

Resilient infrastructure is crucial for communities to weather and recover from disasters. Transportation and communication networks, energy grids, and water pipelines are all critical components of this infrastructure and play important roles in enabling emergency response and recovery efforts. Communities with robust and well-maintained infrastructure are better equipped to handle the effects of emergencies and are more likely to bounce back quickly [1].

Resilient infrastructure is necessary but not sufficient for community resilience. For example, during pandemics, vulnerable populations might suffer even though the infrastructure itself functions well. Therefore, improving resilience of infrastructure and community are both important when it comes to improving the overall resilience of society.

In this paper, we propose to use surface and aerial shared autonomous electric vehicles (SAEVs) to help accelerate infrastructure recovery and mitigate disaster impacts on communities. We refer to the use of SAEVs for improving infrastructure and community resilience as SAEV-R (pronounced “saver”).

SAEVs can relocate energy and material supplies, and provide services (e.g., evacuation, search, and rescue) without human drivers nor the approval of vehicle owners. This is the essence of the SAEV-R system. Sharing-based business models, such as car sharing, peer-to-peer sharing, and co-ownership, can streamline and accelerate the process of recruiting SAEVs during an emergency compared to private vehicle ownership.

Operating without human drivers means that SAEVs can be recruited and deployed quickly and efficiently in emergency situations, allowing communities to evacuate and rescue residents without risking human drivers or deliver supplies to those in need with less human interaction and. Because SAEVs do not require human drivers, they can (i) operate without downtime for longer periods of time; (ii) traverse more dangerous paths and access more dangerous areas; and (iii) transfer energy and serve as an emergency power source during infrastructure repair, thanks to their high-performance, reusable "power banks."

Researchers have proposed to use (shared) autonomous vehicles (including unmanned aerial vehicles, UAVs) [2]–[4] and electric vehicles [5], [6] for improving infrastructure and community resilience. However, we suggest that the combination of the technologies associated with shared mobility, electrification, and automation in SAEVs results in a synergistic effect, where the overall benefit is significantly greater than the sum of the individual resilience benefits of each technology. In other words, SAEVs can significantly improve the resilience of infrastructure and communities in the face of natural and society-induced hazards than, say, shared human-driven electric vehicles, privately-owned autonomous electric vehicles, or shared autonomous vehicles powered by internal combustion engines and fossil fuels. Unlike privately-owned human-driven electric vehicles, emergency response operators can quickly recruit SAEVs without the delays from obtaining owner approvals or waiting for human drivers to operate vehicles. Unlike shared autonomous non-electric vehicles, SAEVs have the advantage of carrying electric power source, which can be utilized for various purposes during disaster recovery.

The strategic deployment of SAEV-R can improve the effectiveness and efficiency of emergency response by allowing for targeted and timely delivery of essential resources and services. Figure 1 illustrates how SAEVs can aid in providing electric power during significant power blackouts by moving electricity from functioning sub-grids to non-functioning sub-grids in a driverless and centrally controlled manner. Figure 2 shows the potential for SAEVs to deliver essential services and resources (such as energy, water, food, medicine) to affected communities. SAEVs can also help in infrastructure recovery, as shown in Figure 3. They can transport repair crews and spare materials directly from their homes or warehouses to the damaged location without delays (from, say private vehicle recruitment or waiting for human drivers to pick up vehicles), and serve as power sources when they arrive.

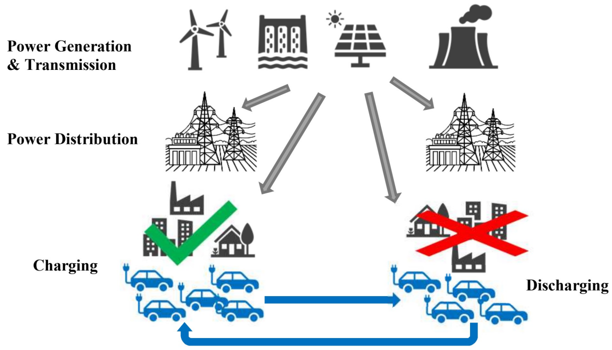

Fig. 1. SAEVs for transferring energy from functional sub-grid (microgrid) to dysfunctional sub-grid (microgrid).

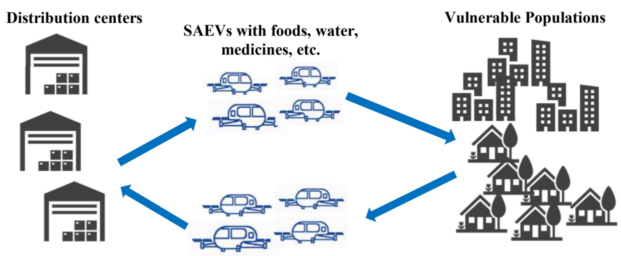

Fig. 2. During a pandemic, agencies can recruit SAEVs to deliver essential services and resources to vulnerable populations with minimum human contacts.

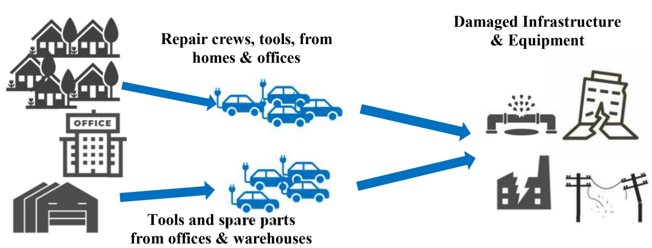

Fig. 3. When infrastructure and equipment are damaged, SAEVs can autonomously pick up repair crew and tools directly from homes, offices, and warehouses to the damaged locations with built-in power sources that can be used during repairment.

To launch SAEV-R, it will be necessary to invest in supporting facilities, such as charging and discharging stations, communication systems, fleet depots, and, for aerial SAEVs, launch/landing sites. Administrative structures (e.g., who has the authority to recruit SAEVs) and operational protocols are also critical. Whether these investments are likely to pay off in the long run needs further study. Therefore, in this paper, we propose a preliminary modeling framework for feasibility analysis and strategic planning of various use cases of SAEV-R under different disaster scenarios.

This study includes two major contributions. First, to the best of our knowledge, this is the first study to suggest utilizing the synergies of the shared economy, autonomous vehicle technologies, and electric vehicle technologies to enhance community resilience and accelerate infrastructure recovery processes. The paper presents concrete use cases in various disruption scenarios.

Second, we propose a modeling framework for efficiently evaluating concepts of operations of various SAEV-R use cases. The framework simplifies and standardizes the evaluation and strategic planning under different scenarios and provides a dynamic and quantitatively consistent approach for assessing the potential benefits and challenges of SAEV-R. We believe that this proposed framework will be a valuable tool for public agencies and businesses looking to leverage the benefits of SAEV-R in their strategic planning. After conducting a feasibility analysis, these entities can exert more targeted analysis efforts to determine the necessary infrastructure, facilities, equipment, and administration for SAEV-R.

The remainder of the paper is structured as follows. Section II reviews literature related to measuring and improving infrastructure and community resilience. Section III presents a modeling framework for preliminary analysis of various uses of SAEV-R. In Section IV, we apply the framework to examine the effectiveness of SAEVs when varying disaster type, fleet size, and disruption severity in three preliminary examples. Section V concludes with the limitations of the proposed SAEV-R and potential future research directions.

II. RELEVANT LITERATURE

Measures of infrastructure resilience often focus on the physical components of a community, such as the condition and capacity of buildings, transportation systems, and utility networks [7]. These measures may include *ex-ante* and *ex-post* indicators. An example *ex-ante* indicator includes the number of infrastructure components that meet or surpass certain standards or the capacity of a transportation system to withstand natural or society-induced disasters. An example *ex-post* indicator includes the average number of interrupted system users per disruption event.

Measures of community resilience, on the other hand, focus on the social and institutional aspects of a community. These measures include indicators such as the availability of emergency response plans, the presence of community organizations, or the level of social cohesion [8].

Researchers and practitioners have proposed a range of strategies to improve infrastructure and community resilience. Examples of pre-event strategies include the increase of infrastructure redundancy, drills, disaster response training programs for community members and emergency response operators, development of emergency response plans, and public outreach [1], [9], [10]. During disasters and disaster recoveries, decision-makers should make timely and non-myopic decisions to ensure the provision of essential supplies to vulnerable populations [11], [12] and effectively allocate resources for infrastructure recovery [13]. Real-time performance monitoring is also critical. For post-event strategies, stakeholders can reflect and learn, but should avoid anchoring preparation for future disasters on prior disasters, as future disruptive events may well be different.

III. MODELING FRAMEWORK

Models that facilitate the conceptualization and strategic planning of SAEV-R require multiple features. Since system decisions are typically made under pressure in response to disruptive events, a model should be dynamic to capture the temporal details of the state of SAEVs, the state of target communities and infrastructures, and the state of services and resources that are expected to be delivered. The model should also be flexible to evaluate a wide range of types and scales of disaster events. Finally, the model should explicitly and economically model variables that are controllable and uncontrollable by decision-makers.

Key decision variables of the emergency response operators include the types of service and resources to provide, service areas and time windows, and SAEV fleet size. Key scenario variables include SAEV battery capacity (i.e., drive range), charging/discharging speed, vehicle storage capacity, infrastructure availability and compatibility (e.g., charging/discharging facilities and UAV take-off and landing platforms), and distance to resource depots and warehouses.

We define $V_t^{(i)} \in \mathbb{R}^+ \cup \{0\}$ as the number of SAEVs in state i at time t, where $i \in \mathbb{I}$ and $t \in [0, T]$. The set $\mathbb{I} = \{1,2, \dots, i, i', \dots, I\}$, contains mutually exclusive and collectively exhaustive SAEV states. $\boldsymbol{V}_t$ is the state vector whose element i is $V_t^{(i)}$. When no confusion arises, we use $\boldsymbol{V}$ instead of $\boldsymbol{V}_t$. We define $v_t^{(i,i')}$ as the rate of SAEVs transitioning from state i to i' at time t, where $i, i' \in \mathbb{I}$ and $t \in [0, T]$. Similarly, $v_t^{(i'',i)}$ is the rate of SAEVs transitioning from state i'' to i. t_0 is the initial time step. t_T is defined as the modeling horizon. We define τ as the simulation time step. For example, $\tau = 1$ minute means that the simulation updates the system state every one (simulation clock) minute. $\delta^{(i,i')}$ is a dummy variable. When SAEVs can directly transition from the state i to the state i', $\delta^{(i,i')} = 1$; otherwise, $\delta^{(i,i')} = 0$.

The dynamics of $V^{(i)}$, therefore, can be formulated as

$$\dot{V}_t^{(i)} = \sum\nolimits_{\forall i'', i \neq i''} \delta^{(i'',i)} v_t^{(i'',i)} - \sum\nolimits_{\forall i', i' \neq i} \delta^{(i,i')} v_t^{(i,i')}, \forall i, i', i'' \in \mathbb{I} \tag{1}$$

Fig. 4. illustrates the concepts using a “tank” analogy, where the boxes represent “water tanks” and the arrows represents “pipelines”.

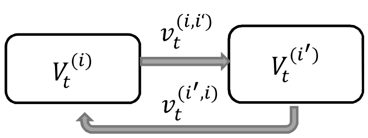

Fig. 4. The number of SAEVs in the state i ($V^{(i)}$) transitioning from/to the state i', with the rate of $v_t^{(i,i')}$ and $v_t^{(i',i)}$, respectively.

Similarly, we can define $X^{(j)} \in \mathbb{R}^+ \cup \{0\}$ as the entities (e.g., community members that need help, damaged infrastructure) that SAEVs aim to serve. Generally, the bigger the disaster, the larger the $X^{(j)}$. $x^{(j,j')}$ are the corresponding transition rates. For example, when a SAEV-R serves 17 people per hour at t, $x_t^{(unserved,served)}$ is 17 people/hour. For another example, when a repair crew can fix two lane miles of collapsed pavement per day at t, $x_t^{(collapsed,repaired)}$ is 2 lane miles/day. We model the state transition rate using negative exponential distributions as shown in Eqn. (2).

$$x_t^{(j,j')} = X_t^{(j)} / D_t^j, \forall j \in \mathbb{J} \tag{2}$$

We define $\boldsymbol{R}$ as the services or resources that SAEVs try to deliver. The unit of $\boldsymbol{R}$ depends on the specific resource that needs to be transported in a specific context. For example, when using SAEVs as a mobile power bank for delivering energy from generators/substations to the communities that experience power blackouts, the capacity is the battery capacity with units of kWh. When using SAEVs for delivering drinking water, the capacity has units of kg, lb, or ton. When using SAEVs for sending repair crew from their homes or their office depots to the dysfunctional locations, the unit is persons.

Let $R^{(k)} \in \mathbb{R}^+ \cup \{0\}$, $k \in \mathbb{K}$, be the resources that SAEVs deliver. $\mathbb{K}$ contains all the states of the resources. $r_t^{(k,k')}$ and $r_t^{(k'',k)}$ are the corresponding state transition rates. We can use Eqn. (3) to numerically approximate the continuous transitions, where τ is the simulation step size.

$$R_{t+\tau}^{(k)} = \left(\sum\nolimits_{\forall k'', k'' \neq k} \delta^{(k'',k)} r_t^{(k'',k)} - \sum\nolimits_{\forall k', k' \neq k} \delta^{(k,k')} r_t^{(k,k')} \right) \cdot \tau, \quad \forall k, k', k'' \in \mathbb{K} \tag{3}$$

IV. Three Case Studies

In this section, we examine three specific SAEV-R use cases, guided by the framework proposed in Section III. The first case study involves utilizing SAEVs to transfer energy during hurricane-caused power outages. The second case examines the use of SAEVs to provide essential supplies to communities affected by a pandemic. Lastly, we examine the use of SAEVs to accelerate infrastructure recovery, where the vehicles are utilized to transport both personnel and repair equipment to the damaged infrastructure sites.

A. Energy Transfer During Hurricane -Induced Blackout

Background. Hurricane Sandy was a powerful Atlantic hurricane (Category 3 when it made landfall on the New Jersey coast) that caused significant damage and loss of life in the Caribbean and the eastern United States in October 2012 (NOAA). The storm induced widespread power outages and the disruption of transportation and communication networks, and some areas were without power or clean water for several weeks (FEMA). Fig. 5. is a photo of lower Manhattan in New York City. Many buildings were left without power for up to a week or more, which caused significant disruptions to businesses and residents in the affected areas, with many people forced to evacuate their homes to relocate to temporary shelters.

Fig. 5. Due to the Hurricane Sandy, a portion of the lower Manhattan experienced blackout for around four days. Photo Source.

SAEV-R Problem. We propose to employ the charging and discharging functions of SAEVs to transfer energy from functioning power sub-grids to dysfunctional power sub-grids, as illustrated in Fig. 1. Based on the proposed framework, we develop a concrete model to study the relationships between the SAEV fleet size and the amount of unmet energy demand that can be served by the SAEVs. The objective is to minimize SAEV recruitment to maximize unmet energy demands. To simplify the analysis, we ignore the possibility that SAEVs may also simultaneously deliver water and other essential resources to the community.

Model. Suppose that SAEVs ($\boldsymbol{V}$) transfer energy ($\boldsymbol{R}$) from areas where there is still energy supply to areas without power. The unserved demand ($\boldsymbol{X}$) is measured in kWh. Fig. 6. shows the (circular) state transition of SAEVs during the delivery, which contains four states: en-route to charge, being charged, en-route to discharge, and serving communities without power.

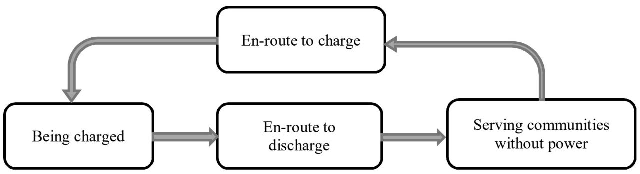

Fig. 6. State transition diagram of SAEVs that serve communities experiencing power outages.

As illustrated in Figure 7, we can model the state transitions of unmet energy demand (in the unit of kWh) corresponding to the aforementioned state transitions of SAEVs.

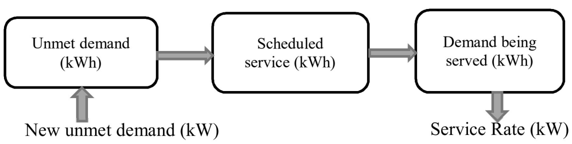

Figure 7. State transition diagram for energy demand.

We assume vehicle battery is 50 kWh with 0.3546 kWh per mile. The distance from a charging (discharging) location to a discharging (charging) location is assumed to follow a negative exponential distribution with a mean of 15 miles, and the average speed is assumed 25 mph. At the initial time step, we assign 10% to the “charging” state and 90% to the “en-route to charge” state. That is, we assume that when the damage is detected (at midnight), 10% of SAEVs are nearly fully charged (and ready to drive to the service locations). We assume that the average charging and discharging times are 5 and 6 hrs, respectively. We use the household-level hour-by-hour energy usage profile (2022 November) from the U.S. Hourly Electric Grid Monitor data of U.S. Energy information Administration (EIA) to approximate the unmet demand pattern.

Results. We tested the impact of different fleet sizes for 72 hours on the unmet energy demand, as shown in Fig. 8. The figure shows that 2500 SAEVs achieve a reasonable trade-off between minimizing the number of SAEVs to recruit and the minimizing unmet energy demand. The minor fluctuations are caused by the fluctuation of the newly unmet demand.

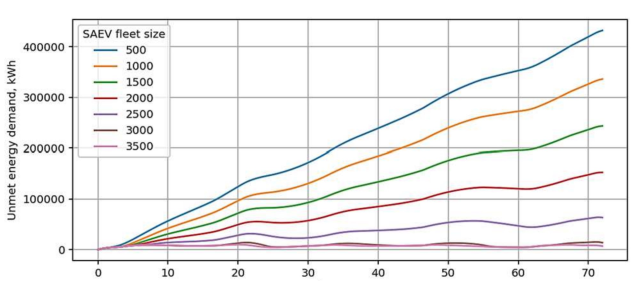

Fig. 8. Profile of cumulative unmet demand with different fleet size

Fig. 9 shows the stacked chart for SAEVs in different states. As the SAEV states gradually reach equilibrium after around 10 hours, we only show the time profile of the first 15 hours. As expected, in the initial hours, a large portion of SAEVs go to charge in the areas with functioning grids.

Implementation. As the charging activities of the recruited SAEVs might impose heavy load on the functioning power subnetworks, future research is needed on the impact of the capacity constraints of the power grids. Fortunately, SAEVs can carry extra battery packs using passenger seat and trunk space, and these *ad hoc* battery packs can be pre-charged as emergency supplies. However, when SAEVs are on the way to pick up these ad hoc battery packs and on the way to discharge, road networks and communication networks might be disrupted due to the hurricane. In this case, the emergency response operators might have to choose aerial SAEVs, some of which need to be used to set up a temporary communication network [14].

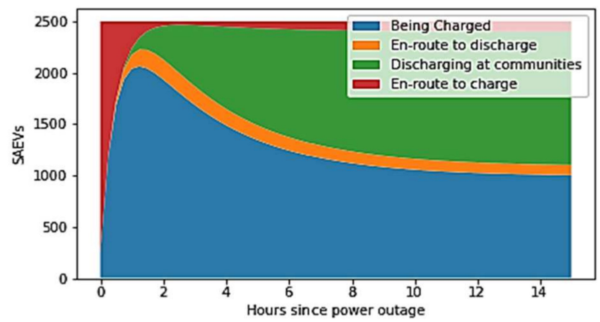

Fig. 9. Stacked chart of SAEVs in different states (with total fleet size as 2500).

B. *Supplying Vulnerable Populations during a Pandemic*

Background. During the COVID-19 pandemic, vulnerable populations in the County of Denver, Colorado included individuals who are older, have underlying health conditions, have lower income and lack access to healthcare, and are members of racial and ethnic minority groups. These populations may be at a higher risk of severe illness or death if they contract COVID-19. It is important for public health officials and community organizations to provide targeted support and resources to these groups to help protect their health during a pandemic.

SAEV-R Problem. We propose to use SAEVs to fulfill the needs of delivering essential resources with minimum human contact, as illustrated in Fig. 2. We substantiate the proposed modeling framework into a concrete quantitative model to help form a preliminary understanding of the SAEV fleet size required to serve a specific number of vulnerable households. The objective is to minimize SAEV recruitment to maximize the portion of households that have essential supplies during a service period.

Model. In this example, we dispatch SAEVs ($\boldsymbol{V}$) to deliver food, medicine, and essential services ($\boldsymbol{R}$) to communities ($\boldsymbol{X}$) with low mobility, immunity, and accessibility during the pandemic. The state transition diagram for vulnerable households is illustrated in Fig. 10. We assume each SAEV can carry supplies for five households on average. As a pandemic can last months or years, we model the within-day dynamics with the initial state in the steady condition. That is, given the number of vulnerable households, average delivery distance, and the number of SAEVs, the multi-day simulations will gradually reach a steady condition, where the initial state of each day is the same. One extreme case of the initial state is that there is no household that needs supplies at the beginning of each day, while the other extreme is that all the households need supplies at the beginning of each day. We assume the SAEVs only operate during the daytime (12 hours a day) to avoid disrupting vulnerable households at nights. We also assume a sufficient supply of SAEVs, so we ignore SAEV charging needs to simplify the analysis.

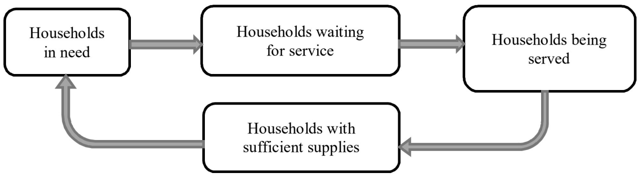

Fig. 10. State transition diagram for vulnerable households

Results. We present sensitivity analysis with respect to changes in the average time for a household to consume one bundle of essential supplies (24, 48, and 96 hours), SAEV fleet size (200, 500, 800, 1100), and average delivery distance (5, 25, 45 miles). Fig. 11 displays the system performance with the uncertainty (sample standard deviation) of the percentage of vulnerable households (uniformly) ranging from 2% to 8% of the 313,926 households in the county. We can see that when the consumption time is low the fleet size and delivery distance have more influence on the percentage of shared households than when the consumption time is high. We can also see that delivery distance has more impact on the percentage of served households when the fleet size and the average consumption time are low, which has implications on the site selection of distribution centers relative to the locations of the (potential) vulnerable populations.

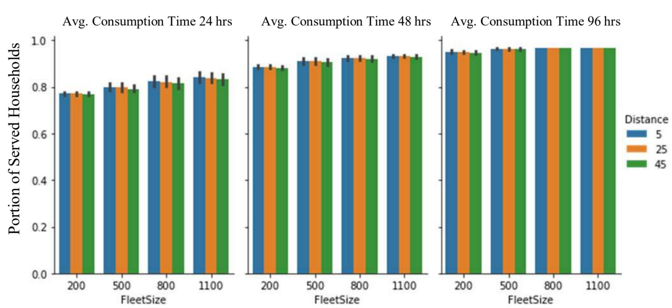

Fig. 11. Avg. percentage of shared served households by avg. consumption time (hours), fleet size (vehicles), and avg. delivery distance (miles) (with uncertainty of percentage of vulnerable households ranging from 2-8%, uniform distribution)

Implementation. To identify vulnerable populations quickly, it is important for the emergency response operators to have comprehensive and updated data on community characteristics at hand *before* disasters, as the definition of vulnerable populations varies in different scenarios. For example, during the HIV/AIDS epidemic, LGBTQ communities were more vulnerable, while during the COVID pandemic, the vulnerable groups included people over the age 65 and those with medical pre-conditions. The "final step" during deliveries is also important to consider. For example, the protocols for how exactly to carry supplies from SAEVs to households needs careful design.

C. *Post-Earthquake Infrastructure Recover*

Background. The San Diego region of California is located on the Pacific Plate, near the boundary with the North American Plate, making it susceptible to earthquakes (USGS). Suppose San Diego, California experienced a major seismic event that causes some key infrastructure to fail.

SAEV-R Problem. We propose to use SAEVs to transport repair crew from their homes and repair tools and spare parts from the inventory/offices, as illustrated in Fig. 3. This way, most repair crews do not need to go back to their offices to pick up equipment and they can "meet" with the tools and spare parts directly at the damaged locations. We establish a quantitative model using the proposed framework to investigate the relationship between the number of SAEVs and the speed of repairing the damaged infrastructure (measured in person hours) at the strategic planning level. To simplify the analysis, we assume that the SAEVs do not simultaneously transfer other essential services (e.g., medical teams) and resources (e.g., energy, water). The objective is to minimize SAEV recruitment to maximize the recovery speed.

Model. For demonstration, we split a fleet of SAEVs into two groups ($\boldsymbol{V1}$ and $\boldsymbol{V2}$). In practice, the task assignment of SAEVs is flexible and adjustable before and during a disaster service. The first group transport repair crew $\boldsymbol{R1}$ (from their homes) directly to the locations of the damaged infrastructure and equipment, and when the crew members reach maximum working hours (we assume 9 hrs), the SAEVs transport them back home to rest, as illustrated in Fig. 12.

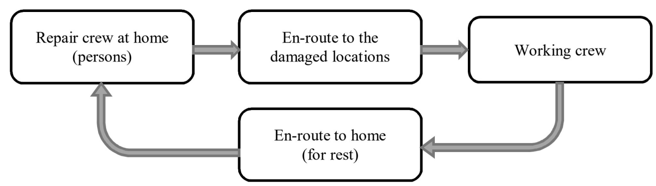

Fig. 12. State transition diagram for repair crew members.

The second group of SAEVs transport repair tools and spare parts ($\boldsymbol{R2}$) from depots to the damaged locations, as illustrated in Fig. 13. When the study needs more details, we can further split $\boldsymbol{R2}$ into $\boldsymbol{R2a}$ and $\boldsymbol{R2b}$ to differentiate repair tools and spare parts. We assume that there are some crew members (or robots) in the offices to help move spare parts and tools from warehouses to SAEVs.

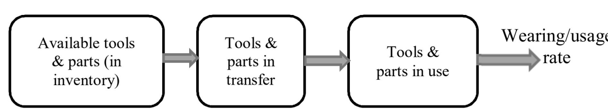

Fig. 13. State transition diagram for repair tools and spare parts.

The repair crew, repair tools, and spare parts "meet" at the damaged locations. We assume the average delivery distance is 15 miles, average driving speed is 25 mph, and each SAEVs can transport 1.1 crew members on average.

Fig. 14 illustrates the state transition of the damaged infrastructure measured in terms of the remaining work/effort ($\boldsymbol{X}$, measured in person hours) required to complete the repair.

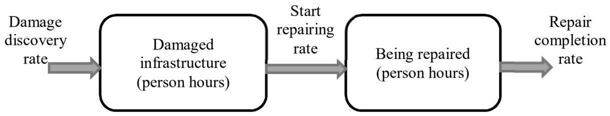

Fig. 14.State transition diagram for damaged infrastructure.

Results. We conducted sensitivity analysis with respect to changes in person hours needed, fleet size (for crew), and total crew members, on the completed repair work. Some key scenarios with 1500 total person hours are illustrated in Fig. 15. As expected, the recovery speed depends mainly on the scarce resources (fleet size or crew).

Implementation. As earthquakes might also lead to damage of communication and transportation infrastructure, emergency response operators might need additional SAEVs to provide communications (SAEVs—esp. UAVs—can potentially serve as temporal communication towers.) When road networks are damaged, it might be necessary to use aerial SAEVs.

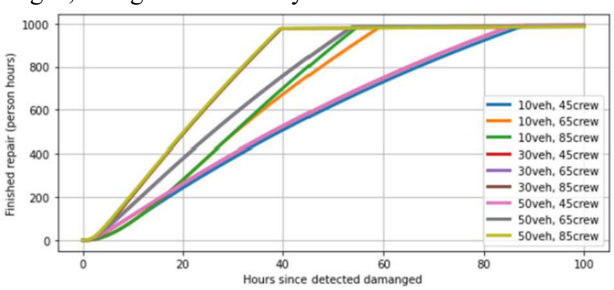

Figure. 15. Time profile of finished repair work (1000 person hours in total) from the moment that the damage was detected.

V. Concluding Remarks

This paper proposes the concept of SAEV-R that leverages the synergies of the sharing economy, automated vehicle technologies, and electrification technologies. Using concrete examples, we show that SAEVs offer an innovative solution to mitigate disaster impact and accelerate infrastructure recovery. We propose an intuitive and standardized modeling framework for evaluating various use cases of SAEV-R. We consider the framework sufficiently general and flexible, as we demonstrated it in three significantly different use cases. We believe that this proposed framework will be a valuable tool for enabling organizations to make informed, strategy-level decisions about how to best utilize SAEVs to enhance their resilience in the event of a disaster.

We identify four main research directions related to SAEV-R. First, each specific SAEV-R use case needs tailored optimization algorithms (e.g., vehicle routing), that consider explicit infrastructure networks and community conditions. Second, future research should explore the feasibility of utilizing SAEVs for multiple purposes simultaneously in disruptive events. The corresponding multi-objective optimization problem with an expanded decision space is not trivial. Third, although we briefly discuss the potential implementation challenges for each use case, we anticipate future research that examines the specific implementation obstacles in detail, especially in terms of infrastructure (e.g., vehicle-to-grid facilities, and for aerial SAEVs, takeoff/landing platforms) and integration with the rest of the emergency response systems. It is also crucial to establish pre-disaster contracts with mobility-as-a-service companies as well as other organizations that have SAEVs available, to ensure their participation in disaster response. Lastly, it is worthwhile to take human decision-makers into account [15] when studying the overall impact of SAEV-R, as the emergency response operators usually make the "final decisions" under risk and pressure [16] on how to allocate SAEVs.

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