Proceedings of the 2024 Winter Simulation Conference
H. Lam, E. Azar, D. Batur, S. Gao, W. Xie, S. R. Hunter, and M. D. Rossetti, eds.

GENAIR: GENERATIVE AI FOR RESILIENT URBAN AIR MOBILITY WITH VTOLS IN DISASTER EVACUATION

Abdullah Alsaheal[1], William Hoy[1], Priscila Haro[1], Asad Rehman[2], and Nurcin Celik[1]

[1]Dept. of Industrial and Systems Engineering, University of Miami, Coral Gables, FL, USA
[2]Dept. of Mathematics and Computer Science, Saint Louis University, Madrid, SPAIN

ABSTRACT

Coastal regions face growing threats, making timely and safe evacuation paramount. Current plans rely heavily on congested ground transportation, leading to delays and heightened stress levels. The emerging field of Urban Air Mobility (UAM), utilizing Vertical Take-Off and Landing Vehicles (VTOLs), promises to alleviate these issues by providing solutions for quick evacuation strategies. Here, we aim to leverage Generative Adversarial Networks (GANs) to expand limited datasets with synthetic data specific to disaster scenarios, evacuation routes, airspace considerations, and the impact of real-time weather events, enabling robust simulation of UAM deployment in disaster evacuations. We identified two applicable scenarios: i) UAM for Extreme Weather Emergency Evacuation and ii) Hospital Evacuations using VTOLs as use cases and illustrated their impact. This research seeks to pave the way for optimized, data-driven evacuation planning with UAM and VTOLs, ultimately enhancing the safety and efficiency of evacuations in the face of extreme events.

1 INTRODUCTION

Sea, ground, underground, and air are humankind's three primary transport modes. While Ground transportation remains the dominant mode for short to medium distances, it often faces gridlock and struggles during emergencies. While air travel is the best alternative, it is primarily occupied by commercial airlines, military aircraft, and specialized helicopters. Urban Air Mobility (UAM), an emerging field that is gaining momentum in recent years, proposes simpler air vehicles, including Vertical Take-Off and Landing Vehicles (VTOLs), for the general public to revolutionize urban transportation (Cohen et al. 2021). This research aims to evaluate the effectiveness of artificial intelligence (AI) models to assist decision making of VTOLs dispatch strategies for hospital evacuation in extreme weather emergency scenarios.

The rising frequency and severity of natural disasters, particularly hurricanes (Pielke Jr 2005), underscores the critical need for robust and adaptable evacuation protocols. In densely populated urban environments, reliance on conventional ground transportation during emergencies often proves inadequate due to congestion and compromised infrastructure. Coastal cities, particularly vulnerable to flooding, face significant challenges with ground-based evacuation inefficiencies. VTOLs present a superior alternative, addressing the limitations of slow dispatch, navigational hazards, and inadequate onboard medical care typically associated with Inflatable Rescue Boats (IRBs). Implementing VTOL technology in these regions accelerates evacuations, enhances safety, and ensures the continuation of essential medical services during transport. Consequently, VTOLs significantly improve disaster response efforts in flood-prone coastal areas.

Traditional evacuation plans exhibit an overreliance on ground-based transportation, resulting in bottlenecks and delays that critically hinder hospital evacuations during disasters. VTOLs offer an attractive alternative by bypassing crowded roads and offering fast escape routes, especially during floods or severe weather conditions. This inherent adaptability renders VTOLs invaluable for hospitals and emergency response personnel, facilitating access to areas isolated by disruptions to ground-based transport. However, implementing Urban Air Mobility (UAM) for disaster evacuations is hindered by a lack of historical data that includes information on disaster scenarios, efficient evacuation routes, and concerns about managing airspace. The lack of this extensive information poses a significant obstacle to effectively deploying VTOLs for emergency evacuation purposes. In response to these challenges, our research contributes by developing an Extreme Weather Emergency Evacuation (EWEE) framework for hospital patients using VTOLs. We employ generative AI models to create and expand limited datasets, facilitating realistic simulations of UAM deployment in emergency scenarios. Additionally, we utilize a reinforcement learning approach to ascertain the optimal number of VTOLs needed, which enhances adaptability to environmental changes and reduces the cost of scenario testing. Our findings also demonstrate the transformative potential of UAM in emergency evacuations, showcasing practical applications of VTOLs.

1.1 UAM for Extreme Weather Emergency Evacuation

Climate change is causing coastal cities to face a heightened risk of street flooding, potentially rendering ground transportation inoperable (Helderop and Grubesic 2019). Ensuring residents' safe and timely evacuation, particularly vulnerable hospital patients, presents a critical and daunting challenge for emergency responders. Current evacuation plans, heavily reliant on ground transportation, often prove inadequate in extreme circumstances. For example, improper planning and coordination of automobiles and transit-dependent residents during Hurricane Rita, which hit the Louisiana and Texas coasts in 2005, resulted in severe highway traffic congestion (Litman 2006). Therefore, there is an urgent need for innovative solutions that can overcome the limitations of traditional evacuation methods using efficient alternatives to conventional ground transport.

Urban Air Mobility (UAM) is defined as an aerial transportation system that utilizes piloted and autonomous aircraft, such as VTOLs, to move passengers and cargo within urban areas (Reiche et al. 2019). This focus on smaller, autonomous VTOLs within UAM offers a compelling alternative to traditional helicopters for emergency evacuation. VTOLs require minimal infrastructure investment in evacuation facilities like hospitals, and their maneuverability allows them to operate safely and efficiently in dynamic, unstructured environments (Kramar et al. 2021). Additionally, VTOLs can potentially function with minimal human supervision, further enhancing evacuation efficiency. Despite their great potential, extreme weather can also impact the safety, cost, and efficiency of UAM operations (Reiche et al. 2019). Therefore, implementing a UAM strategy for extreme weather emergency evacuation (EWEE) scenarios requires careful analysis of the safety and efficiency impact of operating VTOLs in such extreme conditions, with different approaches and standards tailored to the specific characteristics of various extreme weather conditions and their possible impacts.

1.2 Hospital Evacuations using VTOLs

Urban Air Mobility (UAM), combining piloted and increasingly autonomous aircraft (VTOLs), promises to revolutionize urban transportation. This focus on smaller, autonomous VTOLs within UAM offers a compelling alternative to traditional helicopters for emergency evacuation. Current hospital evacuation plans mandated by counties regulations primarily rely on ground transportation, leading to significant disaster-related challenges (Mace and Sharma 2020). Congested roads become overwhelmed as ambulances and evacuation vans carrying both critical and less critical patients compete with the evacuation of residents. This gridlock creates delays, hinders timely evacuation, and contributes to heightened panic among civilians, especially those with compromised health conditions. While certain standards mandate helipads for trauma centers (Floridahealth.gov 2010), this option is unavailable to hospitals lacking dedicated helipads, limiting air evacuation strategies. VTOLs offer the potential to significantly reduce patient transport times and alleviate road congestion during disaster evacuations without major infrastructure investment or modification. Figure 1 provides an overview of our proposed extreme weather emergency evacuation (EWEE) for hospital patients using Vertical Take-Off and Landing Vehicles (VTOLs).

To effectively evaluate our proposed EWEE concept for hospital patients, we must conduct simulations of VTOL evacuations under various disaster scenarios. However, the lack of comprehensive historical data on UAM implementation in disaster planning limits the effectiveness of current simulations. Exise ting data does not sufficiently cover disaster scenarios, evacuation routes, airspace dynamics, and real-time weather events in the context of UAM and VTOLs.

Figure 1: An overview of our proposed extreme weather emergency evacuation (EWEE) for hospital patients using Vertical Take-Off and Landing Vehicles (VTOLs).

To address this, we generate new data and expand limited datasets to improve our flood risk prediction model using Generative Adversarial Networks (GANs). Additionally, integrating Geographic Information Systems (GIS) with GANs in the future will allow for the creation of spatially informed synthetic data, enhancing the realism and geographic relevance of simulations. The rest of the paper is structured as follows: Section 2 discusses previous studies on disaster evacuations of hospital patients, UAM's role in natural disasters as an emerging field, and the complexities and challenges of real-time monitoring of flood data. Section 3 provides a detailed background on the GenAir framework, our methodology, and implementation. Section 4 evaluates various VTOL deployment scenarios to determine the optimal number of VTOLs. Section 5 concludes the paper and outlines future research directions.

2 RELATED WORK

Evidence indicates that climate change and rising population contribute to increased natural disasters, particularly hydrometeorological events (Fergusson and Boden 2014). The exacerbation of this trend is closely linked to anthropogenic greenhouse gas emissions, emphasizing the urgent need for effective climate mitigation and adaptation strategies to minimize disaster risks (López et al. 2018). In response to the challenges posed by extreme weather events, Urban Air Mobility (UAM) emerges as a transformative solution for transportation, logistics, security surveillance, and emergency evacuation (Gillis et al. 2021). Notable among UAM technologies are Vertical Take-Off and Landing Vehicles (VTOLs), which may be piloted or autonomous (Straubinger et al. 2020) and offer potential benefits across multiple sectors, including enhanced logistics, ridesharing convenience, and improved emergency response by reducing dependency on ground transportation (Cohen et al. 2021). Despite limitations imposed by severe weather conditions such as tornadoes and hurricanes (Reiche et al. 2019), strategic deployment of VTOLs before and after disasters could significantly bolster emergency operations, expedite evacuations, and ensure the safety of vulnerable populations, including hospital patients.

Coastal cities, particularly vulnerable to flooding, face significant challenges with ground-based evacuation inefficiencies. While Inflatable Rescue Boats (IRBs) are recognized as a versatile option for emergency evacuations (Barcala-Furelos et al. 2023), their deployment is often hampered by slow response times, vulnerability to debris, and the lack of onboard medical facilities. As a result, we propose VTOLs as an effective alternative. VTOLs leverage airspace to facilitate rapid and efficient evacuations, a critical advantage when rescuing vulnerable groups such as hospital patients who require immediate medical attention. This approach effectively circumvents the logistical challenges inherent in traditional and inflatable boat evacuations.

2.1 Hospital Patients Evacuation in Floods

Hospital evacuations during extreme weather are critical to the public, government, and city planners. Kaliamoorthy et al. (2016) and Cocanour et al. (2002) emphasized the importance of careful planning, effective communication, and coordination with outside facilities. Iwasaki et al. (2019) and Khorram-Manesh et al. (2013) underscored the need for early preparation, regional evacuation plans, and continuous improvement in planning, leadership, and communication. Shi et al. (2023) identifies flood-prone regions using the DBHYDRO database of collected meteorological sensors data using deep learning. Chen et al. (2015) proposed modeling and simulation as tools for improving evacuation processes. Xu et al. (2014) and Celik and Son (2012) advanced multi-fidelity simulation optimization methods for various applications. Bernard and Mathews (2008) highlighted the challenges and creative solutions in evacuating a maternal-newborn area during Hurricane Katrina.

While several studies have mainly focused on the managerial and strategic planning of hospital evacuation during extreme weather conditions, little attention has been given to innovative solutions utilizing different modes of transporting patients to their evacuation points while using real-time data provided by various sensors and connected systems, as proposed in our GenAir framework. For example, many studies have explored the challenges and potential solutions for hospital patient evacuation. Rega et al. (2010) emphasize the need for strategic and tactical guidelines. Manion and Golden (2004) highlight the challenges of evacuating Intensive Care Unit (ICU) patients and Gildea and Etengoff (2005) report a successful simulation of critically ill patients. Gray et al. (2020) and Davis et al. (2017) focus on training and protocol development, with Gray et al. (2020) finding virtual simulation to be effective for nurse-led patient evacuation and Davis et al. (2017) developing an evacuation protocol for patients with ventricular assist devices. Saint Martin et al. (2020) provide real-world examples and future considerations, highlighting the potential of virtual reality simulations for hospital fire evacuation.

Furthermore, many researchers have explored various aspects of hospital patient evacuation, including the performance of trained staff using movement assist devices (Hunt et al. 2015), patient-driven resource planning (Petinaux and Yadav 2013), and the role of the Department of Defense patient movement system in disaster aeromedical evacuation (Lezama et al. 2011). The potential use of Urban Air Mobility (UAM) in this context is supported by studies on the use of Unmanned Aerial Vehicles (UAVs) for prehospital combat casualty evacuation (Maddry et al. 2021) and the cost-effective use of medical air evacuation personnel (Gurland et al. 1995). While the specific application of UAM in hospital patient evacuation has not been extensively addressed in the literature, a few studies have explored air evacuation using helicopters or VTOL aircraft for different disaster evacuation scenarios. Ultimately, we intend to integrate GIS, meteorological sensor data and secured Healthcare Information Systems (HIS) to coordinate the deployment of appropriate evacuation vehicles. This system will inform the utilization of hospital beds and specific patient needs, ensuring that VTOLs are adequately supplied and directed to optimal evacuation points. Furthermore, we employ machine learning models to proactively monitor conditions and autonomously decide on the best times and routes for dispatching VTOLs, enhancing the efficiency and effectiveness of emergency responses

2.2 UAM in Natural Disasters

A range of studies have explored the use of helicopters in flood disaster rescue operations, focusing on scheduling, simulation, and evaluation. Xue et al. (2022) proposed mathematical models and procedures to optimize helicopter use, considering factors such as mission demand points, resettlement points, and lastmile delivery. Zafar et al. (2021) have extended this work by proposing a distributed framework for autonomous drones, which can be used with helicopters to increase task completion rates. Hao et al. (2022) have developed a visual emergency rescue system to enhance the safety and efficiency of helicopter rescue operations. Fang et al. (2019) have contributed a simulated annealing algorithm and coordination model for the configuration and scheduling of aerial disaster response systems, while Li et al. (2022) focused on the modular design of aviation rescue equipment and the optimization of helicopter path planning. These studies collectively provide valuable insights and tools for improving the effectiveness of helicopter rescue operations in flood disasters.

While helicopters are viable for ground evacuation alternatives, they have significant limitations. Helicopters necessitate specific infrastructure for take-off and landing, including ample clearance for blade rotation. Additionally, their operation requires specialized training and licensing. In contrast, Vertical Take-Off and Landing Vehicles (VTOLs) demand less infrastructural investment and can be operated autonomously, streamlining the dispatch process and reducing regulatory burdens related to licensing. VTOLs can also be solar-powered, particularly effective in extreme flooding conditions where traditional fuel supplies may be compromised. Furthermore, the autonomous operation of VTOLs enables the coordination of multiple vehicles, optimizing evacuation planning and execution with minimal human intervention. Therefore, human resources are released to support other critical aspects of the evacuation process.

Moreover, using Vertical Take Off and Landing (VTOL) aircraft in natural disasters presents opportunities and challenges. Doo (2022) highlights the potential for these aircraft in rapid response and relief supply transportation but also identifies key issues such as vehicle development, autonomous operations, and charging system compatibility. Van Gent et al. (2020) discuss the development of early warning systems and observational products to enhance aviation resilience to natural hazards. However, safety concerns are also raised, with Thompson et al. (2022) discussing the need for robust safety systems and hazard identification in electric Vertical Take-off and Landing (eVTOL) and advanced air mobility operations.

3 METHODOLOGY

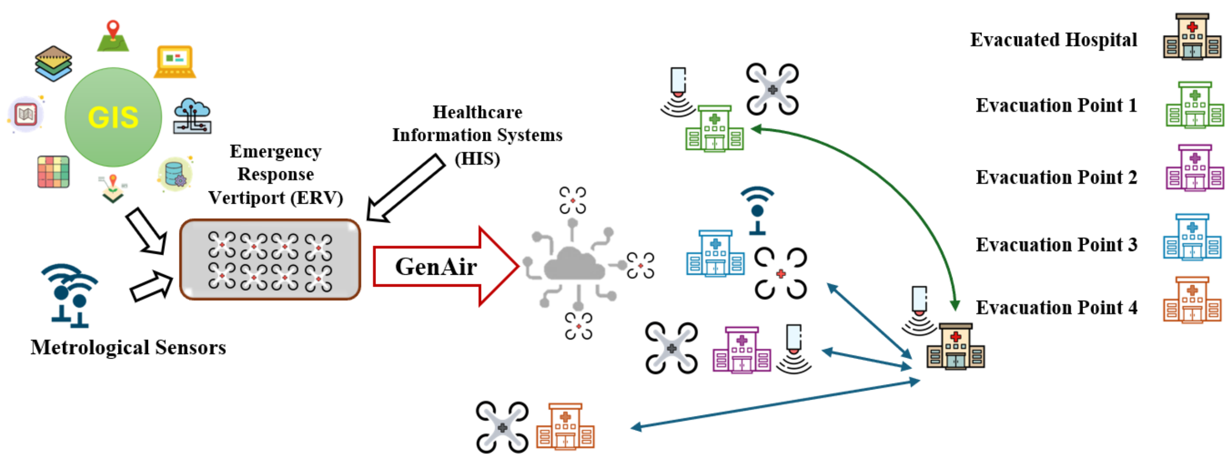

Figure 2: Overview of the proposed GenAir framework.

The envisioned GenAir framework will ultimately integrate multiple systems and datasets to facilitate the emergency deployment of VTOLs to evacuate hospital patients (see Figure 2). This framework will initiate with Geographic Information Systems (GIS) data, meteorological sensors, and hospital patient information. Initially, GIS and meteorological data will be used to predict potential flooding events, triggering an emergency response. Subsequently, patient data will be analyzed to help formulate a comprehensive evacuation plan. In the current stage of this new study, the framework schedules VTOL departures from an emergency vertiport to transport patients to pre-determined safe inland hospitals and optimizes VTOL scheduling by evaluating the impact of different evacuation speeds and the proportion of patients evacuated on overall emergency response effectiveness. In the future, departure schedules will be guided by updated GIS and meteorological insights. Additionally, the framework will account for the care capacity of receiving hospitals, ensuring patient needs are matched with available resources.

3.1 Proposed GenAir Framework Implementation

This research uses a reinforcement learning approach to determine the optimal number of Vertical Take-Off and Landing Vehicles (VTOLs) required to evacuate hospitals where synthetic experiments are conducted on an arbitrarily selected hospital in Florida. Unlike traditional optimization methods that depend on accurate models—which can be costly and inflexible—reinforcement learning operates within an environment, allowing actions and strategies to adapt based on feedback without needing a predefined model. This approach enhances adaptability when environmental conditions change and reduces the costs associated with scenario testing.

The framework employs a model-free, off-policy reinforcement algorithm with a discrete action space Double Deep Q Network (DDQN) (Van Hasselt et al., 2016). DDQN mitigates the overestimation bias by incorporating two neural networks, a target network and a policy network. Actions are chosen via a "greedy" policy, with experiences stored in a replay buffer that informs policy updates through a decay schedule. This method processes batches of experiences to refine the policy network continuously, with the network's weights updated periodically to stabilize learning outcomes. The reinforcement learning environment is configured with discrete actions representing a continuous state space.

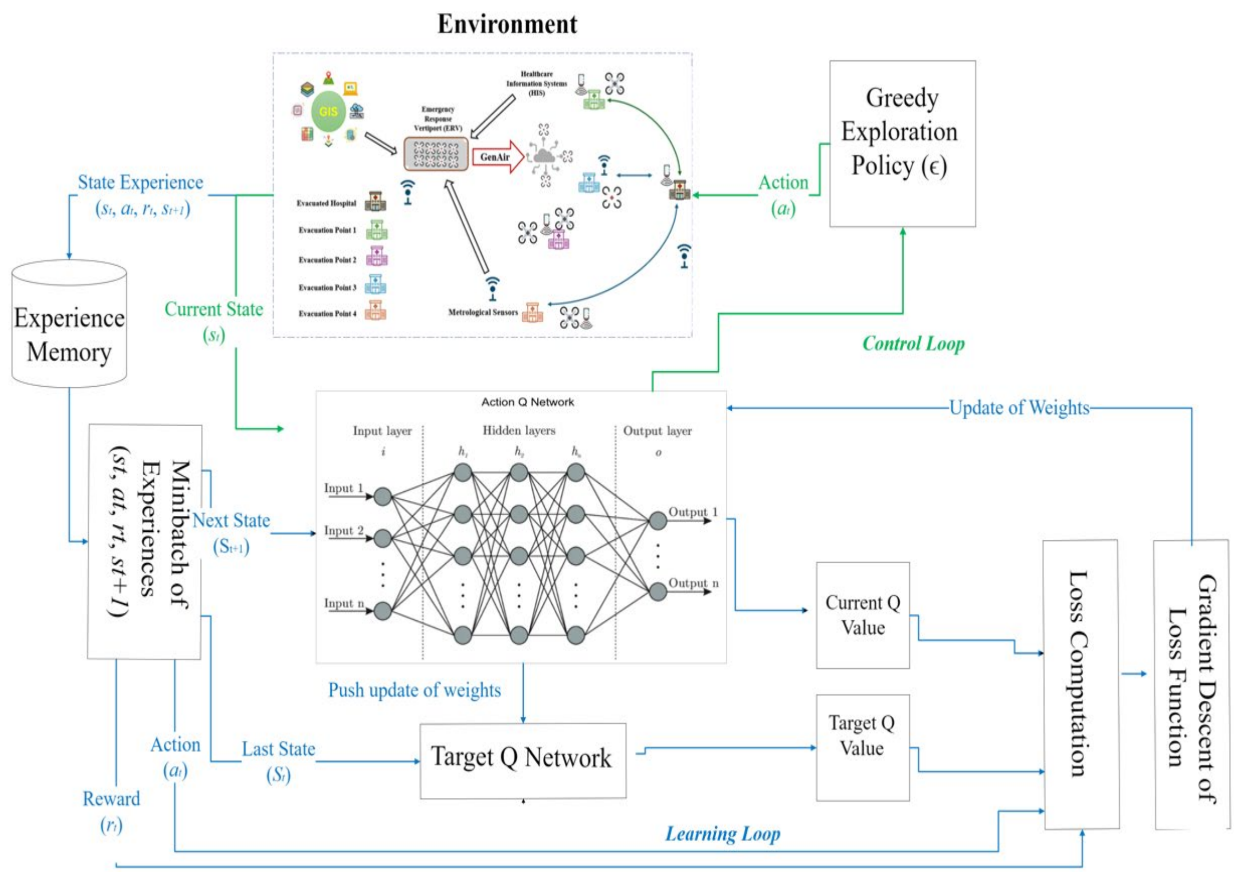

Figure 3: An illustration of DDQN (Van Hasselt et al., 2016) implementation in the GenAir framework.

The DDQN algorithm follows a systematic approach, illustrated in Figure 3, starting with initialization and extending through action selection, execution, experience storage, mini-batch sampling, Q-value computation, loss calculation, network updating, and target network synchronization. The process begins with the initialization of the environment and neural networks. Two distinct networks are established: the Main Q-Network and the Target Q-Network. The Main Q-Network is responsible for action selection and updating Q-values, while the Target Q-Network provides stable target Q-values during learning updates. Additionally, a replay memory buffer is initialized to store experience tuples, each comprising the current state s_t, the action taken a_t, the reward received r_t and the subsequent state s_{t+1}.

In this model, a timestep is initiated whenever the agent begins a discrete action a_t, serving as a measure of action sequences rather than time. The number of timesteps provides context for how quickly the model converges. A large number of timesteps is typically required as the model's complexity increases. The model is considered adequately trained when convergence occurs after executing enough timesteps in the training process. At each timestep, the agent observes nine patients, each with six features including the patient identification number e, which contains encrypted information about the patient's health condition and care requirements, discretized wait time of patient e at timestep t since evacuation was triggered w_e^t, and origin-to-destination distances d_{ij} where i is the evacuated hospital index and j is the evacuation point index, mapped to an encoded vector representing the evacuation points' locations. The simulation penalizes delays beyond a 20-minute wait time, simulating the urgency of evacuation, and rewards successful patient transfers to one of four pre-determined inland hospitals. The model was iteratively tested over one million timesteps until convergence and results were obtained.

Furthermore, at each state s_t, the DDQN agent takes an action a_t corresponding to picking one of the nine passengers observed in the environment that require immediate evacuation and decides on the evacuation point for drop-off. If the wait time exceeds the maximum allowed for a patient evacuation W^{max} , the patient is dropped from the observation space, and the DDQN agent is penalized. Thus, a balance between the criticality of the evacuated patient's health conditions and the maximum wait time constraint must be achieved for optimal evacuation performance.

An evacuation is considered a positive return when a successful evacuation occurs and negative when a patient is dropped due to the maximum wait time constraint, as defined by Equation (1), where v_e is an evacuation value measure of the evacuated patient based on the criticality of their health condition as indicated by e. At this preliminary stage of our study, we consider a fixed value for v_e across all observed patients at each timestep.

$$r_{ev} = \pm d_{ij} \times v_e \tag{1}$$

$$C_{trip} = C_{ev} + C_{lost} \tag{2}$$

We consider operation costs of VTOLs to determine the optimal number to dispatch using Equation (2). The cost of an evacuation trip considers both cases in Equations (3-4): when a successful evacuation occurs and when a patient is dropped from the environment. Here, C_{ev} corresponds to the operation cost of a VTOL when a successful evacuation occurs and C_{lost} is the cost to return from the last evacuation point (EP) to the emergency response vertiport (ERV) when a patient is dropped from the environment due to exceeding W^{max}, respectively. In Equation (3-4), uc_{vtol} is unit cost per distance traveled to operate a VTOL and d_{0k} is the distance from the last EP visited and the ERV. Finally, the reward function is given by Equation (5).

$$C_{ev} = d_{ij} \times uc_{vtol} \tag{3}$$

$$C_{lost} = d_{0k} \times uc_{vtol} \tag{4}$$

$$R = r_{ev} - C_{trip} \tag{5}$$

4 RESULTS AND ANALYSIS

During the preliminary synthetic systematic experimentation, a GenAir framework simulated the evacuation of 650 patients. The study evaluated various VTOL deployment scenarios to determine the number needed for an effective evacuation, considering different travel speeds and evacuation proportions. The analysis calculated the number of patients evacuated per VTOL and measured VTOL idle times to optimize resource utilization. Results, depicted in Figures 4 and 5, highlight the outcomes of over one million timesteps for scenarios with varying VTOL speeds and evacuation requirements. This preliminary study did not account for weather conditions during VTOL dispatches and assigned patients to evacuation points without considering specific medical needs or bed availability at each location.

Table 1: Travel times of VTOLs from the evacuated hospital to each evacuation point.

Travel Times (min)	Evacuation Point 1	Evacuation Point 2	Evacuation Point 3	Evacuation Point 4
Evacuated Hospital	6.5	4.6	7	7.25

Simulation parameters include a total flight time, including a 2-minute boarding period during which VTOLs also charge, thus eliminating the need for additional downtime. Each VTOL is designated to transport one hospital bed, a patient, and a doctor. The arrival rate of patient evacuation requests is modeled using a Poisson distribution reflective of hospital capacity and urgency of evacuation, with variability introduced during peak traffic periods to simulate realistic emergency conditions. The simulation penalizes delays beyond a 20-minute wait time, simulating the urgency of evacuation, and rewards successful patient transfers to one of four pre-determined inland hospitals. The model was iteratively tested over one million timesteps. The designated evacuation targets were marked as Evacuation Points 1, 2, 3, and 4 as in Figure 2. Table 1 summarizes the travel times of VTOLs from the evacuated hospital to evacuation points.

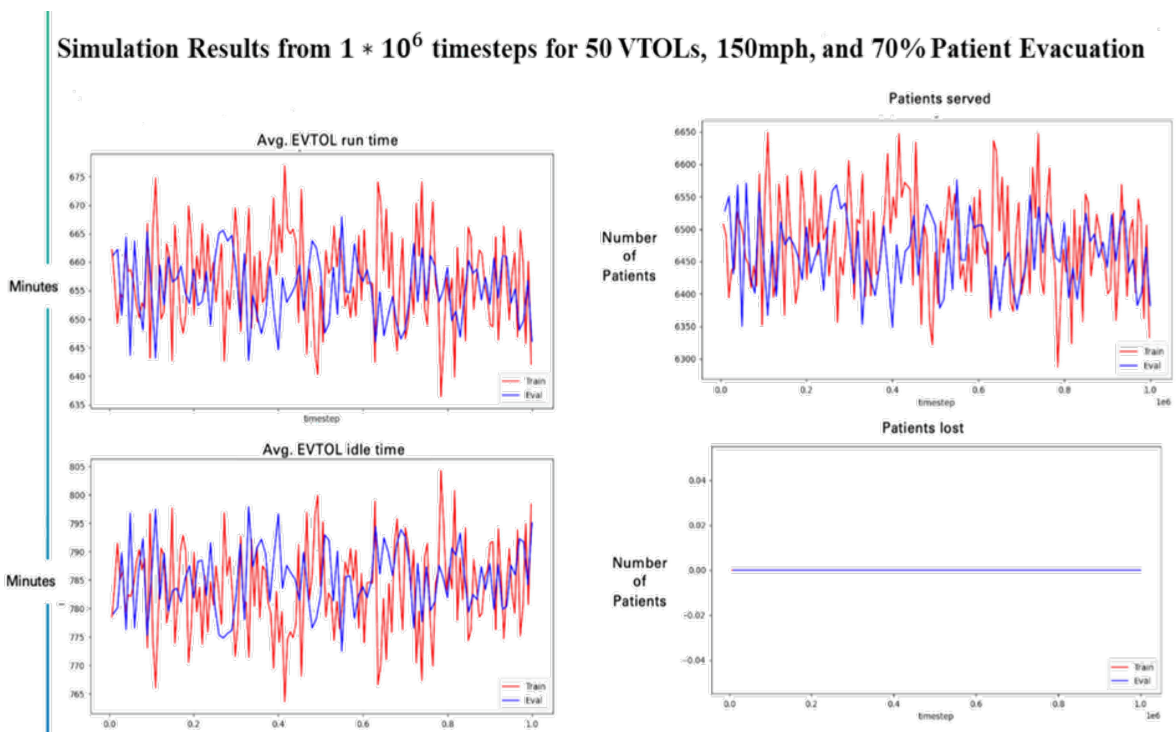

Figure 4: Simulation results for 50 VTOLs, 150mph, and 70% evacuation requirement.

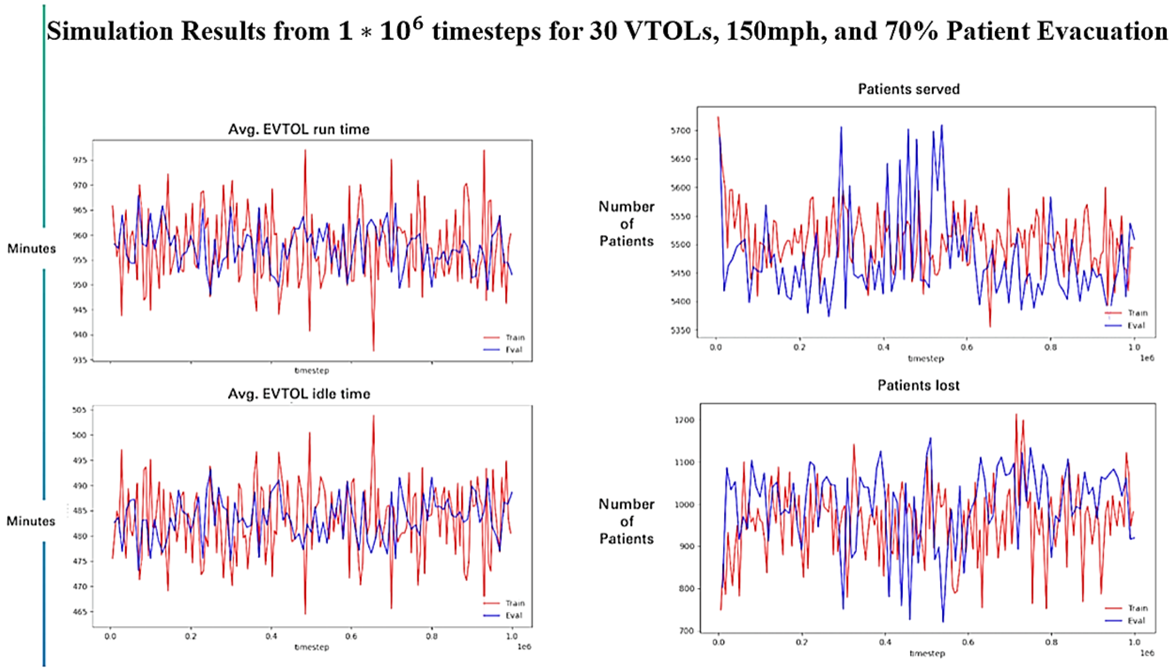

Figure 5: Simulation results for 30 VTOLs, 150mph, and 70% evacuation requirement.

The primary objective of this preliminary study was to determine the optimal number of VTOLs needed to meet incoming evacuation requests efficiently while minimizing idle time and maximizing evacuation completion rates. Our analysis used VTOL speeds of 60 mph, 150 mph, and 300 mph to evaluate performance under hypothetical weather conditions and airspace traffic, although these factors were not explicitly incorporated into the simulations. In addition, the required proportion of evacuations varied from 70% to 100% evacuation requirement for an evaluation of the framework's performance in dynamic, real-time scheduling scenarios when integrated with real-time Healthcare Information Systems (HIS) and meteorological sensors data.

Table 2: Simulation results for the number of VTOLs and percentage of patients evacuated given different speeds and evacuation percentage requirements.

VTOL Speed	Required Evacuation Proportion of Hospital Patients	No. of VTOLs	Percentage of Patients Evacuated	Avg. VTOLs Idle Time (%)
60 mph	70%	50	67%	21%
		30	50%	4%
	85%		-	-
	100%		-	-
150 mph	70%	50	**100%**	55%
		30	85%	**34%**
	85%		**92%**	30%
	100%		80%	25%
300 mph	70%	50	**100%**	76%
		30	**100%**	**62%**
	85%		-	-
	100%		-	-

Table 2 presents the simulation outcomes from the GenAir case study across various scenarios. In simulations requiring a 70% evacuation proportion, deploying 50 VTOLs at an average speed of 150 mph achieved a 100% success rate, compared to only 85% with 30 VTOLs. Although the larger fleet increased service levels by 15%, it also raised the average VTOL idle time from 34% to 55%. Given the critical nature of hospital evacuations, where timely service can be lifesaving, deploying 50 VTOLs was necessary to meet the needs of this scenario. For a 100% evacuation requirement, using 30 VTOLs resulted in at least 80% patient evacuation, with idle times up to 25%. While not tested, increasing the fleet to 50 VTOLs is expected to similarly improve outcomes, as indicated by the 70% evacuation level results. The simulations suggest that a fleet of 50 VTOLs would likely suffice for evacuation proportions ranging from 70% to 90%, achieving over 90% evacuation success at an 85% requirement. Future studies could incorporate acquisition and operational costs to refine the determination of optimal fleet size for varying evacuation percentages.

5 CONCLUSIONS AND FUTURE WORK

Our study has effectively demonstrated the transformative potential of Urban Air Mobility (UAM), specifically utilizing Vertical Take-Off and Landing Vehicles (VTOLs) for enhancing emergency evacuations in extreme weather conditions. The GenAir framework, leveraging generative artificial intelligence models such as Generative Adversarial Networks (GANs), has created realistic simulation environments to evaluate VTOL deployment in disaster scenarios. These simulations have shown that VTOLs can significantly mitigate the limitations of traditional ground-based evacuation methods by providing rapid, flexible, and efficient transport alternatives, particularly in densely populated urban areas.

The future integration of Geographic Information Systems (GIS), real-time meteorological data, and real-time Healthcare Information Systems (HIS) will further enhance the predictive capabilities of the GenAir framework, facilitating more precise and timely responses to emergency evacuation situations. This approach will improve the safety and efficiency of evacuations, ensure better resource utilization, reduce operational delays, and optimize the real-time scheduling and routing of VTOLs during extreme weather emergency evacuation (EWEE) scenarios.

REFERENCES

Barcala-Furelos, R., E. Carracedo-Rodríguez, M. Lorenzo-Martínez, A. Alonso-Calvete, M. Otero-Agra and C. Jorge-Soto. 2023. "Assessment of over-the-head Resuscitation Method in an Inflatable Rescue Boat Sailing at Full Speed. A Non-inferiority Pilot Study". *The American Journal of Emergency Medicine* 70: 70-74.

Bernard, M. and P.R. Mathews. 2008. "Evacuation of a Maternal-Newborn Area during Hurricane Katrina". *MCN: The American Journal of Maternal/Child Nursing* 33(4): 213-223.

Celik, N. and Y.J. Son. 2012. "Sequential Monte Carlo-Based Fidelity Selection in Dynamic-Data-Driven Adaptive Multi-Scale Simulations". *International Journal of Production Research* 50(3): 843-865.

Chen, W., A. Guinet and A. Ruiz. 2015. "Modeling and Simulation of a Hospital Evacuation before a Forecasted Flood". *Operations Research for Health Care* 4: 36-43.

Cocanour, C. S., S. J. Allen, J. Mazabob, J.W. Sparks, C.P. Fischer, J.Romans *et al.* 2002. "Lessons Learned from the Evacuation of an Urban Teaching Hospital". *Archives of Surgery* 137(10): 1141-1145.

Cohen, A.P., S.A. Shaheen and E.M. Farrar. 2021. "Urban air mobility: History, Ecosystem, Market Potential, and Challenges". *IEEE Transactions on Intelligent Transportation Systems* 22(9): 6074-6087.

Davis, K.J., J. Suyama, J. Lingler and M. Beach. 2017. "The Development of an Evacuation Protocol for Patients with Ventricular Assist Devices during a Disaster". *Prehospital and Disaster Medicine* 32(3): 333-338.

Doo, J. 2022. "Unsettled Issues Regarding the Use of eVTOL Aircraft during Natural Disasters". *SAE Technical Paper*. https://www.sae.org/publications/technical-papers/content/EPR2022001, accessed 25th April 2024.

Fang, Z., Y. Zhu, S. Zhang, H. Zhang, H. Zhang and Y. Xie. 2019. "Research on Configuration and Scheduling Model of Aerial Disaster Response System". *IEEE 8th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*, May 24th-26th, Chongqing, China, 1431-1436.

Fergusson, D.M. and J.M. Boden. 2014. "The Psychological Impacts of Major Disasters". *Australian & New Zealand Journal of Psychiatry* 48: 597 - 599.

Floridahealth.gov. 2010. “Trauma Center Standards”. *Department of Health Pamphlet* 150-9. https://www.floridahealth.gov/%5C/licensing-and-regulation/trauma-system/_documents/traumacntrstandpamphlet150-9-2009rev1-14-10.pdf , accessed 27th March 2024.

Gildea, J.R. and S. Etengoff. 2005. “Vertical Evacuation Simulation of Critically Ill Patients in a Hospital”. *Prehospital and Disaster Medicine* 20(4): 243-248.

Gillis, D., M. Petri, A. Pratelli, I. Semanjski and S. Semanjski. 2021. “Urban air mobility: a State of Art Analysis”. In Proceedings *of 21st International Conference of Computational Science and Its Applications (ICCSA 2021)*, September 13th-16th, Cagliari, Italy, 411-425.

Gray, M.M., A.A. Thomas, B. Burns and R.A. Umoren. 2020. “Evacuation of Vulnerable and Critical Patients: Multimodal Simulation for Nurse-Led Patient Evacuation”. *The Journal of the Society for Simulation in Healthcare* 15(6):382-387.

Gurland, B.H., J.A. Asensio and M.D. Kerstein. 1995. “A More Cost-Effective Use of Medical Air Evacuation Personnel”. *The American Surgeon* 61(9): 773-777.

Hao, J., Y. Wang and R. Zheng. 2022. “Development of Visual Helicopter Emergency Rescue System”. *Journal of Physics: Conference Series* 2252(1):12069. IOP Publishing.

Helderop, E. and T.H. Grubesic. 2019. “Social, Geomorphic, and Climatic Factors Driving US Coastal City Vulnerability to Storm Surge Flooding”. *Ocean & Coastal Management* 181: 104902.

Hunt, A., E.R. Galea and P.J. Lawrence. 2015. “An Analysis and Numerical Simulation of the Performance of Trained Hospital Staff Using Movement Assist Devices to Evacuate People with Reduced Mobility”. *Fire and Materials* 39(4): 407-429.

Iwasaki, M., T. Shoko, K. Akahoshi, T. Adachi and K. Yoshikawa. 2019. “One Hospital’s Timeline for In-Hospital Vertical Evacuation during a Flood Disaster”. *Prehospital and Disaster Medicine* 34(s1): s154-s155.

Kaliamoorthy, I., M.S. Reddy, A. Rajakumar, J. Varghese, S. Pandey, B. Pillai *et al.* 2016. “Safe Emergency Evacuation of a Tertiary Care Hospital during the “Once in a Century” floods in Chennai, India”. *Indian Journal of Critical Care Medicine: Peer-reviewed, Official Publication of Indian Society of Critical Care Medicine* 20(2): 104-108.

Khorram-Manesh, A., C. Angthong, A. Pangma, S. Sulannakarn, R. Burivong, R. Jarayabhand et al. 2013. “Hospital Evacuation; Learning from the Past? Flooding of Bangkok 2011”. *British Journal of Medicine and Medical Research* 4(1): 395-415.

Kramar, V., G. Nikolakopoulos, J. Röning and F. Tomasello. 2021. “Urban Air Mobility Overview—The European Landscape”. *30th Conference of Open Innovations Association FRUCT*, October 27th-29th, Oulu, Finland, 99-106. IEEE.

Lezama, N. G., L.M. Riddles, W.A. Pollan and L.C. Profenna. 2011. “Disaster Aeromedical Evacuation”. *Military Medicine* 176(10): 1128-1132.

Li, Y., Z. Liu, K. Chen, J. Qi and C. Li. 2022. “Research on Modular Scheme of Aviation Emergency Rescue for Natural Disasters”. *Journal of Physics: Conference Series* 2364(1):12030. IOP Publishing.

Litman, T. 2006. “Lessons from Katrina and Rita: What Major Disasters Can Teach Transportation Planners”. *Journal of Transportation Engineering* 132(1): 11-18.

López, R., V. Thomas and P. Troncoso. 2018. “Climate Change and Natural Disasters” . *Working Document Series (Preprint),* Faculty of Economics and Business, University of Chile.

Mace, S. E. and A. Sharma. 2020. “Hospital Evacuations Due to Disasters in the United States in the Twenty-First Century”. *American Journal of Disaster Medicine* 15(1): 7-22.

Maddry, J. K., A.A. Arana, A.G. Mora, C. A. Perez, J. E. Cutright, B. M. Kester *et al.* 2021. “Advancing Prehospital Combat Casualty Evacuation: Patients Amenable to Aeromedical Evacuation via Unmanned Aerial Vehicles”. *Military Medicine* 186(3-4): e366-e372.

Manion, P. and I.J. Golden. 2004. " Vertical Evacuation Drill of an Intensive Care Unit: Design, Implementation, and Evaluation”. *Disaster Management and Response* 2(1): 14-19.

Petinaux, B. and K. Yadav. 2013. “Patient-Driven Resource Planning of a Health Care Facility Evacuation”. Prehospital and Disaster Medicine 28(2): 120-126.

Pielke Jr, R.A. 2005. “Are There Trends in Hurricane Destruction?”. *Nature* 438(7071): E11-E11.

Rega, P.P., G. Locher, H. Shank, K. Contreras and C.E. Bork. 2010. " Considerations for the Vertical Evacuation of Hospitalized Patients Under Emergency Conditions”. *American Journal of Disaster Medicine* 5(4): 237-246.

Reiche, C., C. McGillen, J. Siegel and F. Brody. 2019. “Are We Ready to Weather Urban Air Mobility (UAM)?”. *Integrated Communications, Navigation and Surveillance Conference (ICNS)*, April 9th-11th, Herndon, VA, USA, 1-7. IEEE.

Saint Martin, V.B., E.G.Q. Palmeira, V.B. Gonçalves, L.N.C. dos Santos, J. J. M. Melazzo, E. A. L. Júnior *et al.* 2020. “Virtual Reality Simulations for Hospital Fire Evacuation: A Systematic Literature Review”. *22nd Symposium on Virtual and Augmented Reality (SVR)*, November 7th-10th, Porto de Galinhas, Brazil, 313-320. IEEE.

Shi, J., Z. Yin, R. Myana, K. Ishtiaq, A. John, J. Obeysekera *et al.* 2023. “Deep Learning Models for Water Stage Predictions in South Florida”. *ArXiv Preprint* arXiv:2306.15907.

Straubinger, A., R. Rothfeld, M. Shamiyeh, K.D. Büchter, J. Kaiser and K.O. Plötner. 2020. " An Overview of Current Research and Developments in Urban Air Mobility–Setting the Scene for UAM Introduction”." *Journal of Air Transport Management* 87: 101852.

Thompson, E. L., A.G. Taye, W. Guo, P. Wei, M. Quinones, I. Ahmed *et al.* 2022. "A Survey of eVTOL Aircraft and AAM Operation Hazards". *American Institute of Aeronautics and Astronautics (AIAA) Aviation Forum*, June 27th-July1st, Chicago, IL, USA, 3539. ARC.

Van Gent, J., H. Brenot, N. Theys, L. Clarisse, S. Wilson, R. Clarkson *et al.* 2020. "Prototyping of a Multi-Hazard Early Warning System for Aviation and Development of NRT Alert Products within the EUNADICS-AV and OPAS Projects". *IGARSS - IEEE International Geoscience and Remote Sensing Symposium*, September 26th-October2nd, Waikoloa, HI, USA, 6859-6862. IEEE.

Van Hasselt, H., A. Guez and D. Silver. 2016. "Deep Reinforcement Learning with Double Q-Learning". *Proceedings of the AAAI Conference on Artificial Intelligence* 30(1):10295. https://doi.org/10.1609/aaai.v30i1.10295.

Xu, J., S. Zhang, E. Huang, C.H. Chen, L. H. Lee and N. Celik. 2014. "An Ordinal Transformation Framework for Multi-Fidelity Simulation Optimization". *IEEE International Conference on Automation Science and Engineering (CASE)*, August 18th-22nd, New Taipei, Taiwan, 385-390. IEEE.

Xue, Y., Y. Gao, Y. Tian, H. Liu and X. Wang. 2022. "Helicopter Rescue for Flood Disaster: Scheduling, Simulation, and Evaluation". *Aerospace* 9(12): 822.

Zafar, Z., M. Awais, A. Jaleel and F. Majeed. 2021. "A Distributed Framework of Autonomous Drones for Planning and Execution of Relief Operations During Flood Situations". *The International Arab Journal of Information Technolog* 18(1): 16-24.

AUTHOR BIOGRAPHIES

ABDULLAH ALSAHEAL is a Ph.D. candidate in Industrial and Systems Engineering at the University of Miami. He received his B.Sc. in Industrial Engineering from the University of Miami, and M.Sc. in Industrial and Systems Engineering from the University of Southern California in 2015 and 2016, respectively. He has extensive experience in developing and implementing operations and decision support systems for organizations' operating units to aid higher-level decision-making. His current research efforts have focused on optimizing decision-making for smart grids empowered by 5G and beyond 5G technology. His email address is a.alsaheal@miami.edu. His website is https://simlab.coe.miami.edu/team/.

WILLIAM HOY is a master's student in Industrial and Systems Engineering at the University of Miami. He received his B.Sc. in Mechanical Engineering from the University of Miami in 2018. His research interests include autonomous vehicles, machine learning, and large-scale complex and dynamic systems modeling. He was part of a Finalist UM Team at the 2023 FAA Data Challenge. His email address is wjh58@miami.edu.

PRISCILA HARO is an undergraduate Industrial and Systems Engineering student at the University of Miami and an undergraduate research assistant at the Simulation and Optimization Research Lab (SimLab). Her email address is pxh383@miami.edu.

ASAD REHMAN is an Associate Professor of Mathematics and Computer Science at Saint Louis University Madrid. Prior to joining SLU-Madrid, he was a Visiting Scholar at Telenor Research ASA, Norway. His research interests are in reliability of future cities, and his efforts has been supported by different EU-funding mechanisms. He is an active member of the Smart Cities Community, IEEE, and IEEE Future Networks Community. His email address is asad.rehman@slu.edu.

NURCIN CELIK is a Professor in the Department of Industrial and Systems Engineering at the University of Miami (UM). She received her M.S. and Ph.D. degrees in Systems and Industrial Engineering from the University of Arizona with magna cum laude. Her research interests are in the development of integrated modeling and decision-making methodologies for large-scale, complex, and dynamic systems with learning capabilities. Prof. Celik received the Presidential Early Career Award for Scientists and Engineers from the White House in 2017. The PECASE Award is the highest honor bestowed by the U.S. government on outstanding scientists and engineers beginning their independent careers. Her email address is celik@miami.edu. Her website is https://simlab.coe.miami.edu/team/.