



**NAVAL
POSTGRADUATE
SCHOOL**

MONTEREY, CALIFORNIA

THESIS

**EVACUATION PLANS FOR NAVAL STATION
NEWPORT AND AQUIDNECK ISLAND UNDER
UNCERTAINTY**

by

Christina K. Domanowski

September 2022

Thesis Advisor:
Second Reader:

Daniel Eisenberg
David L. Alderson Jr.

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REPORT DOCUMENTATION PAGE			<i>Form Approved OMB No. 0704-0188</i>
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington, DC 20503.			
1. AGENCY USE ONLY (Leave blank)	2. REPORT DATE September 2022	3. REPORT TYPE AND DATES COVERED Master's thesis	
4. TITLE AND SUBTITLE EVACUATION PLANS FOR NAVAL STATION NEWPORT AND AQUIDNECK ISLAND UNDER UNCERTAINTY		5. FUNDING NUMBERS RNQC3	
6. AUTHOR(S) Christina K. Domanowski			
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000		8. PERFORMING ORGANIZATION REPORT NUMBER	
9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES) Strategic Environmental Research and Development Program (SERDP), 4800 Mark Center Drive, Suite 16F16, Alexandria, VA 22350		10. SPONSORING / MONITORING AGENCY REPORT NUMBER	
11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.			
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release. Distribution is unlimited.		12b. DISTRIBUTION CODE A	
13. ABSTRACT (maximum 200 words) Aquidneck Island, RI, is vulnerable to hurricanes; hence, evacuation plans are critical to the welfare of on-island military installations and communities. Coordination among communities is important as there are few on-island shelters and evacuation will require military and civilian evacuees to egress across the same bridges. Previous work studied optimal vehicle routing to minimize clearance times and coordinate evacuation. However, past work does not consider uncertainty involved in go (evacuate)/no-go (shelter-in-place) decisions. Under hurricane conditions, high winds will force bridge closures and calling an evacuation too late forces populations to shelter-in-place. In contrast, calling an evacuation too early for threatening, non-striking storms might direct evacuees off-island toward danger. We develop a model that can consider these tensions by combining synthetic forecasts for past storms, stochastic hurricane trajectory, expected evacuation demands, and optimal routing. We apply our model to two historical storms: Hurricane Bob in 1991 and Hurricane Gloria in 1985. Results show our model performs well for striking storms by evacuating the majority of vulnerable communities. However, our model also leads to large evacuations for threatening, non-striking storms. We conclude our model forms a good basis for evacuation planning yet needs additional analysis prior to use.			
14. SUBJECT TERMS Aquidneck Island, Newport, NAVSTA, naval station, military, transportation, infrastructure, interdependency, robust optimization, uncertainty, stochastic		15. NUMBER OF PAGES 131	
		16. PRICE CODE	
17. SECURITY CLASSIFICATION OF REPORT Unclassified	18. SECURITY CLASSIFICATION OF THIS PAGE Unclassified	19. SECURITY CLASSIFICATION OF ABSTRACT Unclassified	20. LIMITATION OF ABSTRACT UU

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**EVACUATION PLANS FOR NAVAL STATION NEWPORT AND AQUIDNECK
ISLAND UNDER UNCERTAINTY**

Christina K. Domanowski
Ensign, United States Navy
BS, United States Naval Academy, 2021

Submitted in partial fulfillment of the
requirements for the degree of

**MASTER OF SCIENCE IN APPLIED SCIENCE
(OPERATIONS RESEARCH)**

from the

**NAVAL POSTGRADUATE SCHOOL
September 2022**

Approved by: Daniel Eisenberg
Advisor

David L. Alderson Jr.
Second Reader

W. Matthew Carlyle
Chair, Department of Operations Research

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ABSTRACT

Aquidneck Island, RI, is vulnerable to hurricanes; hence, evacuation plans are critical to the welfare of on-island military installations and communities. Coordination among communities is important as there are few on-island shelters and evacuation will require military and civilian evacuees to egress across the same bridges. Previous work studied optimal vehicle routing to minimize clearance times and coordinate evacuation. However, past work does not consider uncertainty involved in go (evacuate)/no-go (shelter-in-place) decisions. Under hurricane conditions, high winds will force bridge closures and calling an evacuation too late forces populations to shelter-in-place. In contrast, calling an evacuation too early for threatening, non-striking storms might direct evacuees off-island toward danger. We develop a model that can consider these tensions by combining synthetic forecasts for past storms, stochastic hurricane trajectory, expected evacuation demands, and optimal routing. We apply our model to two historical storms: Hurricane Bob in 1991 and Hurricane Gloria in 1985. Results show our model performs well for striking storms by evacuating the majority of vulnerable communities. However, our model also leads to large evacuations for threatening, non-striking storms. We conclude our model forms a good basis for evacuation planning yet needs additional analysis prior to use.

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List of Acronyms and Abbreviations

BPR	U.S. Bureau of Public Roads
CDC	Centers for Disease Control and Prevention
DBN-RTCPM	Dynamic Bayesian Network-Based Real-Time Crash Prediction Model
EMDSS	evacuation management decision support system
FAR	False Alarm Rate
FEMA	Federal Emergency Management Agency
HURREVAC	Hurricane Evacuation Decision Support Tool
mbar	millibars
MIRR	Military Installation Resilience Review
m/s	meters per second
NAVSTA	Naval Station
NHC	National Hurricane Center
NOAA	National Oceanic and Atmospheric Administration
NPS	Naval Postgraduate School
NUWC	Naval Undersea Warfare Command
NWC	Naval War College
PWM	Parametric Wind Model
SLOSH	Sea, Lake and Overland Surge from Hurricanes
SRIA	Sandy Recovery Improvement Act

URI University of Rhode Island

USACE U.S. Army Corps of Engineers

VPH vehicles per hour

Executive Summary

The New England region is threatened by seasonal hurricanes, which can result in serious repercussions for the population and infrastructure. Aquidneck Island in Rhode Island, home to Naval Station Newport, the Naval Undersea Warfare Center, Newport City, and townships of Portsmouth and Middletown, is particularly vulnerable to future storms when combined with anticipated sea level rise and coastal flooding. While few hurricanes made landfall on Aquidneck Island in the past, the hurricanes that have were detrimental to both military and civilian communities. Examples include Hurricane Bob in 1991 and Hurricane Gloria in 1985, which are considered to be some of most devastating hurricanes to strike the region. Both ended in millions of dollars in damages and storm-related casualties due to heavy winds and rain alongside infrastructure impacts like power outages. Hurricane planning for future storms is critical to the island to ensure military missions can remain operational and to protect communities from harm.

While the damages to infrastructure may be unavoidable without significant investment, preventing loss of life can be achieved with evacuation plans that direct vulnerable communities to safety. However, evacuation is a difficult activity to manage. As a storm approaches, authorities need to decide whether it is better to evacuate or shelter-in-place, boiling down to a go/no go decision. Unfortunately, this decision is rife with uncertainty, including the strength of the oncoming storm and the timing and destination of its landfall. These uncertainties become less prevalent the closer a storm is to landfall, which is problematic for evacuation decisions. If an evacuation is called, military and civilian communities need enough time to evacuate across bridges to safety before hurricane winds close bridge access. Choosing to evacuate too late for storms that strike the island forces vulnerable communities to shelter-in-place at times of high danger. Choosing to evacuate too early for storms that threaten, but do not strike, might direct vulnerable populations towards more dangerous areas.

The goal of the thesis is to develop a model that can help emergency managers make go/no-go decisions for uncertain, oncoming storms. Past work by Jones (2021) developed an optimization model for Aquidneck Island that produces vehicle routing to minimize evacuation clearance times for military and civilian communities. Yet, this model assumes

evacuation is called and coordinated for all communities simultaneously. We build on this work to incorporate uncertain evacuation demands that can form across the island given both striking and threatening storms. Then, we study go/no-go decisions given historical storm tracks. Towards this end, we perform the following model and analysis tasks:

1. *Create Synthetic Hurricane Forecasts:* We generate hurricane tracks for Hurricane Bob and Hurricane Gloria to represent forecast scenarios that were possible, yet unrealized for the historical storms. For each storm, we collect data on the original, best track from the National Hurricane Center (NHC) and produce three synthetic tracks. This results in four forecasts: the original track, a worst-case track, and two that represent western and eastern drift based on the NHC cone of uncertainty (referred as the 180° and 90° track, respectively).
2. *Identify a Dangerous Region for Aquidneck Island:* We identify the geographic region where, if Hurricane Bob or Gloria strikes, Newport Bridge will close due to high winds. We determine this region using a parametric wind model to estimate maximum sustained wind speeds experienced at Newport Bridge for each track and interpolate across the latitudes where each forecast makes landfall. We consider storms that cross this region as a *strike* and others as *threatening* and *non-striking*. This analysis categorizes each synthetic track as either striking or non-striking. Results for Hurricanes Bob and Gloria produces two tracks that strike (original and worst-case) and two that threaten, but do not strike (180° and 90°). This analysis was completed in collaboration with experts at the University of Rhode Island.
3. *Calculate Likelihood of Strike as a Hurricane Approaches:* We create a stochastic track generation procedure to estimate how likely Hurricane Bob or Gloria were to strike at each point in their forecast. This procedure estimates the uncertainty in whether a storm would strike the most dangerous region with respect to its lead time before landfall. While striking storms eventually close bridges as they make landfall (i.e., a likelihood of strike = 1), even non-striking storms may have a large enough strike probability to initiate some level evacuation during their approach.
4. *Estimate Evacuation Demands:* Using the likelihood of strike, we estimate expected evacuation demand (in vehicles) for each storm for each track. We estimate evacuation demands for each time period prior to landfall using a function that combines the total number of possible evacuees for a given community, the hurricane strike probability,

and a credible time window for evacuation. This analysis results in expected evacuation demands for each scenario that can be used in deterministic optimization models for evacuation routing.

5. *Evacuation Model Formulation:* We extend the Jones (2021) model to consider time-varying evacuation demands driven by oncoming storms. The resulting model assigns evacuating populations to shelters or to cross bridges and determines the optimal route and flow of vehicles to minimize vehicle clearance times.
6. *Analysis:* Using the network defined in Jones (2021) and our modified model, we study evacuation for each storm track for Hurricane Bob and Hurricane Gloria.

Results raise critical questions for evacuation planning. We find that different forecasted tracks for the same storm can produce different evacuation plans. For example, optimal routing would send 447 more vehicles over Mt. Hope Bridge for the original Hurricane Bob track over its worst-case track, even though both scenarios strike Aquidneck Island. This means the timing of when evacuation demands occur relative to an oncoming storm can lead to large differences in the optimal routing even when scenarios produce the same outcome. Moreover, we find the only on-island hurricane shelter — Gaudet Middle School — never reaches full capacity and is under-utilized across all scenarios for both storms. Future work should assess the sensitivity of evacuation timing on routing and egress.

Results also indicate that our model is only moderately effective for future evacuation planning. A perfect model would recommend full evacuation given a striking storm and all populations to shelter-in-place given a non-striking storm. We find our model does well at recommending evacuation for striking storms, producing nearly complete evacuation for all striking scenarios for both storms. However, our model also produces large evacuations for threatening, but non-striking storms for all but one scenario (Hurricane Gloria, 180° track).

Future work could improve model results for future evacuation planning. While the current model is a good proof of concept, it requires further analysis to determine its validity for different storm scenarios. For example, updating methods with more realistic stochastic storms, improving the expected demand function, or incorporating scenarios into a multi-stage stochastic program may improve overall results.

References:

Jones AM (2021) *Mission-Informed Evacuation Models for Naval Station Newport and Aquidneck Island*. Master's thesis, Naval Postgraduate School, Monterey, CA, <http://hdl.handle.new/10945/68337>.

Acknowledgments

To Dr. Daniel Eisenberg and Dr. David Alderson, thank you for always encouraging my academic growth and for guiding me through this process. Thank you for all the incredible academic and professional opportunities you presented me with. I truly appreciate the unwavering patience, dedication, and effort put into this thesis until we reached completion. I am proud of the high quality work we accomplished.

To Deb Crowley, thank you for collaborating with me on this thesis. Without your commitment and extraordinary work, this thesis would lack crucial information and ideas. Thank you for helping and verifying the accuracy of the work in this thesis.

To my family, thank you for being there for me every single step of the way. I am grateful for every minute spent on the phone talking with each and every one of you. Thank you for always reminding me of my strengths and for celebrating every milestone with me.

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CHAPTER 1: Introduction

Aquidneck Island, located in Narragansett Bay in the State of Rhode Island, is a critical location for the U.S. Navy. Both Naval Station (NAVSTA) Newport and the Naval Undersea Warfare Command (NUWC) are located on Aquidneck Island surrounded by the City of Newport and Townships of Middletown and Portsmouth. As part of the NAVSTA Newport mission to educate leaders, the U.S. Naval War College (NWC) in Newport offers graduate-level degrees to further the military training and education of military leaders (U.S. Naval War College 2021). In addition to Aquidneck Island's historic military sites, major military complexes located in Newport, Middletown and Portsmouth are essential for housing military families stationed at NAVSTA Newport (NAVSTA Newport Homes 2021).

Currently, the military installations and civilian communities on the island lack a coordinated hurricane evacuation plan that can manage future storms and climate change. Future disasters are rife with uncertainty, including the amount of flooding on roadways, the capacity of the evacuation shelters, and the timing of evacuations. The existing models and planning efforts rely on high certainty data to recommend evacuation routes and estimate shelter demands, such that uncertainty in data makes it difficult to know if resulting plans will be effective in future disasters. These vulnerable communities require a dynamic strategy for various climate change projections.

1.1 Hurricanes and Aquidneck Island

Aquidneck Island has experienced several major historical and recent storms that motivate the need for coordinated evacuation plans.

1.1.1 Historical Major Storms

The 1938 Hurricane is considered to be one of the most devastating and deadly hurricanes to hit the New England area. When the hurricane hit Rhode Island on September 21, the powerful winds and extreme flooding destroyed thousands of properties and caused hundreds of casualties (Lawrence 2018). The incredibly high tides created storm surges of

14 to 25 feet and reached a maximum wind speed of 160 mph, obliterating every structure on the Rhode Island coast except for large stone mansions located in Newport (University of Rhode Island 2022). Due to the lack of technology available, there were no established evacuation efforts or warnings, leaving the communities completely unprepared to face the storm (Rather 2005). Because of this mass devastation, the National Archives Catalog and several government organizations maintain the records of the event to help with the preparation for future disasters (Lawrence 2018). Specifically, the U.S. Army Corps of Engineers (USACE) New England District “undertook several projects to fortify interior and coastal areas vulnerable to hurricane damage and flooding” (Lawrence 2018). These efforts serve to remind the public about the importance of preparing communities for hurricanes to minimize the damage from hurricanes.

Rhode Island has suffered through the destruction caused by several other hurricanes, such as the 1991 Hurricane Bob and the 1985 Hurricane Gloria. The 1991 Hurricane Bob hit the region with extremely high winds and created a “10- to 15-foot storm surge” that results in 18 casualties (Tucker 2021). The 1985 Hurricane Gloria resulted in 8 casualties, but there was “heavy rainfall and enough wind to knock out power to 2,000,000 residents” (Tucker 2021). These two hurricanes consistently are considered to be some of the worst storms to hit the New England region.

Other coastal areas have suffered under the destructive impacts of hurricanes. When Hurricane Sandy tore through the coasts of New York and New Jersey on October 29, 2012, the high tides and storm surges flooded the streets and tunnels in New York and destroyed homes and businesses (Rafferty 2012). New York residents were left with restricted access to food, healthcare, and other services while the City of New York incurred billions of dollars in damages (City of New York 2022). However, a large workforce of public services mobilized to help the city combat the detrimental impacts (City of New York 2022). Congress signed the Sandy Recovery Improvement Act (SRIA) of 2013 and the Disaster Relief Appropriations Act, 2013 into law to allow the Federal Emergency Management Agency (FEMA) “greater flexibility in administering assistance programs, improving the Nation’s ability to efficiently respond to and recover from disasters” (FEMA 2017). These acts have led to improved emergency preparedness and recovery for communities after natural disasters.

In recent hurricane preparedness across the country, there is a substantial push for resi-

dents living in areas vulnerable to hurricanes to educate themselves about hurricanes and to develop an evacuation plan for their household. The Centers for Disease Control and Prevention (CDC) provides a guide for households to plan their hurricane evacuations and perform the other preparations needed before a hurricane hits (CDC 2022). In the event of a hurricane, authorities may authorize spontaneous, voluntary, mandatory, short-noticed, or no evacuations to residents in a specific area (Federal Highway Administration 2022). Residents are expected to abide by authorities' decisions to evacuate their homes or to shelter in place. This coordination among the communities and authorities during a hurricane is essential to ensure necessary evacuations occur.

1.1.2 Hurricane Henri and Recent Evacuation Planning Needs

The events of 2021 motivate the need for coordinated evacuation plans that incorporate disaster uncertainty, especially for hurricanes. The location of Aquidneck Island is susceptible to hurricane damages, impacting its dense population of residents and military personnel. These hurricane damages can compromise military installations and objectives as seen in the storm Hurricane Henri, which landed near Westerly, Rhode Island on Sunday, August 22, 2021 (Lada 2021). Hurricane Henri was the eighth named storm of the 2021 hurricane season (Lada 2021). Although the hurricane was considered a storm at the time, its sustained winds of 60mph left 74,000 Rhode Island residents without power and facing immense rainfall and flooding (The Guardian 2021). If Henri were more destructive, both NAVSTA Newport, NUWC Newport, and island communities would have needed to evacuate.

One of the key issues for evacuation decisions revealed during Hurricane Henri is the limited number of routes residents can take to travel off island. If an evacuation were declared, the vast majority of coastal communities vulnerable to storm surge and flooding would need to travel off island to safety via three bridges: Newport Bridge (West), Mt. Hope Bridge (North), and Sakonnet River Bridge (East). Figure 1.1 displays the location of the different bridges used for evacuations and the cardinal direction residents will evacuate off Aquidneck Island.

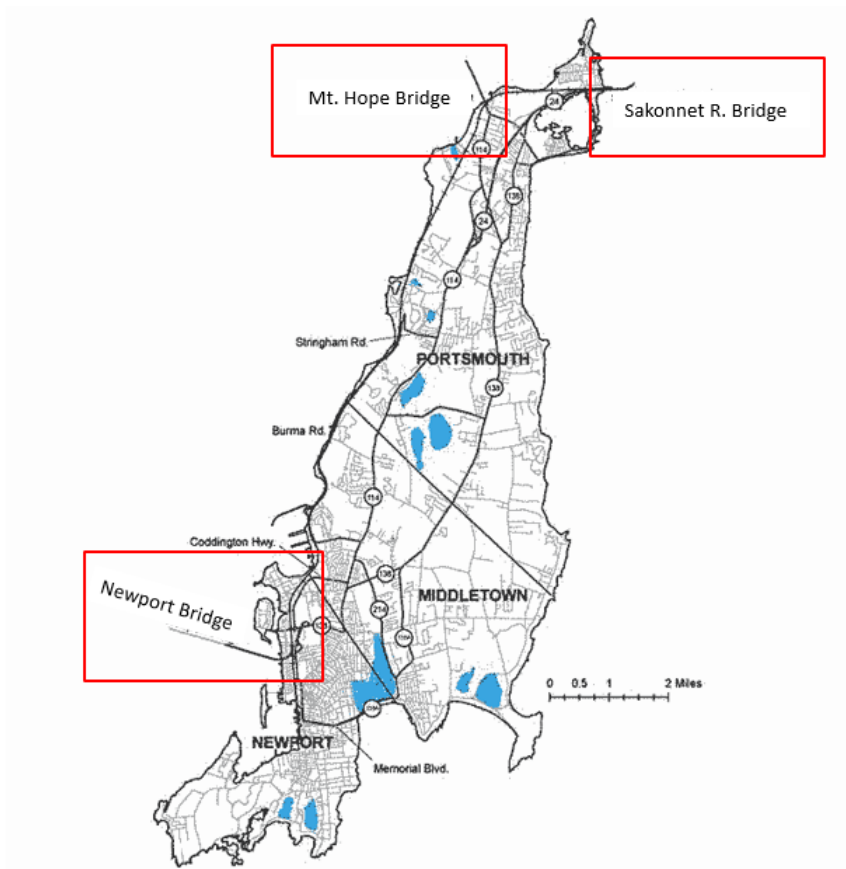


Figure 1.1. Location of Bridges on Aquidneck Island. Here, we identify the communities Portsmouth, Middletown, and Newport as well as the three bridges used in evacuations. The bridges are outlined in a red box. The Mt. Hope Bridge evacuates residents north of the island, the Sakonnet Bridge evacuates residents east of the island, and the Newport Bridge evacuates residents west of the island. Adapted from Newport Rhode Island (2021).

Recent estimates for evacuating off island suggest it could take upwards of 14 hours to clear vulnerable populations including military staff and family (Jones 2021). However, Hurricane Henri's landfall in Westerly precluded evacuation over Newport Bridge, such that, if evacuation were declared, vehicles could travel only North or East. Evacuation times given this reduction in road capacity are estimated to take over 24 hours (Jones 2021). This increase in clearing time corresponds to needing to make evacuation decisions with greater uncertainty, as projections for hurricane impacts and evacuation needs are more difficult to make the further a storm is from landfall. Moreover, recent discussions with emergency

managers also suggests that Mt. Hope Bridge is not officially designated an evacuation route (Aquidneck Island Emergency Management 2022), suggesting even more time to evacuate communities will be required for future disasters.

1.1.3 Climate Change and Anticipated Future Storms

The evacuation planning issues recently revealed during Hurricane Henri are compounded with climate change, as best science predicts more frequent and destructive storms in the future. Due to climate change, sea levels are expected to rise anywhere from 1 to 9.2 feet in Narragansett Bay by 2100 (Coastal Research Management Council 2017). NAVSTA Newport and NUWC Newport are located on the coastline and are vulnerable to sea level rise and coastal flooding such that most Navy facilities will need to be evacuated in future storms. Experts anticipate hurricane damages will worsen, translating to greater impacts to critical missions housed at NAVSTA Newport (Climate Change Collaborative 2021).

Past efforts in evacuation planning do not account for today's current climate of rising water levels, temperatures, wind speeds, and precipitation. With the escalation in these elements, Ramirez (2021) reports that the increase of flooding risk and intensity of storms complicate existing evacuation plans and future predictions of hurricane behaviors. The projections of climate change require hurricane evacuation plans to accommodate these dangerous prospects.

Overall, Aquidneck Island needs evacuation plans that can support decisions under uncertainty and across military and civilian communities. Decisions to evacuate should take into account roadway capacities for multiple scenarios and the increased damages expected in future storms. Plans must also consider how military and civilian communities need to coordinate their evacuation to ensure the flow of vehicles leaving an installation or city do not inhibit residents from reaching shelters and vulnerable populations from traversing bridges. If these communities are not coordinated, evacuees may induce worse traffic and longer evacuation travel times when they fill up shelters or take sub-optimal evacuation routes. A coordinated plan that can handle uncertainty and helps military and civilian emergency managers work together can alleviate these issues.

1.2 Evacuation Planning and Decision-Making

In this section, we overview the purpose of evacuation plans for hurricanes. The goal of this section is to provide more detail for readers unfamiliar with hurricane evacuation planning.

1.2.1 What Does a Hurricane Evacuation Plan Look Like?

The purpose of an evacuation plan is to provide decision support for coordinating the immediate removal of people from highly vulnerable areas and/or sheltering-in-place during a disaster. Accordingly, an evacuation plan is meant to provide a system of recommendations that support multiple municipalities with making the decision of when to evacuate and how to coordinate the evacuation. Plans generally consist of identifying which populations may need to evacuate, which destinations they should travel to (e.g., shelters, off-island), and which routes are most appropriate for each community.

Hurricane evacuation plans are multifaceted and require significant preparedness from both households and authorities. Because hurricanes include multiple threats, such as high winds, flooding, and storm surge, hurricane evacuation plans often involve greater coordination than other disasters. For example, hurricane evacuation plans need to consider evacuating specific zones at different times based on their risk as the storm approaches and identifying safe and clear routes for travel that may become flooded or blocked with debris. This is compounded with the movement of a hurricane, where safe zones may become dangerous as a storm progresses. Thus, frequent communication and direction between the public and the local officials is more relevant for hurricane evacuation than for other disasters that do not cause multiple, time-varying disruptions.

1.2.2 What Decisions Need to Be Made?

Fundamentally, an evacuation plan boils down to a decision between “go” (evacuate) and “no-go” (shelter-in-place). Difficulty in implementing an evacuation plan stems from how individual and city-wide actions impact the efficiency of go/no-go decisions. Ultimately, individual households decide whether or not to shelter-in-place or to evacuate their homes. Meanwhile local officials issue evacuation orders to specific areas depending on their risk to the hurricane and the information currently available to them. Ideally, if residents are ordered to evacuate an area, they should have the shortest travel time possible to minimize

their exposure to the threat. The routes taken should also be as far away from the threat as possible. The combination of these decisions influence the traffic flow on the roads and routes available for travelers.

Before residents begin their evacuation, safe evacuation routes should be predetermined. Best practices base evacuation routes on information from previous hurricanes *and* predictions of current threats. Thus, hurricane evacuation plans need to include recommendations for routes that can apply across multiple storms and be flexible to handle the specific threat of an approaching storm that may change needs. This extends beyond routes to include decisions about when to evacuate specific areas, the public shelters available, and the timing of evacuations before the disaster hits.

1.2.3 Where Does Uncertainty Come From?

Even in hurricane-prone regions, each oncoming storm is rife with uncertainty making go/no-go decisions difficult to make appropriately. Uncertainty exists in both the information for decisions and the decisions made across individual and community scales.

As a hurricane approaches, there is uncertainty in key parameters that dictate storm damages, such as hurricane motion (e.g., velocity, direction), maximum wind speed or central pressure, and the amount of rain the storm holds and may release. This means there is also uncertainty in the actual track of the hurricane, where the damage will amass after landfall, and when and which roads are available for travelers if evacuation is necessary. Generally, uncertainty in storm parameters decreases the closer a hurricane is to landfall, meaning the faster an evacuation can be called and implemented, the more time emergency managers will have to determine the best course of action.

However, there is also uncertainty in what actors do that confounds go/no-go decisions even if all storm parameters were known with certainty. For example, individual households may choose to evacuate or shelter-in-place even if that is against the recommendations of authorities. This means total number of evacuees leaving any community is uncertain and the total number can vary widely throughout days (e.g., rush hour vs. middle of the night) and seasons (e.g., evacuation during high or low tourist seasons in vacation destinations like Aquidneck Island). And the best routes for evacuees may differ depending on whether vehicles follow planned routes or go another direction.

Taken together, evacuation plans can only include partial recommendations about future go/no-go decisions due to the unpredictable nature of hurricanes. It makes sense to establish plans on past storms and the best knowledge about current and future populations, roads, and driver behavior. Still, elements of an evacuation plan need to be flexible to accommodate uncertain information and real-time data. An evacuation plan needs to account for as much uncertainty as possible.

1.3 Thesis Objective and Outputs

The objective of this thesis is to develop an evacuation planning model to be applied in many cases and recommendations for Aquidneck Island that accommodate hurricane uncertainty. As described above, there are two general classes of uncertainties in evacuation plans — uncertainty in storm parameters and uncertainty in human behavior. In this work, we focus on updating past evacuation models and studies to consider uncertainties in storm parameters (e.g., storm approach, landfall, damages, etc.). Moreover, we consider the implications of storm approach on bridge availability to consider the uncertainty of evacuation clearance time experienced during Hurricane Henri. We do this assessment for past storms that have sufficient data to fully realize their possible impacts and evacuation needs if they were to happen again in the future. The overall output of this assessment is to determine if and when go/no-go decisions should have been made for past storms if they happened with current population and road data. Thus, this historical perspective can help emergency managers think through possible evacuation timing and needs for future storms.

There are several key outputs from this thesis that dictate success, including:

- **Model:** Developing a stochastic mathematical program that outputs optimal evacuation plans and clearance times given storm parameter uncertainty. The goal is to recommend the best routes available for communities as an uncertain storm approaches to minimize clearance time and maximize community safety.
- **Analysis:** Studying evacuation for several historical major storms to determine if and when evacuation should have been called for individual communities. Here, we also compare the output of stochastic evacuation models vs. equivalent deterministic models to estimate the value of the stochastic approach for uncertain future storms.
- **Real-world impact:** Ultimately, the success of this work depends on how it is adopted

by the U.S. Navy and the Aquidneck Island communities in their real evacuation plans. Towards this end, results from our model and analysis will be shared with installation and city planners involved in emergency management for Aquidneck Island. This work will also be incorporated into an ongoing Military Installation Resilience Review (MIRR) and supports analysis efforts led by the University of Rhode Island (URI) to ensure coastal community resilience.

The remaining thesis is organized as follows. Chapter 2 reviews literature related to the various types of evacuation models, focusing on evacuation models that include uncertainty. Chapter 3 builds on past deterministic models developed for Aquidneck Island to develop a stochastic program that can make evacuation recommendations under uncertainty. Chapter 4 presents two case studies for historical storms given current population and road data to determine go/no-go decisions and evacuation routes. Chapter 5 presents our conclusions and contributions for this work.

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CHAPTER 2: Literature Review

This chapter reviews models and decision tools that support evacuation plans. We concentrate on studies specific to Aquidneck Island communities and general literature that explores how to incorporate hurricane uncertainty in evacuation models. We conclude with specific methods that can expand past studies to consider uncertainty in go/no-go decisions.

2.1 Deterministic Evacuation Models and Decision Tools

The following evacuation models and decision tools address several pressing components in evacuation plans, such as which regions should evacuate first, when to schedule evacuations for each region, and the optimal travel routes for each region. However, these methods either do not consider uncertainty about storm parameters and human behavior (i.e., require perfect information), or require any known uncertainties to be dealt with in data processing steps prior to making recommendations (e.g., via algorithms or heuristic methods). We refer to models and tools with these characteristics as *deterministic* because uncertainties are pre-processed before assigning go/no-go decisions, evacuation routes, and clearance times.

2.1.1 HURREVAC

The tool for evacuation planning most commonly used by emergency managers across the U.S. is the Hurricane Evacuation Decision Support Tool (HURREVAC). HURREVAC software was developed by the partnerships of FEMA, the USACE, and the National Oceanic and Atmospheric Administration (NOAA) National Hurricane Center (NHC). The software provides Sea, Lake and Overland Surge from Hurricanes (SLOSH) outputs and interactive maps that chart a hurricane's track, wind speeds, and flood levels as well as inform emergency managers of the time a community has to implement their hurricane evacuation plan (Hurrevac 2021).

The main purpose of HURREVAC is to support decisions for safely evacuating a community under a hurricane threat. For the emergency managers of Aquidneck Island, this tool is

paramount to their decisions to evacuate or not. In its most common use case, an emergency manager can access hurricane track information from the NHC and NOAA, determine a safe time frame for declaring an evacuation, and combine decision times with best-track info to determine when go/no-go decisions must be made for an oncoming storm. Due to its wide adoption and easy integration with historical and real-time data sets, emergency managers heavily rely on this tool to support their evacuation decisions.

However, there are limitations to the recommendations HURREVAC provides. The program considers only historical evacuation studies that are not adaptive to the current number of evacuees on island, for example military officers and families that might not have been considered in previous studies. Similarly, HURREVAC does not provide traffic levels and routes for where vehicles should travel to evacuate. Taken together, ignoring these uncertainties leads HURREVAC to overestimate the capacities of roads, resulting in unrealistic go/no-go decision times. This critique is echoed by Yang et al. (2019), who argue HURREVAC does not explicitly state a course of action, which is viewed as detrimental to evacuation decisions.

For example, evacuation recommendations for Aquidneck Island are based on technical studies with data from 2012 to 2015 (U.S. Army Corps of Engineers, New England District 2016). These recommendations do not include information from recent evacuation statistics from hurricanes, which may lead to inaccuracies in the current evacuation recommendations. Yang et al. (2019) also argues that HURREVAC allows for analysis of evacuation clearance times based on the forecasted track of the hurricane, but cannot account for any uncertain hurricane behaviors that may occur, such as changes to evacuation zones, road capacity, and evacuation demand. These are integral pieces of information that would potentially reclassify the unsafe areas during a hurricane, and the software does not effectively capture these dynamic relationships in its analysis. In addition, Regnier (2008) remarks that HURREVAC only performs a one-time decision that fails to identify improvements gained from reducing evacuation costs and/or reducing clearance time. Moreover, it only considers limited lead times for decisions that do not “motivate planning for evacuations initiated with less than the designated lead time” already built-in to the software (Regnier 2008).

2.1.2 Network Flow Models

Whereas HURREVAC supports go/no-go decisions, other models support vehicle routing and egress. The most common models developed in the literature for this purpose are network flow models. Network flow models are a mainstay of operations research (see Ahuja et al. 1993, for an introduction and overview). With respect to evacuation, these types of optimization models are often used to make decisions about routing, for example from dangerous nodes to safe nodes through a network representing roads and intersections. For example, Yuhas (2011) uses a network flow model to study the evacuation of multiple counties in the Sacramento, California delta region during catastrophic flood, and Malveo (2013) uses a network flow model to study the evacuation of multiple counties in Alabama and Florida in support of hurricane planning.

Network flow optimization models typically require complete information about the network, including its capacities and costs. For evacuation models, the routing decisions also need to consider traffic congestion in order to minimize travel time and/or maximize throughput for evacuees. In situations where information is incomplete, or when decisions have to be made in real-time, this is particularly challenging.

One way to overcome these challenges is through the use of heuristic algorithms to pre-process network data and model solutions. In general, heuristic algorithms provide “a feasible solution derived from prescriptive analysis that is not guaranteed to yield an exact optimum” (Rardin 1998). Ahuja et al. (1993) agree that these types of algorithms can be used when network problems become too complex and computationally expensive. Although heuristic algorithms allow analysts to recommend solutions to an optimization problem, Rardin (1998) asserts that we lose a sense of certainty in our recommendations.

Heuristic Algorithm Example

A common approach is to combine a heuristic algorithm with a deterministic network flow model. Here, we present one example of this approach applied to evacuation problems, as developed by Lim et al. (2016).

Lim et al. (2016) propose a network pre-processing algorithm that obtains “the most up-to-date evacuation network for developing an alternative path” when an evacuation route is unsafe due to an incident. In order to reroute evacuees to different paths, the algorithm

identifies the impacted evacuation routes and chooses alternative paths based on the flow capacity of the roads (Lim et al. 2016). The algorithm requires information on which routes will be impacted and the duration of time that these routes are unavailable (Lim et al. 2016). Unfortunately, this is information that may not always be accessible during the pre-processing steps.

Lim et al. (2016) further explain that this algorithm can be used in conjunction with a multi-commodity network flow optimization model that maximizes the total number of evacuees from sources and determines the alternative paths and their flow rates. The authors introduce the idea of maximizing the number of evacuees that safely reach their destination instead of minimizing the evacuation clearance time, an approach commonly used by evacuation optimization models. Together, the algorithm and model provides alternative routes as well as the length of time the alternative routes were used until the original route was restored. Lim et al. (2016) conclude from these results that the combination of the algorithm and optimization model efficiently determine the possible paths evacuees could use to avoid delays during evacuation.

This deterministic model allows for dynamic changes in its evacuation plan through the random selection of routes chosen to be unavailable at specific points in time. However, there is no real uncertainty involved since information about the length of incidents on different paths is known during pre-processing.

2.1.3 Network Models Applied to Aquidneck Island

Previous studies using network flow models for Aquidneck Island follow a similar approach to Lim et al. (2016). Specifically, Jones (2021) develops a similar approach to minimize the evacuation clearance time and identify optimal shelters using a time-phased traffic assignment model. The model incorporated data for populations, the road network, and evacuation destinations specifically tailored to Aquidneck Island and considered climate change projections for vulnerable communities. The model determines the fastest route for each at-risk community based on the capacity and traffic flow of the available roads to their target destinations.

The model developed by Jones (2021) provides a basis for testing different hurricane scenarios. For example, Jones (2021) used the model to study Hurricane Henri and provided

clearance times for NAVSTA Newport in preparation for the storm. Still, model solutions do not include uncertainties in the parameters. By using deterministic parameters, this solution is less reliable in both short-term planning as hurricane tracks and size can change and long-term planning to manage future climate change.

2.2 Sources of Uncertainty

Although there are aspects of evacuation that can be studied with deterministic models, the data and variable assumptions made in these models restrict their ability to provide effective recommendations. There are several sources of uncertainty that must be considered to improve solutions, including uncertainty associated with the hurricane event and uncertainty introduced in the act of modeling itself.

2.2.1 Forecasts

Emergency managers and local officials are faced with the primary decision of when to evacuate, which depends on uncertain hurricane forecasts. As noted by Regnier (2008), hurricane forecasts tend to increase in accuracy as the hurricane advances towards its landing point. However, as the lead time narrows, the window that emergency managers and local officials have to call an evacuation is considerably reduced, adding an immense amount of pressure to the decision-makers. Regnier (2008) suggests that there must be a balance between delaying the evacuation decision and increasing accuracy of the hurricane forecast. As advised by Regnier (2008), “the solution will lie in making the best possible use of available forecasts, taking into account their uncertainty, and balancing the lead time required for completing evacuation against the information that can be gained by waiting.”

The timing of evacuations rely on the relationship between hurricane and evacuation behavior (Lindell and Prater 2007). Specifically, a hurricane has different elements that determine when an evacuation plan should be initiated. (Lindell and Prater 2007) explain how its track determines where the hurricane will hit while the hurricane eye depicts how far its conditions reach. There are 5 risk areas that correspond to the 5 intensity categories of a hurricane (Lindell and Prater 2007). Based on these features, decision-makers can estimate which risk areas need to evacuate, the length of time to evacuate the areas, and if they can completely clear the risk areas before the storm hits. A hurricane’s track and radius of eye

can estimate the hurricane’s arrival time as well as how an evacuation arc can estimate if an evacuation plan can fully remove evacuees from risk areas based on the evacuation time estimates before experiencing the impacts of the storm (Lindell and Prater 2007).

However, the timing of an evacuation plan is dependent on the hurricane’s behavior, which is an uncertainty that needs to be quantified. A hurricane’s track, speed of approach, category, and size can vary, which complicates the decision to evacuate or not (Lindell and Prater 2007). As shown in Figure 2.1, the decision to evacuate or not for an incoming hurricane depends on the probability of the hurricane striking an area, which can be represented in a decision tree (Lindell and Prater 2007).

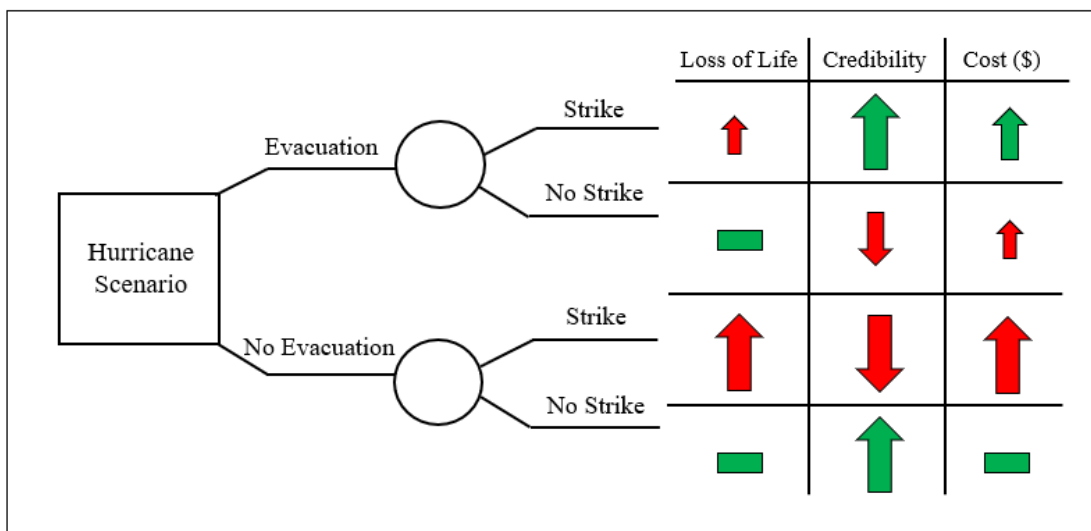


Figure 2.1. Evacuation Decision Tree and Outcomes. Decision-makers must decide to evacuate or not evacuate. However, this decision depends on the strike probability, which is the chance that the hurricane will hit land. The overall decision to evacuate or not impacts the number of lives lost, credibility of the decision-makers, and the costs associated with evacuating. Adapted from Lindell and Prater (2007).

To elaborate further on the strike probability, Lindell and Prater (2007) explain that “the National Hurricane Center’s *maximum* strike probabilities are 18% at 48 h, 25% at 36 h, and 50% at 24 h” (Lindell and Prater 2007). Clearly, the strike probabilities are increasing

as the lead time decreases. Based on the provided data, we can conclude that a low strike probability indicates that there is a high likelihood of choosing not to evacuate. However, this is a decision that is not always seen in evacuation decisions. Currently, local authorities act cautiously and often revert to choosing an evacuation even if the hurricane has a lower strike probability.

2.2.2 Hurricane Costs

The expected damages experienced from a storm inform the need to whether evacuation or sheltering-in-place are the best decisions. Go/No-Go decisions are concerned with the consequences from the evacuation decision itself and if the hurricane hits or not. Figure 2.1 shows the relationship between costs measured by the losses of life, the credibility of the local authorities involved in the evacuation decision, and the costs associated with evacuations (Lindell and Prater 2007). If the decision is made to evacuate and the hurricane hits, casualties will occur but the number of overall lives lost will decrease (Lindell and Prater 2007). In this case, the credibility of the local authorities will greatly increase while the costs will increase dependent on the damage from evacuating. However, if an evacuation is called and the hurricane does not land, there is a major loss to the credibility of the decision-makers and increase in costs despite there being no lives are lost (Lindell and Prater 2007). The worst case scenario is choosing to not evacuate if the hurricane hits, which leads to outstanding increases in lives lost and costs while the credibility among local authorities will significantly decrease (Lindell and Prater 2007). On the other hand, the best case scenario is choosing not to evacuate and the hurricane does not land, resulting in no lives lost, an increase in credibility and no evacuation or damage costs incurred (Lindell and Prater 2007).

Building on this work, Lee and Kockelman (2021) provide a cost function capturing uncertainty in an evacuation for an approaching storm:

$$C_{vijt} = \Psi_{vijt} + |\Phi_i - \Delta_{vij}|. \quad (2.1)$$

Here, C_{vijt} is “the evacuation cost of vehicle v departing from i to j at time t ” (Lee and Kockelman 2021). The evacuation cost function consists of the travel time of a vehicle Ψ_{vijt} , the vehicle’s time of departure Δ_{vij} , which is derived from a Poisson distribution, and the

start time of the natural disaster Φ_i (Lee and Kockelman 2021). The uncertain parameter in this function is Φ_i , where the difference between Φ_i and Δ_{vij} estimates the additional costs incurred when evacuation is called too early or too late for a threatening storm.

In contrast to Lee and Kockelman (2021), where costs are only measured for a single, approaching storm, Regnier (2008) introduces a cost function called the False Alarm Rate (FAR) which is based on Markov decision models and historical hurricane tracks. The FAR is a function meant to measure of the quality of the forecast that includes a “decision rule used to determine whether a given strike probability will trigger an evacuation” (Regnier 2008). The author uses the FAR to define the trade-off between a possible false alarm and the threat of failing to evacuate on time. The author applies these concepts to different locations, and the results generally indicate that the FAR decreases as lead time shortens. This generates function that increases as a storm approaches and simulates the knowledge emergency managers have for hurricane evacuations. This allows for a better understanding of the risks present at a specific point in time in the evacuation decision process.

2.2.3 Models

The act of creating a model also introduces uncertainty in and of itself. Model uncertainty can exist in various model elements: parameters, data, objective functions, etc. Because there are several different ways to structure an optimization model and its inputs, Reilly et al. (2021) specifies that there needs to be careful considerations of specific system uncertainties that will impact the model design and the uncertainties in the model outputs. Since system and modeling uncertainties influence each other, this relationship provides a better understanding of the limits of a model used and identifies the crucial uncertainties to consider in a model (Reilly et al. 2021).

2.3 Optimization Under Uncertainty

This section reviews the most common methods to incorporate uncertainty in optimization models and their use for different transportation and evacuation problems.

2.3.1 Stochastic Programming

Stochastic programming is one form of optimization that incorporates uncertainty in its objective, variables, parameters, and/or constraints. The goal of a stochastic program is solve for expectations of parameters, rather than known values. For example, a stochastic evacuation model might solve a network flow problem for an uncertain number of evacuees represented by an expectation from a probability distribution (e.g., mean, median) rather than a known quantity.

Several authors have used stochastic programs to support hurricane evacuation. For example, Wang et al. (2016) discusses how uncertainty on different time phases plays an important role in understanding the speed of emergency responsiveness. As shown in Figure 2.2, it takes time to start the evacuation process after a natural disaster hits. Wang et al. (2016) show that evacuation models focus mainly on the egress time because it is difficult to accurately estimate individualistic responses.

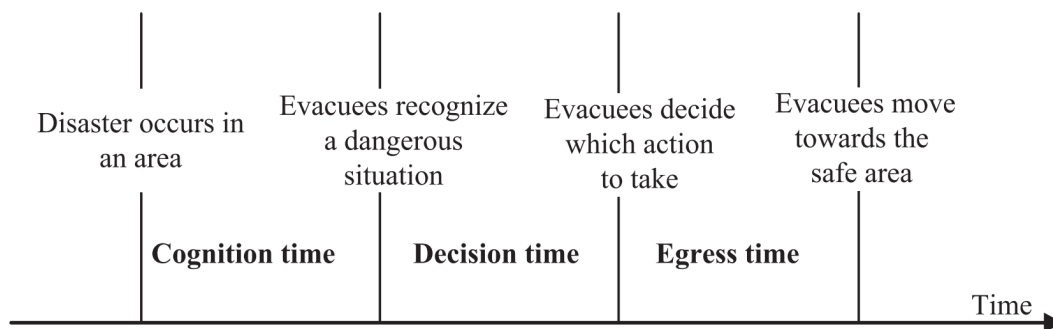


Figure 2.2. Time Periods During an Evacuation. Evacuation planning needs to consider three different time periods: cognition time to recognize the need to evacuate, decision time to choose to evacuate, and egress time leaving dangerous areas for safety. Due to the difficulty to estimate cognition and decision time, the majority of evacuation models only consider egress time. Source: Wang et al. (2016).

Wang et al. (2016) develop a stochastic programming problem with side constraints and present three evacuation models, each with different objective functions, that aim to find evacuation routes and execute evacuation plans shortly after disaster. Because the capacity

of roads decrease as travel time increases when the disaster magnitude increases, the authors consider a fixed upper bound on the distance in the side constraints. In their network model, the capacity constraint limits the number of evacuees on a link and can be relaxed with a probability confidence level, “which is determined according to the decision makers’ preferences” on risk while the side constraints “[guarantee] that the resource of generated path is within the predetermined upper limit”. The authors offer multiple objective functions that capture the decision-maker’s attitude which influences the resulting evacuation plan. It is important to realize that evacuation plans can be sensitive to the decision-maker implementing evacuation plans, suggesting that there is uncertainty in which uncertain parameters will be addressed in the model.

Wang (2020) implements a “two-stage stochastic programming model that considers both *a priori* (pre-disaster) and adaptive (post-disaster)” plan to evacuate the public, depending on the roads impacted. Using a min-cost flow strategy, the author describes that the first stage has probabilistic link capacities and travel time while the second stage determines the evacuation plan based on the probabilities. Wang (2020) states that the uncertain flow and capacity must be met before the robust evacuation plan is executed. With this problem, real-time data can be used to influence the evacuation plan, demonstrating the robustness in the plan. While the current model lacks some complexity, the model conveys the idea of administering evacuation plans before the disaster.

2.3.2 Cardinal Robust Optimization

An extension of stochastic programming considers situations where specific bounds, uncertainty sets, or perturbations to the network are more relevant for decisions than expectations. In these situations a perturbation set and/or designated level of robustness is provided in model solve, creating a robust optimization model (Sharkey et al. 2021). Here, the goal of robust optimization is to provide a solution that achieves evacuation goals within a set tolerance. An example of a robust evacuation model would be one that solve a network flow problem given a set of roadway perturbations that may happen and lead to rerouting.

Bertsimas and Sim (2004) developed one of the earliest and most prevalent methods for robust optimization called *cardinal robust optimization*. This generic approach deals with uncertainty in data through the use of a Γ parameter, which determines the number of

changes to the coefficients and the level of robustness included. Bertsimas and Sim (2004) explain that the Γ parameter manages the degree of conservatism in the solutions, since the areas of uncertainty are chosen. In short, there is a “probabilistic guarantee that even if more than $[\Gamma]$ change, then the robust solution will be feasible with high probability” (Bertsimas and Sim 2004). Although there are limits to the amount of uncertainty, this technique allows for more flexibility with robustness and maintaining a deterministic ally feasible solution.

Several authors have employed a cardinal robust optimization approach in models relevant for evacuation planning. For example, Sun et al. (2021) implement a bi-objective robust optimization model that allocates and transports resources to emergency facilities after an earthquake using this method. Specifically, the authors set model conservatism on uncertainties in the number of casualties, medical supply demand, and casualty transportation time. Sun et al. (2021) discuss that the model focuses on the minimizing casualties, sending various forms of transportation, such as helicopters to deliver supplies to temporary facilities or hospitals, depending on the classification of the causality cluster.

Yahyaee and Bozorgi-Amiri (2019) employ a cardinal robust optimization approach to solve a relief logistic network when probabilities of disruption of distribution centers and uncertain demand exist. After analyzing the results, Yahyaee and Bozorgi-Amiri (2019) indicate that a randomly-generated disruption probability allows us to understand how uncertainty impacts the relief network and how responsive the plan is to these changes. The authors argue that the incorporation of these probabilities supports efforts in creating a formulation for the uncertainty of hazards in different evacuation environments.

Similarly, Kulshrestha et al. (2011) include an uncertainty budget set to account for the demand uncertainty, the uncertain number of evacuees that need public shelters in a robust shelter location model. The authors state that one of the main assumptions to this model is that authorities predetermine the number of shelters, their locations, and their capacities. The authors develop a model that minimizes the cost of operating the shelters and uses a cutting plane algorithm to solve a restricted robust shelter location model. After using this model on the Sioux Falls network, the authors indicate that the robust approach is “100% reliable in satisfying the evacuee demand and meeting the travel time requirement” in the worst-case scenario (Kulshrestha et al. 2011). Using this method, a solution will be guaranteed to work even in the worst possible situation, which is unattainable in a deterministic model.

There are clear benefits to using a robust approach to handle uncertainty, but this model presents exchanges that must be considered. In this case, the robust solution produced the most expensive plan but was the most reliable. Ideally, we want a formulation of a robust evacuation model that would provide recommendations with a better balance to risk and costs.

2.3.3 Chance Constraints

In some cases, the uncertainty in an optimization can be captured entirely in the constraints. Moreover, the goal of the optimization is to find a solution that ensures a tolerance to a certain level of uncertainty in constraint values. Models that take this form are referred to as using *chance constraints*. There are several examples of chance constraints used in evacuation planning.

Vogiatzis et al. (2013) form two models: a vehicle routing problem and a time-sensitive maximum network flow problem to create a vehicular evacuation plan that will transport as many livestock as possible from a catastrophic event, such as a nuclear power plant disaster. Vogiatzis et al. (2013) describe that their maximum network model uses the following constraint,

$$\sum_t \sum_{(i,j) \in A} f_{i,j}^t p_{i,j}^t \geq \epsilon \sum_t \sum_{(i,j) \in A} f_{i,j}^t \quad (2.2)$$

which uses probabilities to determine the operational level of a route at a given time t . Here, $f_{i,j}^t$ is a decision variable that represents the number of livestock at arc (i, j) at time t and $p_{i,j}^t$ is “the known probability that arc $(i, j) \in A$ will be available at time t ” (Vogiatzis et al. 2013).

Using a probabilistic tolerance allows for understanding of when and which routes become nonfunctional. By deriving probabilities from previous data, we obtain a more realistic approach that can predict the likelihood of a route becoming unavailable based on data that we know rather than relying on other metrics to determine unusable routes. For the most part, Vogiatzis et al. (2013) use heuristic methods on an integer problem and not a robust formulation. However, the model presents another technique to use to deal with availability of routes in a disaster.

Additionally, Lim et al. (2019) restructure a deterministic path-based model and incorporate robust chance-constraints in a robust chance constraint program to account for demand uncertainty in which the constraints are satisfied by a predetermined confidence level. Lim et al. (2019) demonstrate that the probability distribution of the demand must be known in order to solve a deterministic reformulation with a constraint where “the desired probability level [is] imposed individually on each constraint” (Lim et al. 2019).

When the probability of distribution is unknown, Lim et al. (2019) use “a robust tractable approximation that can be used when only the mean, variance, support, and/or symmetry information is available for the underlying random demand.” Lim et al. (2019) recommend three robust chance constraint program propositions that describe the family of probability distributions to derive a robust linear approximation of the uncertain demand, S_i , which is an estimation of the demand at each source node to achieve the chosen feasibility. After using the shortfall determination algorithm, Lim et al. (2019) find that the robust chance constraint programs result in longer evacuation clearance times and conservative solutions when there are uncertain demand distributions. In Lim et al. (2019)’s robust chance constraint program approach, the model addresses uncertainty in the starting time of the evacuation plan since the programs generate long clearance times. Again, the probabilistic approach attains high-quality evacuation plans with minimal information. This approach is especially practical for evacuation planning, considering how often information is not always readily available.

Liang et al. (2019) recommend a two-stage stochastic programming model that includes chance constraints on the uncertain evacuation demand and a risk measure to aid in minimizing the total clearance time and determine the shelter locations. Liang et al. (2019) mentions the commonly used U.S. Bureau of Public Roads (BPR) function in evacuation models that estimates traffic times “where $t(x)$ is the travel time when the traffic volume on the road is x , c denotes the maximum flow capacity, t^0 is the free-flow travel time at zero volume” (Liang et al. 2019):

$$t(x) = t^0 \left(1 + \gamma \left(\frac{x}{c} \right)^\beta \right). \quad (2.3)$$

By creating an expectation-based objective function with the BPR function, Liang et al. (2019) propose that a risk measure can be applied in conjunction to evaluate the conservativeness of the solution. This model includes several components that measure and include

uncertainty. The risk measure is valuable to the model and allows for customized evacuation plans.

2.3.4 Multistage Robust Optimization

Although robust optimization usually finds a solution for the worst-case scenario, there are several approaches to address uncertainty in all types of optimization models. In general robust optimization problems, uncertainty sets are used to capture the uncertainty in the data. By creating robust counterparts, we obtain an equivalent deterministic optimization model to solve. For multi-stage optimization problems, Gorissen et al. (2015) illustrates that an adjustable robust optimization can be used to allow for adjustment in decision variables at another point in time, depending on a decision rule based on a function of the uncertain data. Both techniques require uncertainty sets that capture the robustness in the variables and feasibility.

Building off of an integrated scenario-based evacuation formulation, Yang et al. (2019) add inland flooding to the framework. Yang et al. (2019) argue that the combination of coastal flooding, inland flooding, and wind is integral to include in this type of framework to capture the uncertainties from hurricane behaviors and other collateral impacts from hurricanes. Generally, Yang et al. (2019) demonstrate how this technique: develops the probabilistic scenarios that can occur, uses a tree to represent the uncertainty at each time step, and applies this data to a multistage stochastic programming model. After applying the model to Hurricane Matthew in North Carolina, the authors conclude that the inclusion of inland flooding demonstrates that dangers can materialize at any point in time and recommendations need to account for these consequences (Yang et al. 2019). This formulation manages uncertainty through its analysis of how decisions can change over time based on specific elements.

Public Transportation Evacuation Models

Because of uncertainty in the number of evacuees, Gao et al. (2019) propose a robust two-stage configuration: the first stage determines the designated pick-up points while “[minimizing] the total walking time of the evacuees”, and the second-stage aims to “minimize the total transit-based transportation time and minimize the total number of vehicles simultaneously to satisfy the time-window contain in each of the pick-up points” (Gao et al.

2019). Gao et al. (2019) explain that the first-stage is solved by a hybrid genetic algorithm while the second-stage uses an interval/roundtrip-based routing and scheduling heuristic algorithm. Gao et al. (2019) observe that one of the bigger concerns in evacuation modeling is obtaining the distribution for the number of evacuees. Gao et al. (2019)'s approach addresses this concern by determining pick-up points in the first-stage problem instead of predetermining these points. The solution also minimizes resources, such as the number of vehicles used (Gao et al. 2019). By using two-stages, a higher number of objectives and uncertainties can be incorporated into the models.

Robust Bus Evacuation Problems

Mass public transportation should be considered in evacuation plans for those who do not have access to their own automobile and rely on public transportation. The strategies for bus evacuation plans account for the uncertainty inputs of the number of evacuees and assist in developing changes to decisions and information over time.

In Goerigk and Grün (2014)'s approach for a robust bus evacuation problem, a mixed-integer linear program and robust two-stage model that minimize the longest travel time for all buses for a route are introduced. Goerigk and Grün (2014) explain that the objective of these models is to account for the uncertainty in the number of passengers and when buses should leave based on what information is known. Goerigk and Grün (2014) identifies that a tabu search heuristic algorithm would allow this model to avoid revisits to previous solutions, contributing in the construction of the bus route. After an analysis of the results for randomly generated instances and on the military concentrated city of Kaiserslautern, Germany, Goerigk and Grün (2014) suggest that this formulation coordinates an evacuation plan that can be used if communication is lost. By including uncertainty in the type and number of buses in this model, the model enables manpower to respond quickly in situations where information may be unavailable.

Goerigk et al. (2015) present a robust bi-criteria two-stage evacuation model that continuously updates bus schedules based on the uncertainties in travel times, the number of evacuees, and the number of buses. By considering multiple uncertain elements, a more realistic and specific solution can be obtained for different scenarios. The formulation evaluates the worst possible evacuation time and the number of changes to the bus schedule (Goerigk et al. 2015). From analyzing the results on the city of Kaiserslautern, Germany,

we conclude that this formulation supports several uncertainties that allow for changes in a scheduled evacuation plan. Handling uncertainty in this way reinforces the idea that complexity is essential in large-scale evacuation plans.

Pourrahmani et al. (2015) also consider uncertainty in public transportation by introducing uncertain demand as a fuzzy variable in a vehicle routing problem. By using the fuzzy credibility theory, Pourrahmani et al. (2015) demonstrate that their model will not suffer computationally and the uncertain parameter can be estimated based on previous information. Pourrahmani et al. (2015) argue that the fuzzy variables, which are the uncertain demand at each pick-up point, allow for greater uncertainty due to the lack of hard boundaries. However, the model predetermines evacuation routes, leading to failures that increase travel time. The model does not consider routes for public buses at individual time steps and is unable to account for the uncertainty in road availability.

2.3.5 Other Probabilistic and Bayesian Methods

As expressed by Wiesemann et al. (2014), robust optimization approaches that solve the robust counterpart and stochastic programming often yield too conservative solutions and do not contain “ambiguity (exposure to uncertainty about the probability distribution of the outcomes).” Since data is not always guaranteed to be accurate, Wiesemann et al. (2014) incorporate the decision-makers’ attitude towards uncertainty and introduce the distributionally robust counterpart in which there is an ambiguity set of probability distributions that are uncertain. Using robust expectation constraints in distributionally robust optimization problems paves the way for the use of other techniques to create solvable linear programs. Wiesemann et al. (2014) introduce several methods to incorporate the decision-makers’ objectives and directly address the uncertainty in the probability distributions of the data.

Liu et al. (2021) present a Dynamic Bayesian Network-Based Real-Time Crash Prediction Model (DBN-RTCPM) that predicts traffic crashes on segments of roads in urban expressways based on their likelihood of occurrence for short time intervals. Liu et al. (2021) describes that the DBN-RTCPM highlights how dynamic traffic flows are and the complexity from the coupling interdependency present. The analysis suggests various metrics to understand the model performance and accuracy of real-time crash predictions. Overall, Liu et al. (2021) recognize the various interactions among factors and the complexity it

adds to the problem when solving.

2.4 Our Contribution

This chapter identifies deterministic models, sources of uncertainty, and optimization methods to make evacuation decisions. Our review of the literature reveals several key tensions that need to be reconciled to support evacuation planning for Aquidneck Island:

- current methods used by NAVSTA Newport and Aquidneck Island communities for evacuation planning are based on deterministic models and data;
- deterministic models cannot consider uncertainty involved in hurricane evacuation planning, that can stem from forecasts, expected costs, and model development;
- there are several standard methods that can incorporate uncertainty in optimization solutions that serve different purposes;
- the majority of optimization models are used for long-term planning (e.g., shelter placement, egress) rather than real-time decisions (e.g., go/no-go decisions); and,
- few optimization models that include uncertainty are studied using real data for real communities.

Our contribution is to address these tensions by building on existing deterministic models developed for Aquidneck Island and extending their formulation to support stochastic and robust solutions. The goal is to consider existing network flow models based on real community data and uncertainties associated with real storm forecasts. The output of the models is to support go/no-go decisions, rather than long-term planning decisions. Thus, our proposed work blends each area to advance evacuation planning capacity for Aquidneck Island.

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CHAPTER 3: Methods

We develop methods to study go/no-go decisions for Aquidneck Island communities, including military installations and service members. Our methods incorporate a mix of detailed hurricane modeling and synthetic forecasts to measure storm uncertainty. Given the updated methods we develop here, we are specifically interested in answering the following questions:

- Would historical storms that impacted Aquidneck Island have led to evacuations?
- If yes, how many vehicles would likely evacuate given current population estimates?
And,
- What routes would these evacuating vehicles take to ensure optimal routing and clearance times?

Our methods to answer these questions are organized in the following analysis tasks completed in order:

1. **Synthetic Forecasts of Historical Storms:** We collect data on historical hurricane forecasts and wind profiles and generate synthetic forecasts that match information commonly presented to real-world decision-makers.
2. **Identifying the Most Dangerous Strike Region:** Using a parametric wind model and synthetic tracks, we determine the region in space that, if a hurricane were to pass through, would be dangerous for Aquidneck Island. For the purposes of this work, we define the “most dangerous region” as the locations where storm would cause closure of bridges and prevent an island-wide evacuation.
3. **Hurricane Strike Estimation:** Using synthetic forecasts and a stochastic hurricane model, we estimate the probability that historical storms would “strike” Aquidneck Island in the dangerous region. These strikes are assumed to require evacuation.
4. **Expected Evacuation Demands:** We combine strike probability with common go/no-go decision time windows to estimate stochastic evacuation demands produced by a synthetic forecasts.
5. **Optimal Evacuation Routing:** We solve a network flow problem to determine opti-

mal routing and clearance times given stochastic evacuation demands.

Each of these analysis tasks consists of a series of subtasks presented below. Completion of these tasks required broad expertise in hurricane and evacuation modeling that brought together a multi-university team from the Naval Postgraduate School (NPS) and URI. In general, Analysis Tasks 1 and 2 were completed in part by the NPS team and by researchers at URI led by Dr. Isaac Ginis and Deborah Crowley. Analysis Tasks 3, 4, and 5 were completed by the NPS thesis team. Throughout this chapter, we denote the team that completed each analysis subtask for this work.

Unless otherwise stated, we use the open source tools based on the Python programming language to conduct analyses (Rossum et al. 2009). We use QGIS software for data management (QGIS Development Team 2022), GeoPandas (GeoPandas 2022) and turfpy (Turfpy Development Team 2005) in Python to modify and generate geospatial data for the hurricanes, Pyomo (Hart et al. 2011) to construct evacuation models in Python, CPLEX (IBM ILOG CPLEX 2009) optimization studio to solve models, and Plotly in Python to visualize the immediate and final results (Plotly Technologies Inc. 2022).

3.1 Synthetic Forecasts of Historical Storms

The first step towards stochastic evacuation modeling is to develop synthetic hurricane forecasts. A synthetic forecast consists of realistic estimations of a storm size, intensity, and approach, which are the key storm parameters emergency managers use to decide go/no-go evacuation. As described in Ch. 2, synthetic forecasts can be made using a diversity of methods, from drawing a track by hand to using models such as stochastic models in Regnier (2008) and physics-based models in Snaiki and Wu (2020). For the purposes of this work, we want our synthetic tracks to be based on real storms that impacted Aquidneck Island. We complete the following analysis subtasks to generate a synthetic forecast:

1. Acquire historical storm track data for storms that affected Aquidneck Island (NPS, URI); and,
2. Develop synthetic storm tracks for possible storm tracks that could have happened for each historical storm. We generate these tracks based on the NHC *cone of uncertainty* (described below) and worst-case strike location for Newport Bridge (NPS).

3.1.1 Historical Storm Track Data

For the synthetic tracks, we strategically choose different types of historical hurricanes that impacted the New England area to determine the range of evacuation decisions that could be made. Specifically, we want to analyze hurricanes that were the most damaging to the region and had the most powerful winds. For this reason, we choose to conduct our analysis for two major storms that impacted Aquidneck Island: Hurricane Bob (1991) and Hurricane Gloria (1985). We choose these events as they are some of the most destructive storms on record that have data available in the NOAA hurricane database HURDAT2 (National Oceanic and Atmospheric Administration 2022b).

Hurricane Bob (1991): We study Hurricane Bob because it caused significant destruction in Rhode Island and approached the region very quickly compared to recent storms. Figure 3.1 presents the actual track Hurricane Bob took in 1991. Hurricane Bob was a surprisingly fast storm and only took 90 hours to directly hit Rhode Island from when it first formed (National Oceanic and Atmospheric Administration 2022a). Not only did the storm quickly gain strength, historical data recounts that Newport faced wind gusts up to 115 mph that damaged the homes of the coastal community (National Oceanic and Atmospheric Administration 2022a). Thus, by using Hurricane Bob as source data, we can understand the worst-case scenario in terms of evacuation for when a hurricane track is on course to directly hit Rhode Island with limited lead time to make a decision.

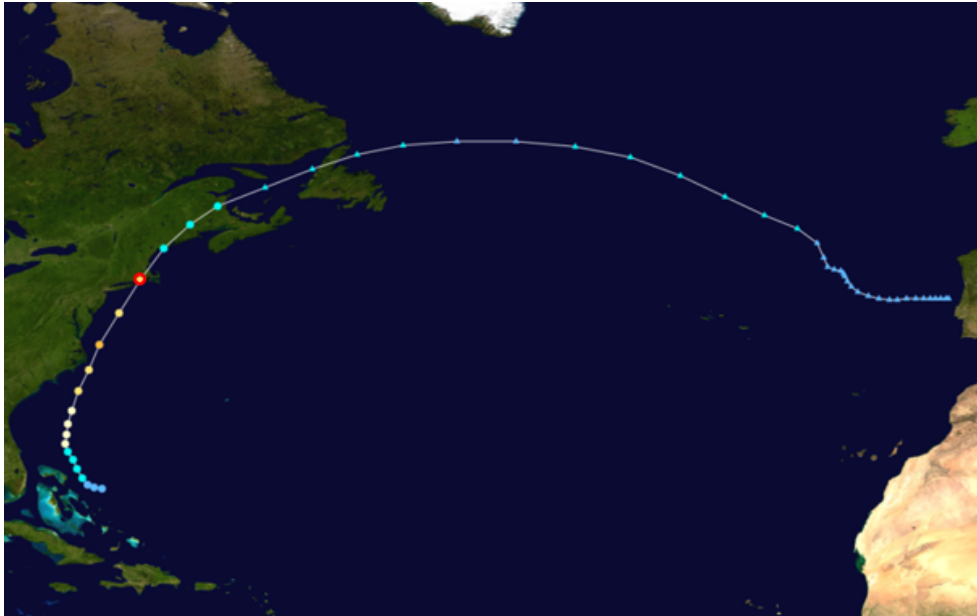


Figure 3.1. Track of Hurricane Bob (1991). This figure depicts the best predicted track for Hurricane Bob. The hurricane spanned from August 16, 1991 to August 20, 1991 forming in the Caribbean and dissipating near the coast of Spain. It made landfall in Rhode Island on August 19, 1991. An estimate for the location of Aquidneck Island is circled in red. Adapted from National Weather Service (2022a).

Hurricane Gloria (1985): Additionally, we use Hurricane Gloria from 1985 to simulate forecasts since this hurricane also produced strong winds and resulted in significant damage for Aquidneck Island communities (Ambrose 2021). Figure 3.2 shows the track taken by Hurricane Gloria. Hurricane Gloria’s approach spanned across multiple days, resulting in more time to react than Hurricane Bob.

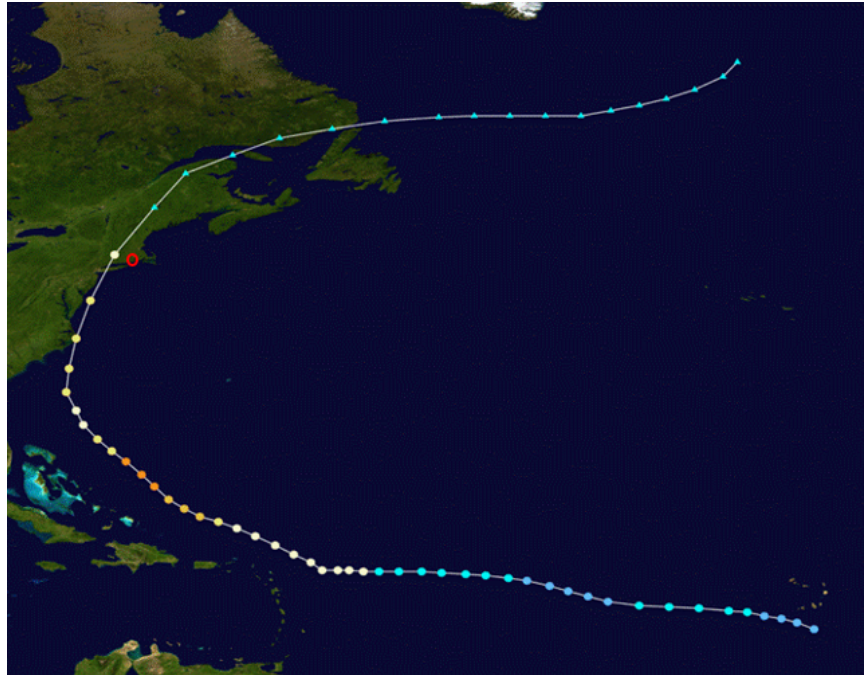


Figure 3.2. Track of Hurricane Gloria (1985). This figure depicts the best predicted track for Hurricane Gloria. The hurricane spanned from September 15, 1985 to September 28, 1985, forming between Africa and South America and dissipating south of Greenland. It made several landfalls across the Eastern United States, including Long Island and Connecticut, impacting Rhode Island, on September 27th. An estimate for the location of Aquidneck Island is circled in red. Adapted from National Weather Service (2022b).

3.1.2 Synthetic Storm Tracks Based on the Cone of Uncertainty

For each hurricane, we generate synthetic tracks based on the NHC *cone of uncertainty*. The cone of uncertainty is a measure of forecast uncertainty based on historical track forecast error, where “the entire track of [a] tropical cyclone can be expected to remain within the cone roughly 60-70% of the time” (National Hurricane Center 2022a). Figure 3.3 presents an example of a cone of uncertainty provided by the NHC to emergency managers for the recent 2020 named hurricane Laura. *Note:* similar images for Hurricane Bob and Gloria do not exist because the storms predate its use.

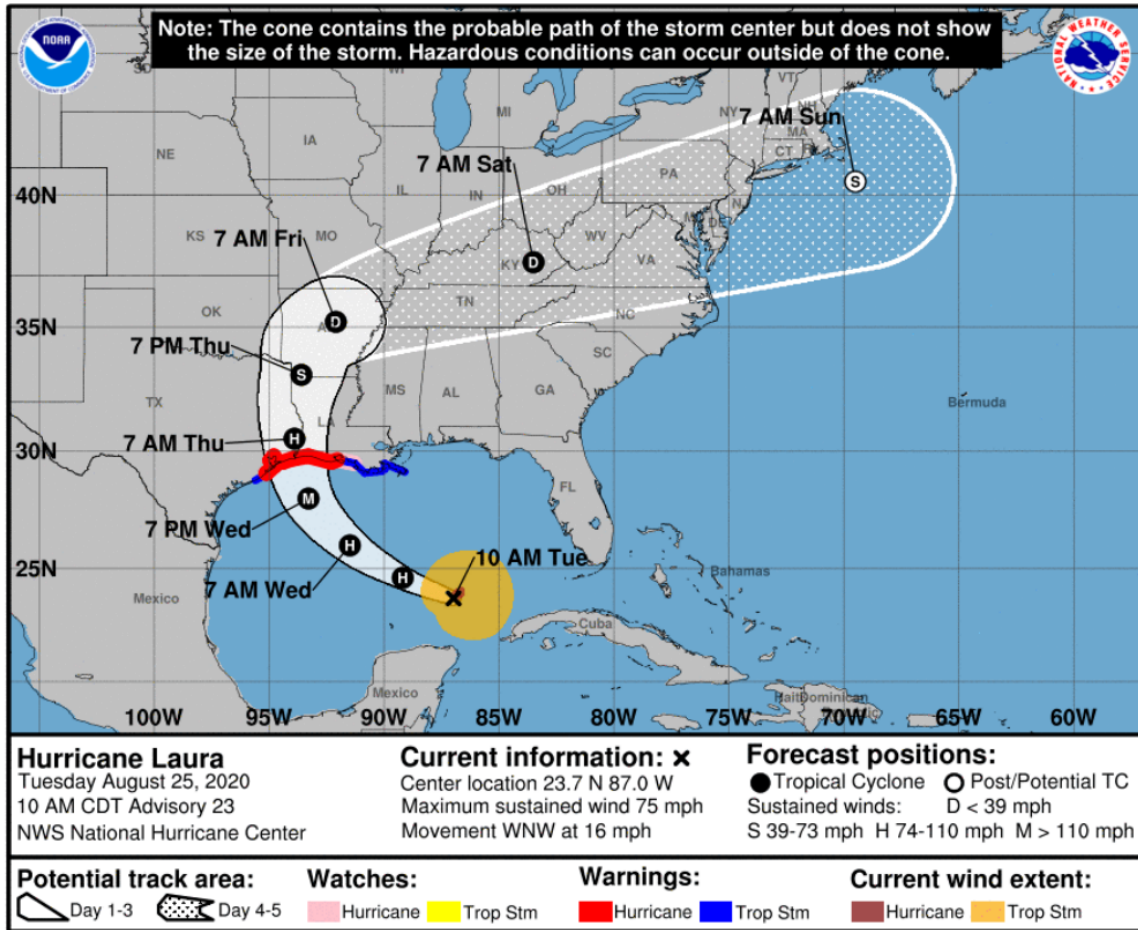


Figure 3.3. Cone of Uncertainty Example. The cone of uncertainty for Hurricane Laura (2020) on Tuesday, August 25, 2020 at 10:00 AM. The cone provides an estimate of possible areas that the track could travel at specific times in the future. Source: National Hurricane Center (2022b).

The NHC cone of uncertainty is comprised of increasing forecast errors given in distances from predicted track (in km) at specific time intervals from the current storm position. As described in Ch. 2, forecast error increases with time, such that the forecast error increases monotonically into the future. Currently, the NHC provides forecast error distances for the following future time steps: 12, 24, 36, 48, 60, 72, 96, and 120 hours (National Hurricane Center 2022a). To model error estimates in between these time steps, we assume a linear relationship between forecast error values and interpolate between forecast periods. This approach forms a similar straight-line cone to what is depicted in Figure 3.3. Table 3.1

presents the actual error distances provided by NHC alongside interpolated distances used in this study.

Table 3.1. NHC’s Cone of Uncertainty for the Atlantic Basin. Adapted from National Hurricane Center (2022a).

Forecast Period (Hours)	2/3 Probability Circle, Atlantic Basin (Kilometers)
6	23.73
12	47.45*
18	59.32
24	71.18*
30	83.04
36	94.90*
42	108.57
48	122.23*
54	137.77
60	153.30*
66	167.90
72	182.50*
84	220.83
96	259.15*
108	312.08
120	365.00*

Values marked with an asterisk (*) are provided by the NHC (National Hurricane Center 2022a). All other values based on linear interpolation.

We generate two synthetic storm tracks based on the cone of uncertainty. Specifically, we generate one track for the “right” edge of the cone representing eastern drift and a track for the “left” edge of the cone representing western drift. Since the NHC suggests that 2/3 of all storms lie within the cone of uncertainty, then creating tracks that follow the right and left edges of the cone estimate a region in physical space that will experience storms that deviate no more than one standard deviation from the mean (i.e., best track). Throughout the rest of this thesis, we refer to the right and left tracks as the 90° track and the 180° track, respectively, referring to their bearing drift in reference to the best track.

Hurricane Bob (1991): In the data pulled from HURDAT2 for the hurricanes (National Oceanic and Atmospheric Administration 2022b), we are given: time, date, coordinate positions of the track, maximum (max) sustained winds (knots), minimum wind pressure (millibars) as well as other identifying information for a given hurricane. For the 1991 Hurricane Bob data, we reduce the data to include 14 different forecast periods, each associated with a coordinate that depicts the location of the hurricane track at that point in time. Each forecast period is 6 hours long. These 14 coordinates become the original Hurricane Bob track that we use throughout this thesis. The first forecast period for this track begins on August 16, 1991 at 1800, and the last forecast period ends on August 20, 1991 at 0000, meaning that the Hurricane Bob track provides a lead time of 78 hours before making landfall past the region of Aquidneck Island. We ensure that these 14 coordinates pass through the region of Aquidneck Island and that the length of the lead time before landfall is sufficient to accurately resemble how evacuation decisions are made.

Based on this original track for Hurricane Bob, we generate the 90° and 180° tracks based on the cone of uncertainty (Figure 3.4). Each coordinate in the 90° and 180° tracks are offset from the original track by the specified distance at each forecast period as shown in Table 3.1. For these synthetic forecasts, we assume that the speed, minimum wind pressure (millibars), and maximum sustained winds (knots) are the same as the original track. Accordingly, these tracks also contain 14 coordinates and have the same starting position as the original track.

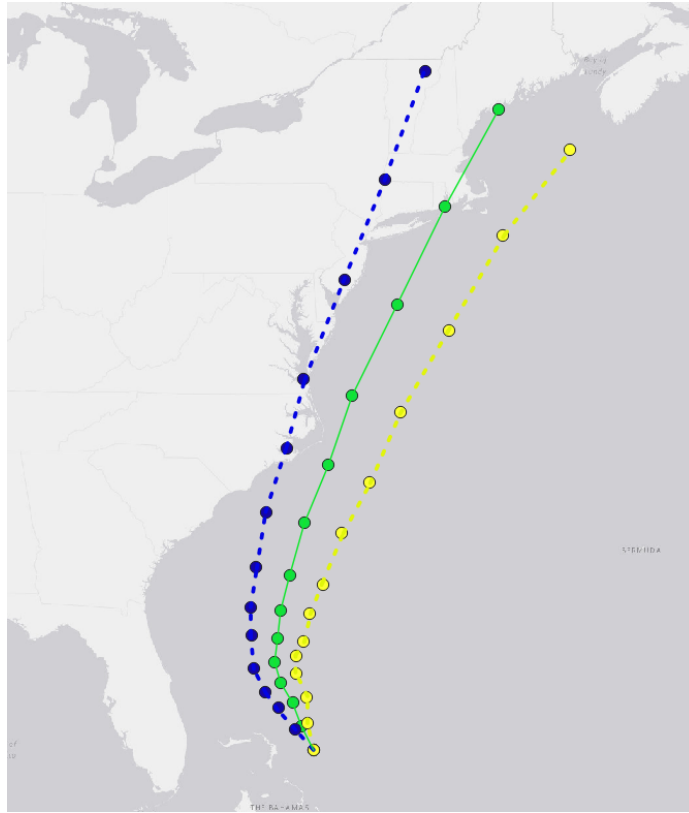


Figure 3.4. Hurricane Bob (1991) Cone of Uncertainty Synthetic Forecasts. The original forecast track for the 1991 Hurricane Bob displayed in green, the right side (90°) of the cone of uncertainty displayed in yellow, and the left side (180°) of the cone of uncertainty displayed in blue. Figure produced using QGIS software.

Hurricane Gloria (1985): We apply the same procedures to Hurricane Gloria. Since Gloria lasted a much longer time than Bob from formation to dissipation, there are many more data points that could be used for synthetic forecast. We filter the HURDAT2 data to retain 14 forecast periods with 6-hour time steps, similar to our forecast for Hurricane Bob. The 14 data points contain coordinate positions, maximum sustained winds, minimum wind pressure and other identifying information to form the Hurricane Gloria track for use in this thesis. The first forecast period for this track starts on September 24, 1985 at 1800 while the last forecast period ends on September 28, 1985 at 0000. Thus, we maintain a lead time of 78 hours before the Hurricane Gloria track will pass through the region of Aquidneck Island.

After producing a data set for the original track for Hurricane Gloria, we create synthetic forecasts for the 90° and 180° tracks based on the cone of uncertainty. Figure 3.5 shows the resulting best historical track and synthetic forecasts. The cone of uncertainty tracks and the original track contain 14 coordinates, begin at the same starting location and forecast period, and are plotted in QGIS using the coordinate reference system EPSG:4326.

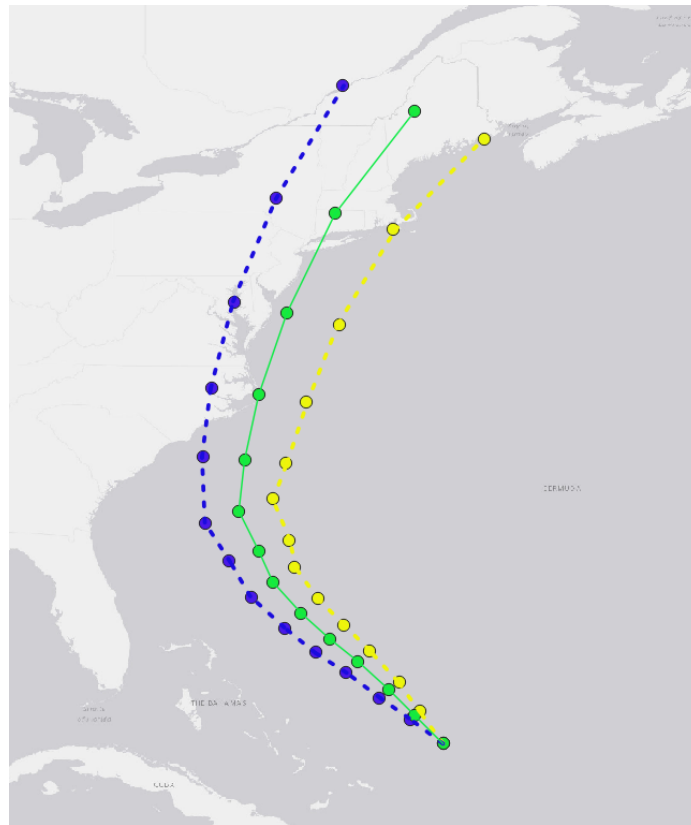


Figure 3.5. Hurricane Gloria (1985) Cone of Uncertainty Synthetic Forecasts. The original forecast track for the 1985 Hurricane Gloria displayed in green, the right side (90°) of the cone of uncertainty displayed in yellow, and the left side (180°) of the cone of uncertainty displayed in blue. Figure produced using QGIS software.

3.1.3 Synthetic Storm Tracks for a Worst-Case Scenario

To prepare for a range of evacuation decision scenarios, we consider a synthetic track that will create the most damage and have the strongest winds impacting Aquidneck Island. Previous studies show that the loss of Newport Bridge can be significantly detrimental to evacuation and the region (Jones 2021). Thus, we want to generate a worst-case scenario track for both Hurricane Bob and Gloria that causes the greatest impact to Newport Bridge.

Due to the shape and size of an Atlantic cyclone, the strongest winds they produce are often found on their eastern side, rather than in their center. Thus, the worst-case scenario is not caused by a direct hit — i.e., a storm track making landfall at Aquidneck Island — but rather an oblique hit where the eastern portion of the storm with highest winds impact Aquidneck Island.

We generate a worst-case storm for Aquidneck Island by shifting the best track to ensure highest eastern winds are directly above Newport Bridge. To do this, first we generate a sample point (target) for Newport Bridge where we wish to generate maximum winds. Then, we estimate the distance from the eye (center) of each storm to the radius of highest winds. We use a radius to maximum winds equation developed by Vickery et al. (2000) and presented in Chen et al. (2018) to estimate the radius of maximum wind:

$$\ln R_{max} = 2.636 - 0.00005086\Delta p^2 + 0.0394899\psi \quad (3.1)$$

As explained by Chen et al. (2018), R_{max} is the radius of maximum winds (in km), Δp is the difference between the central pressure and the environmental pressure (in hectopascal or millibars) and ψ is the latitude of the storm center (in degree).

Using Eq. 3.1, we can determine the distance we need displace the center of a storm west of Newport Bridge to cause greatest impacts. For all calculations in this thesis, $\psi = 41.5^\circ$, the latitude of the Newport Bridge.

Hurricane Bob (1991): Using Eq. 3.1 for the 1991 Hurricane Bob, we estimate R_{max}^{Bob} . We use a central pressure of 1010 mbar and an environmental pressure of 964 mbar to estimate Δp . The environmental pressure is accessed from the HURDAT2 data set at the time that

the original Hurricane Bob (National Oceanic and Atmospheric Administration 2022b). We find $R_{max}^{Bob} = 71.71$ km from the Newport Bridge.

After obtaining this value, we shift the Hurricane Bob best track to target this location. In the current data set, Hurricane Bob makes landfall near the latitude of Newport Bridge at its 13th coordinate. Thus, we shift this coordinate west by 71.71 kilometers. We continue to offset the original Hurricane Bob track west by the distance of the radius divided by the coordinate number. Figure 3.6 presents the results of this process. The resulting worst-case scenario track lies in between the original Hurricane Bob track and the 180° cone of uncertainty track.

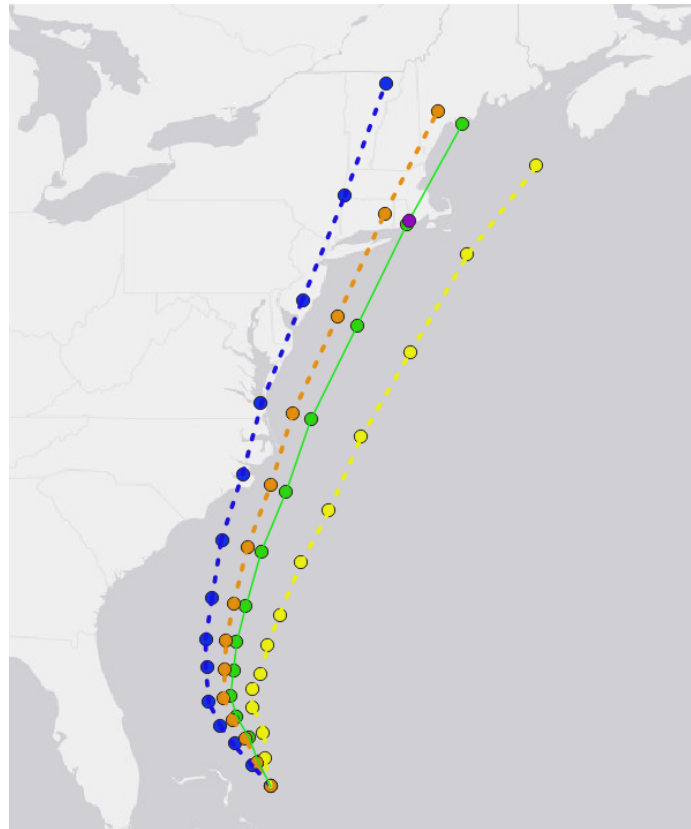


Figure 3.6. Hurricane Bob (1991) Worst-Case Forecast Track. Using $R_{max}^{Bob} = 71.71$, we shift the best track (green) west to generate worst-case winds at Newport Bridge (purple). This worst-case track (orange) lies between the best track (green) and the 180° (blue). Figure produced using QGIS software.

Hurricane Gloria: We follow a similar procedure to create the worst-case scenario track for Hurricane Gloria. Based on historical record, Hurricane Gloria has the same central and environmental pressures as Hurricane Bob (National Oceanic and Atmospheric Administration 2022b). Thus, we use the same radius of 71.71 km. Unlike Hurricane Bob, Gloria made landfall west of this location, so we shift the 13th forecasted point east to be the correct distance from Newport Bridge. The resulting worst-case scenario track lies in between the original Hurricane Gloria track and the 90° cone of uncertainty track as shown in Figure 3.7.

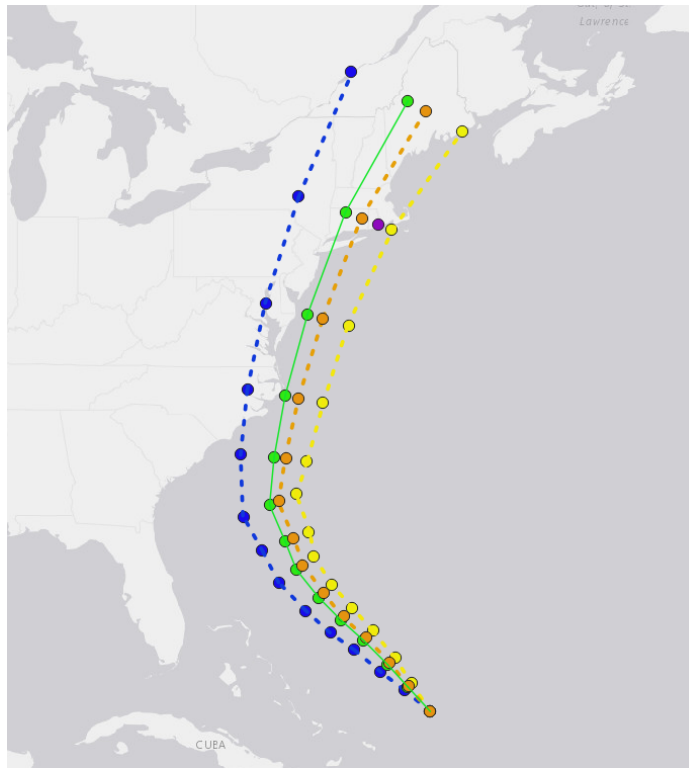


Figure 3.7. Hurricane Gloria (1985) Worst-Case Forecast Track. Using $R_{max}^{Gloria} = 71.71$, we shift the best track (green) east to generate worst-case winds at Newport Bridge (purple). This worst-case track (orange) lies between the best track (green) and the 90° (yellow). Figure produced using QGIS software.

3.2 Most Dangerous Region Identification

We are most concerned about the closures of the three major bridges used during evacuations: the Newport Bridge, Mount Hope Bridge, and the Sakonnet River Bridge. We identify a dangerous region in space where, if historical storms pass through it, it would cause these bridges to close and high winds for local communities. For the purposes of this thesis, we define a hurricane “strike” as a storm that enters this dangerous region. We define a threatening, but not striking storm as one that may enter this region, but does not.

Due to differences in hurricane size, shape, and wind, the most dangerous region for one storm might not be the same as another. We determine the most dangerous region for each historical storm separately via the following subtasks:

1. Use a parametric storm intensity model to estimate the wind speed intensity experienced at Aquidneck Island bridges for each synthetic storm track (URI);
2. Develop a wind intensity profile across storm tracks to estimate the most dangerous region for the historical storm to make landfall to shut down bridges (NPS, URI);

3.2.1 Parametric Wind Speed Modeling

We collaborate with Dr. Isaac Ginis and PhD candidate Deborah Crowley from URI to determine maximum wind speeds for synthetic storm tracks. Specifically, we use a Parametric Wind Model (PWM) to simulate the maximum wind speeds experienced across a forecast.

The PWM has been used in previous studies for synthetic storms impacting Rhode Island (Chen et al. 2018). The model outputs predictions for maximum wind speeds over marine exposure and provides a field of wind vectors and atmospheric pressure at each coordinate point for each time step. Model inputs are data from the HURDAT2 dataset (National Oceanic and Atmospheric Administration 2022b) and estimated parameters, including a forecast track’s coordinates, their corresponding forecast period, associated maximum wind speeds in meters per second (m/s), and the estimated and calculated central pressure in millibars (mbar) (Ginis and Crowley 2022). The PWM uses inflow angles and translation speeds of 3, 6, and 9 m/s where the inflow angles are meant to “create cross-isobar (ageostrophic) wind component and the translation speed imposes asymmetry to the axisymmetric tropical cyclone vortex” (Chen et al. 2018). The PWM combines the maximum wind speeds, the radius of maximum winds, the inflow angles, and translation speeds to

build the final wind fields (Chen et al. 2018). An example of the PWM's output for peak wind speeds at different bridges on Aquidneck Island is shown in Figure 3.8 and an example of the output for the predicted maximum wind speed swaths for a single track is shown in Figure 3.9. Maximum wind speeds are generated for each track for Hurricane Bob and Gloria.

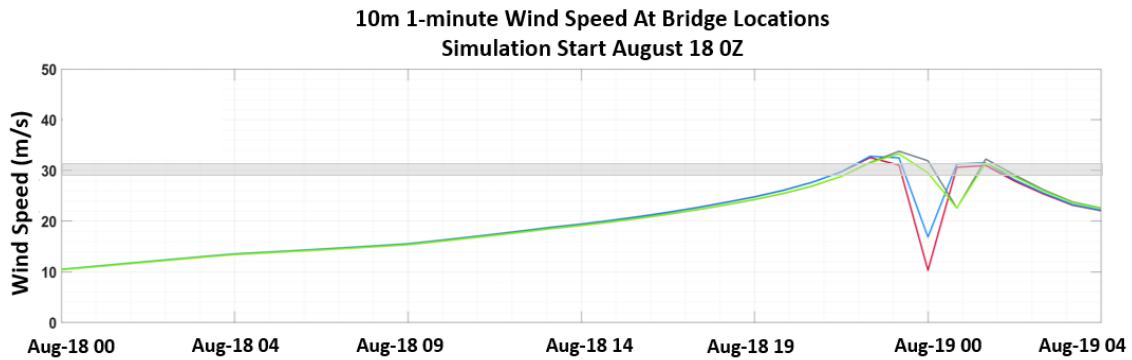


Figure 3.8. Example of Predicted Winds from the Parametric Wind Model. A simulation of the wind speeds predicted at the Jamestown Bridge, Newport Bridge, Sakonnet Bridge, and Mt. Hope Bridge over time. The red line displayed is the Jamestown Bridge, the blue line displayed is the Newport Bridge, the grey line displayed is the Sakonnet Bridge, and the green displayed is the Mt. Hope Bridge. Wind speeds in the grey region (starting at 30 m/s) become dangerous to cross bridges and may lead to their closure.

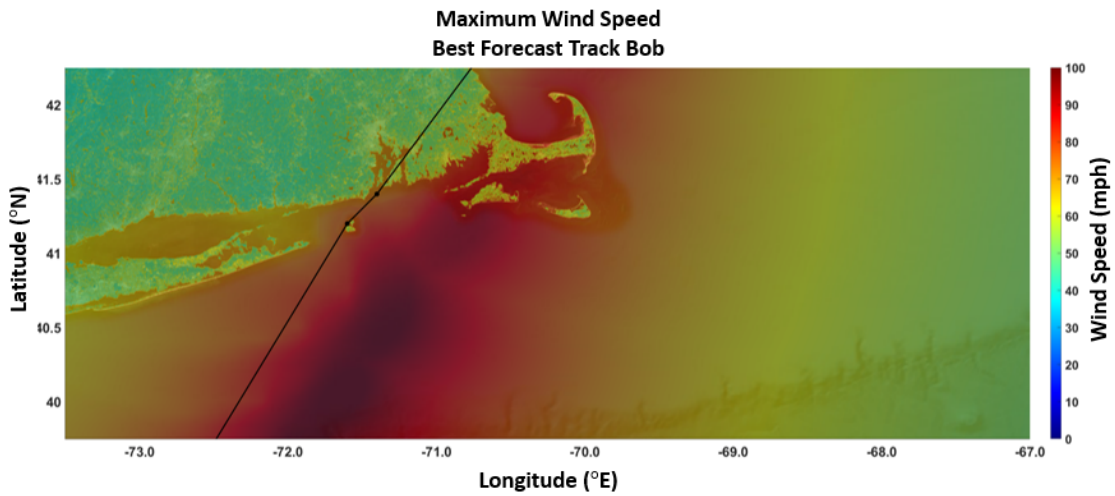


Figure 3.9. Example of Maximum Wind Swath for a Hurricane Track from the Parametric Wind Model. The black line in this figure represents the best forecasted track of Hurricane Bob. The wind speeds are color-coded in the figure and correspond to the wind speed key on the left. Here, there are winds reaching up to 100 mph to the east of the best forecasted track, while the west side of the track remains under 80 mph.

By using the PWM, we predict the maximum wind speeds for each of the bridges on Aquidneck Island for Hurricanes Bob and Gloria. Tables 3.2 and 3.3 present PWM output for the NHC best tracks and synthetic tracks developed in this thesis. Results reveal which tracks will be more severe than others and if the maximum wind speed experienced at a bridge will exceed wind thresholds, resulting in bridges closing and triggering likely evacuation.

Table 3.2. Maximum Wind Speeds Experienced by Aquidneck Island Bridges for Hurricane Bob Real and Synthetic Tracks.

Track	Max Wind Speed (mph)	Max Wind Speed (mph)	Max Wind Speed (mph)
	Newport Bridge	Sakonnet Bridge	Mount Hope Bridge
Original Bob Track	73.4	75.6	74.5
Right (90°) Bob Track	57.2	56.8	56.6
Left (180°) Bob Track	69.9	68.7	69.5
Worst-Case Bob Track	91.9	88.0	89.2

Table 3.3. Maximum Wind Speeds Experienced by Aquidneck Island Bridges for Hurricane Gloria Real and Synthetic Tracks.

Track	Max Wind Speed (mph) Newport Bridge	Max Wind Speed (mph) Sakonnet Bridge	Max Wind Speed (mph) Mount Hope Bridge
Original Gloria Track	76.3	74.6	75.5
Right (90°) Gloria Track	57.4	56.1	55.5
Left (180°) Gloria Track	59.9	59.2	59.6
Worst-Case Gloria Track	93.4	86.7	89.1

3.2.2 Dangerous Regions

On Aquidneck Island, wind warnings for bridges begin when winds reach over 30 mph, and specific vehicles are prohibited to travel when wind speeds reach 50 mph and 60 mph (Rhode Island Turnpike and Bridge Authority 2022). However, sustained wind speeds over 70 mph will likely close a bridge to all traffic (Rhode Island Turnpike and Bridge Authority 2022). These guidelines dictate a maximum wind threshold for the bridges. In such scenarios, we want to know when these wind speeds are reached in order to account for the greater evacuation clearance time and ensure the community’s safety when evacuation decisions are made. Importantly, without the use of these bridges during evacuations, there is essentially no other option for Aquidneck Island communities but to shelter-in-place. Thus, we assume an evacuation will occur if the bridges close.

From Tables 3.2 and 3.3, we find for some tracks maximum sustained winds at bridges exceed 70 mph, where for others, winds are below this threshold. Specifically, for Hurricane Bob, the original, worst-case, and 180° tracks would initiate bridge closures. For Hurricane Gloria, only the original and worst-case tracks would initiate bridge closure.

We find minimal deviation in max wind speeds amongst the bridges, suggesting that if a single bridge closes, all bridges will close. The maximum difference in wind speed across bridges is between Newport Bridge and Sakonnet River Bridge during worst-case tracks — 3.9 mph for Hurricane Bob and 6.7 mph for Hurricane Gloria. Thus, for any one track, it is likely that when a single bridge is closed due to high winds, then all bridges will close.

Thus, we study a single bridge — Newport Bridge — and determine the most dangerous

region in space that would lead to its closure and assume this region is appropriate for all bridges. Specifically, we use a linear interpolation across max wind speeds from Tables 3.2 and 3.3 and the longitude of each forecast track to identify the region.

Figures 3.10 and 3.11 present the results of this interpolation. As shown in Figure 3.10, we identify that if Hurricane Bob made landfall in any longitude between -73.4 and -71.0, it would result in closure of Newport Bridge (i.e., winds 70 mph or greater). Similarly, as shown in Figure 3.11, we identify that if Hurricane Gloria made landfall in any longitude between -74.1 and -71.5, it would result in closure of Newport Bridge (i.e., winds 70 mph or greater). Thus, we find the most dangerous region for each storm is the same size — 2.6° or 156 nautical miles — but, shifted by 0.5° (30 nautical miles).

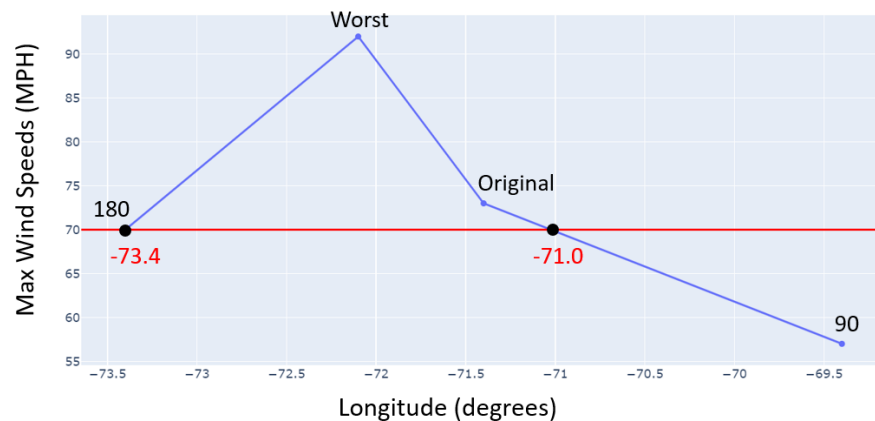


Figure 3.10. Determining the Most Dangerous Region for Hurricane Bob (1991). We interpolate max wind speeds for synthetic storms versus their longitudes when passing the latitude of Newport Bridge. This interpolation allows us to determine all possible storms that would exceed 70 mph at Newport Bridge. Here, Hurricane Bob is dangerous if it makes landfall between longitudes of -73.4 and -71.0. Each longitude is labeled by its respective track in black.

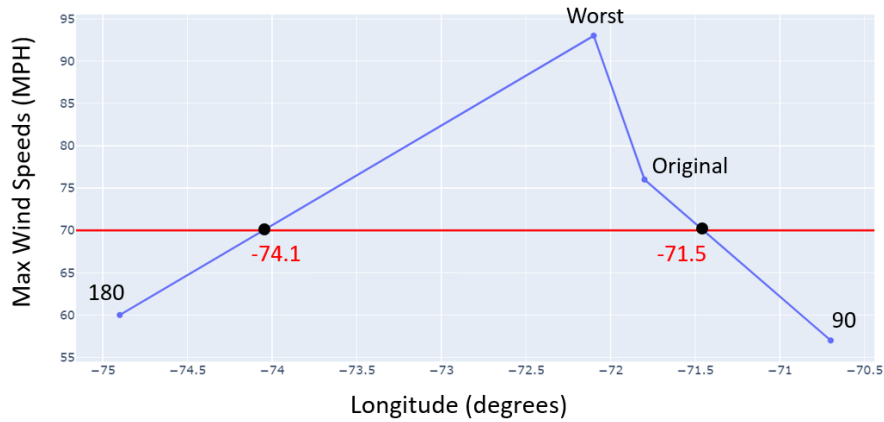


Figure 3.11. Determining the Most Dangerous Region for Hurricane Gloria (1985). We interpolate max wind speeds for synthetic storms versus their longitudes when passing the latitude of Newport Bridge. This interpolation allows us to determine all possible storms that would exceed 70 mph at Newport Bridge. Here, Hurricane Gloria is dangerous if it makes landfall between longitudes of -74.1 and -71.5. Each longitude is labeled by its respective track in black.

3.3 Hurricane Strike Estimation

After obtaining the dangerous regions for Hurricane Bob and Gloria, we calculate the likelihood that different forecasts will pass through that region. We create stochastic tracks to represent the different forecasts that can occur if they have the same characteristics as Hurricane Bob or Gloria, such as maximum speeds and central pressures. This translates our synthetic tracks from a single instance into a probability of striking the most dangerous region and initiating evacuation.

3.3.1 Stochastic Hurricane Track Generation Procedure

Our current synthetic tracks represent possible realizations of historical hurricanes. However, the likelihood that any single track is accurate is only known in retrospect. As a storm approaches, the actual track taken can deviate from predictions, with increasing error into the future. We develop a stochastic track generation procedure that incorporates this uncertainty to estimate how likely strike is given the lead-time on a storm.

Note: Throughout this section and for the remainder of the thesis, we use τ to denote time (in hours) counting up to possible strike (i.e., from 0 to 72 hours) and lead time (in hours) counting down to strike (i.e., from 72 to 0 hours). We use these two conventions as τ simplifies simulation and optimization methods, where lead time simplifies discussion of evacuation decisions.

Figure 3.12 is a visual representation of our stochastic track generation procedure. First, we start at a point that is assumed to be known based on a historical or synthetic track. In Figure 3.12 this is assumed to be $\tau = 0$ or the initial forecast point for a storm. We generate the next track point based on the forecast forward movement of this initial point. Specifically, we estimate possible hurricane motion 6 hours in the future using a Gaussian distribution centered on the forecast track position with a standard deviation $\sigma = 23.73$ km based on the NHC cone of uncertainty. We repeat this process for the next track point, maintaining previous bearing and using forecast magnitude of forward motion from the historical track.

Figure 3.13 presents example stochastic tracks using the Hurricane Bob best track initial point for $\tau = 0$ and $\tau = 48$. We generate stochastic tracks starting at each point up until the coordinate 13, which is the point that contains the location of the Newport Bridge on the original track. The closer the final stochastic track point is to the final track point to the actual best track, the more likely the stochastic track would strike the most dangerous region for Newport Bridge. Hence, stochastic storms starting at a forecast point closer to Rhode Island (i.e., with less lead time to evacuate, respond) are more likely to produce strikes.

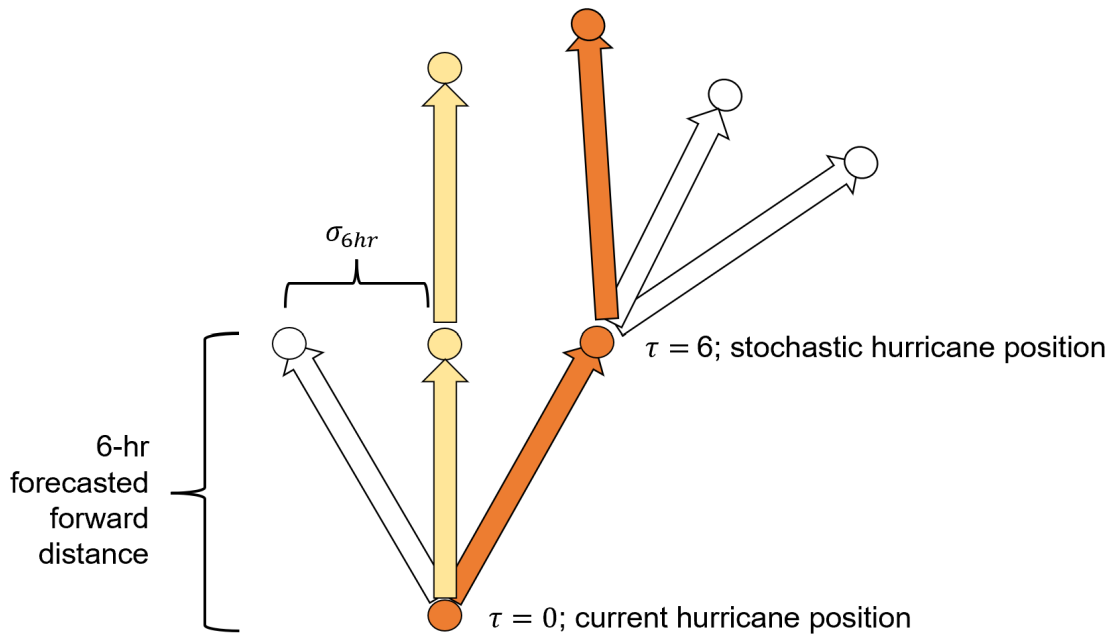


Figure 3.12. Stochastic Hurricane Track Generation Procedure. We generate stochastic tracks based on synthetic forecasts. Each track has a starting point, here donated at $\tau = 0$. The original forecast (in yellow) predicts forward motion at a specified bearing (here, 0° , North). However, using the cone of uncertainty error provided by the NHC, we estimate that a storm can travel in many different directions indicated by white arrows. We estimate stochastic motion using a Gaussian distribution where forecast track is the mean with standard deviation $\sigma_{6hr} = 23.73$ km. Using this method, we estimate a stochastic track that follows the orange path, rather than the yellow path. This procedure is repeated for 6-hour time steps for the entire hurricane approach.

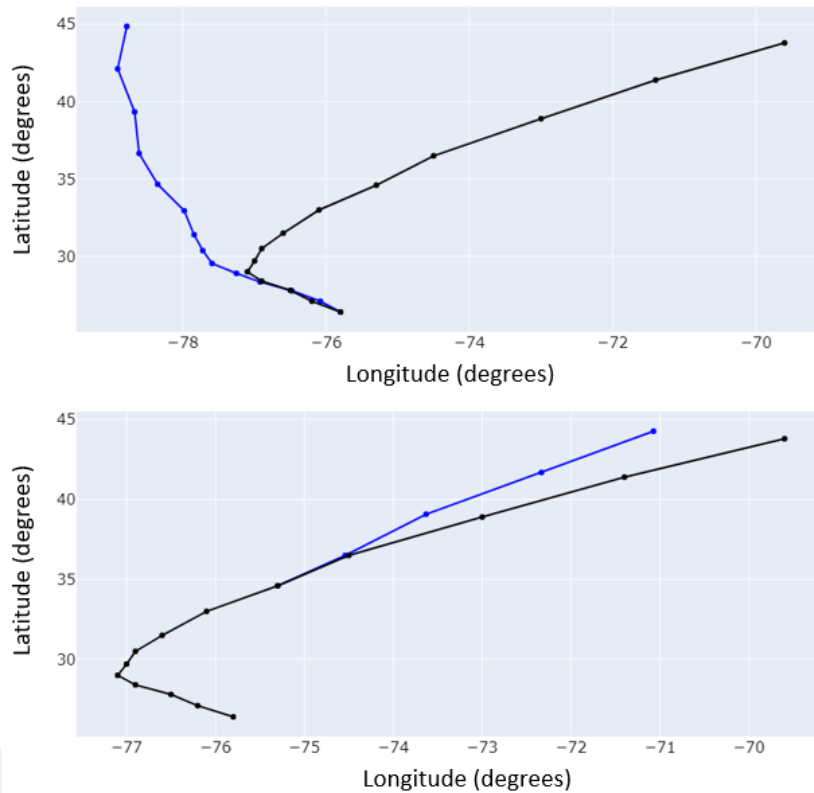


Figure 3.13. Examples Stochastic Tracks for Hurricane Bob. Using the procedure from Figure 3.12, we generate examples of stochastic tracks Hurricane Bob. The black line in both figures is the original track for Hurricane Bob (1991) while the blue line is a stochastic track generated starting at $\tau = 0$ (top) and $\tau = 48$ (bottom). Stochastic tracks deviating at an earlier time when Hurricane Bob is far from actual landfall (small τ) have a low probability of striking the most dangerous region for Aquidneck Island. In contrast, stochastic tracks that deviate at a later time when Hurricane Bob is near landfall (large τ) have a high probability of strike.

3.3.2 Stochastic Tracks for Hurricane Bob

We use the stochastic track generation procedure to determine the likelihood that a strike would occur for each τ for each Hurricane Bob forecast (Figure 3.14). We generate 500 stochastic tracks starting at $\tau = 0$ and ends at $\tau = 72$ for each forecast. Each subplot in Figure 3.14 shows the total outcome of this procedure relative to the original best or synthetic forecast. In some cases, stochastic track direction and final position significantly

vary in comparison to each synthetic forecast. For example, we see large variation in the 90° track since many of its stochastic tracks veer to southeast and southwest away from Rhode Island. This indicates that 90° track is likely to have a lower probability of strike than the other synthetic tracks across the entire forecast. Although there may be less variation for the other synthetic tracks, the likelihood of strike for each track will depend on its bearing towards Rhode Island and how close its position is to the most dangerous region.

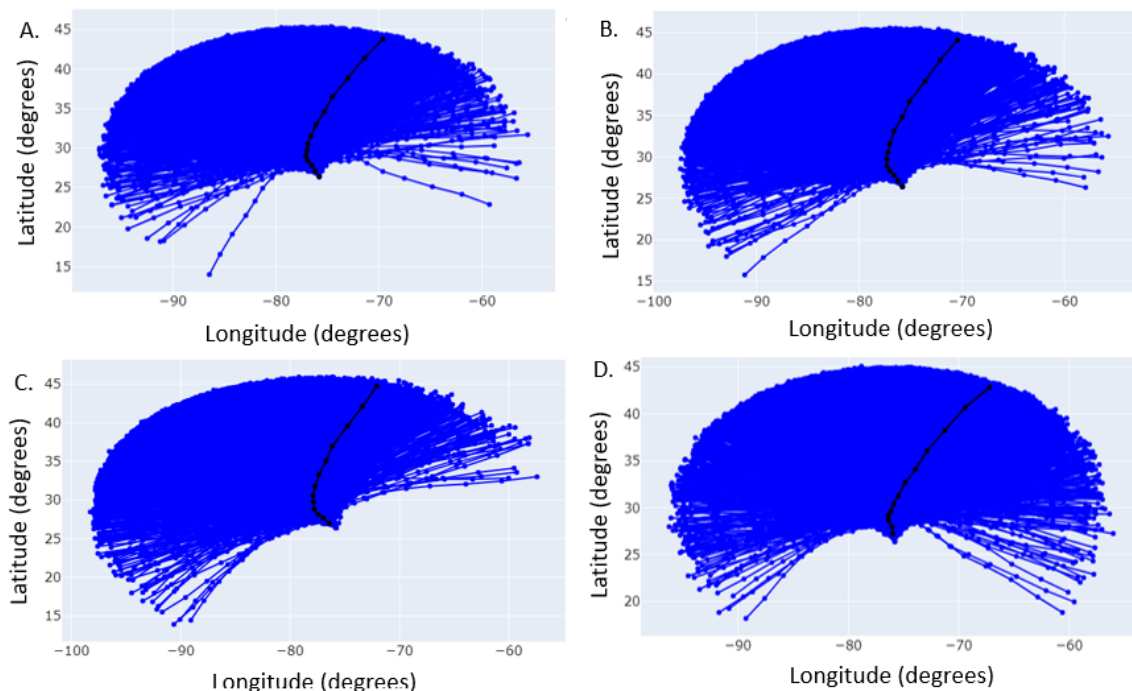


Figure 3.14. Stochastic Hurricane Tracks for Artificial Tracks for Hurricane Bob (1991). Subplot (A) contains the original track, (B) contains the worst-case synthetic track, (C) contains the 180° track, and (D) contains the 90° track. In each subplot there are 6,500 stochastic tracks, or 500 generated for each time step considered. Stochastic tracks are displayed in blue, and the original and synthetic tracks displayed in black.

We count the number of stochastic tracks that strike the most dangerous region to determine the likelihood of strike. Table 3.4 presents the likelihood of each hurricane track striking the most dangerous region for each lead time. These results allow us to know the expectation of strike depending on the lead time available. We can see that as lead time gets closer to

strike, the probability of strike increases for tracks that end in strike (i.e., best and worst-case tracks). However, the probability of strike when lead time = 0 remains low for the 180° and 90° tracks. This is because the final position of these tracks are located far from the most dangerous region, resulting in low probabilities of strike. Importantly, there is an appreciable expectation of strike for all tracks during intermediate time periods ($12 \leq \text{lead time} \leq 42$). Thus, there is a potential for evacuation even for storms that do not ultimately strike the most dangerous region.

Table 3.4. Likelihood of Hurricane Bob-Based Hurricane Striking the Most Dangerous Region.

Lead Time (Hours)	Probability of Strike (Original Bob)	Probability of Strike (Worst Bob)	Probability of Strike (180° Bob)	Probability of Strike (90° Bob)
72	.044	.056	.032	.06
66	.062	.054	.028	.06
60	.028	.026	.026	.052
54	.066	.05	.024	.09
48	.102	.11	.084	.112
42	.128	.14	.088	.144
36	.226	.182	.148	.236
30	.378	.26	.124	.252
24	.46	.5	.304	.16
12	.682	.526	.176	.21
6	.654	.92	.276	.008
0	.878	1	.056	0

Results produced via stochastic track generation procedure. *Note:* Results presented in lead time counts down to possible strike, where τ counts up to strike.

3.3.3 Stochastic Tracks for Hurricane Gloria

We repeat the process for Hurricane Gloria as shown in Figure 3.15. The stochastic tracks also start at each $\tau = 0$ and end at $\tau = 72$. Here, we see the most deviation from final strike in the 180° track since the majority of the stochastic tracks veer west.

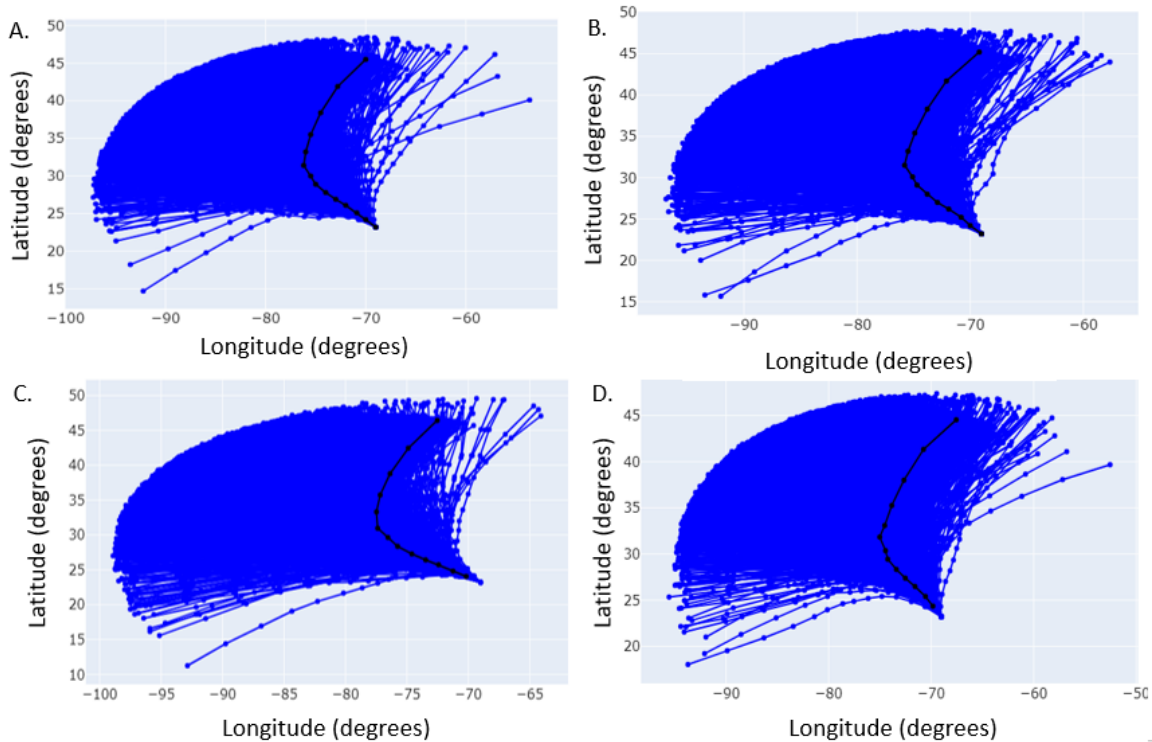


Figure 3.15. Stochastic Hurricane Tracks for Artificial Tracks for Hurricane Gloria (1985). Subplot (A) contains the original track, (B) contains the worst-case synthetic track, (C) contains the 180° track, and (D) contains the 90° track. In each subplot there are 6,500 stochastic tracks, or 500 generated for each time step considered. Stochastic tracks are displayed in blue, and the original and synthetic tracks displayed in black.

The results in Table 3.5 show the likelihood of each hurricane track striking the most dangerous region for Hurricane Gloria. We can see that as lead time gets closer to strike ($\tau = 72$), the probability of strike greatly increases for the original and worst-case scenario tracks. However, the probability of strike is 0 for both the 180° and 90° tracks at the end of the forecast. Again, the final position of these tracks are too far from the most dangerous region, which results in low probabilities of strike. The probability of strike for the 180° track remains low throughout the forecast whereas the other tracks maintain higher probabilities of strike.

Table 3.5. Likelihood of Hurricane Gloria-Based Hurricane Striking the Most Dangerous Region.

Lead Time (Hours)	Probability of Strike (Original Gloria)	Probability of Strike (Worst Gloria)	Probability of Strike (180° Gloria)	Probability of Strike (90° Gloria)
72	.026	.038	.018	.006
66	.022	.056	.006	.07
60	.016	.012	.008	.04
54	.004	.014	0	.02
48	.008	.016	.006	.024
42	.008	.024	0	.036
36	.042	.054	.004	.182
30	.008	.006	0	.044
24	.272	.47	.014	.288
12	.534	.696	.018	.464
6	.87	.954	.004	.338
0	1	.998	0	0

Results produced via stochastic track generation procedure. *Note:* Lead time counts down to possible strike, where τ counts up to strike.

For the tracks of Hurricane Bob and Gloria to achieve higher probabilities of strike, the synthetic tracks need to generally be positioned within a close range to the most dangerous region. This can be achieved when the synthetic tracks directly target the Newport Bridge and will travel through the region. The probabilities of strike for these tracks greatly influence the following calculated parameters.

3.4 Expected Evacuation Demands

Following the work of Lee and Kockelman (2021) presented in Chapter 2, Section 2.2.2, we estimate the evacuation demands as an uncertain number of vehicles based on anticipated hurricane strikes. We develop a function to estimate $D_{s,\tau}$, the evacuation demand for vulnerable community s at time τ relative to hurricane approach, that incorporates these uncertain elements:

$$D_{s,\tau+1} = Veh(D_{s,\tau}) * hit(\tau) * C(\tau) \quad (3.2)$$

Here, we assume $D_{s0} = 0$, i.e., the oncoming hurricane is far enough away at $\tau = 0$ that there would never be an evacuation demand. Then, $D_{s,\tau+1}$ is calculated for each time step using three separate equations:

- $Veh(D_{s\tau})$: the number of vehicles needing to evacuate a vulnerable community dependent on evacuation demands in previous time steps;
- $hit(\tau)$: the time dependent probability of strike; and,
- $C(\tau)$: an evacuation credibility function for when authorities are likely to call an evacuation.

We combine the vehicle demands, strike probability, the credibility of authorities to create the expected evacuation demands for each community for each track. Each equation is described in more detail below.

Note: $D_{s\tau}$ uses a τ in one-hour increments, where related calculations given above use multi-hour increments (e.g., 6-hour forecast periods). This is to relate evacuations that occur in one-hour intervals to forecasts that are made in 6-hour intervals. Where methods and analysis are in multi-hour increments, we assume time steps in-between these periods take on these values. For example, $hit(\tau)$ and $C(\tau)$ for $6 \leq \tau < 12$ will receive the same value based on of 6-hour forecast data.

3.4.1 Vehicle Demand

Based on the work of Jones (2021), there are 6985 vehicles that are needing to evacuate Aquidneck Island. The Table 3.6 indicates the breakdown of the number of population nodes in the network model for Aquidneck Island as well as the number of vehicles from each of the 5 municipalities: Newport City, NAVSTA Newport, Portsmouth, Middletown, and NUWC.

Table 3.6. Population Nodes and Vehicle Data for Each City on Aquidneck Island. Adapted from Jones (2021).

City	Population Nodes By City	Total Vehicles
Newport	16	3084
Portsmouth	16	1570
Middletown	2	116
NAVSTA Newport	13	1892
NUWC	8	323

Each municipality is then broken up into a set of community nodes, denoted S , representing contiguous houses that will evacuate using the same route. For each community node $s \in S$, the number of vehicles wanting to evacuate at time τ is calculated as:

$$Veh(D_{s\tau}) = z_s - \sum_{\tau} D_{s\tau} \quad (3.3)$$

Eq. 3.3 estimates the possible number of vehicles wanting to evacuate at time τ . z_s is assumed to be the maximum number of vehicles from community s , where the total demand cannot exceed this value. We assume z_s is a known value relevant for vulnerable populations in Aquidneck Island from Jones (2021).

3.4.2 Probability of Strike

Evacuation will only occur if there is an anticipated risk of strike. We develop a function $hit(\tau)$ to estimate this probability:

$$hit(\tau) = \begin{cases} 0, & \text{if } \phi_{\tau} < \phi_c \\ \phi_{\tau}, & \text{otherwise} \end{cases} \quad (3.4)$$

Here, ϕ_{τ} is the probability of strike produced at time τ produced via our stochastic methods presented in Section 3.3 above and ϕ_c is a minimum strike probability that must be met for communities to decide to evacuate. Specifically, for Hurricane Bob, we set ϕ_{τ} based

on strike probabilities from Table 3.4, and for Hurricane Gloria, we use strike probabilities from Table 3.5.

In some cases, individual households do not want to consider evacuating in a time period τ if ϕ_τ is extremely small. In these situations, one can set a ϕ_c that sets a minimum threshold on strike probability for evacuation. For this work, we assume $\phi_c = 0$ suggesting that any strike probability to lead to some amount of evacuation demand.

3.4.3 Credible Evacuation Period

Local authorities also need to establish a credible time window to call evacuations. In general, emergency managers do not want communities to evacuate or to call an evacuation too early on the chance the storm changes direction and does not impact communities. On the other hand, authorities do not want communities to evacuate or to call an evacuation too late, as the risk of death is highest for vehicles stuck on the roads when a hurricane makes landfall. Thus, following the convention from Lee and Kockelman (2021), we define a “credible” period in which authorities will allow an evacuation to happen.

We establish a *credible evacuation period* to represent when authorities are likely to call an evacuation:

$$C(\tau) = \begin{cases} 0, & \text{if } \tau < \tau_b^c \\ 1, & \text{if } \tau_b^c \leq \tau \leq \tau_a^c \\ 0, & \text{if } \tau > \tau_a^c \end{cases} \quad (3.5)$$

$$\tau_b^c = T - (\tau_s^{evac} + \tau_b) \quad (3.6)$$

$$\tau_a^c = T - \tau_s^{evac} + \tau_a \quad (3.7)$$

$C(\tau)$ is based on the following parameters: T , the total time available before the hurricane strikes, τ_s^{evac} the time it takes a population to evacuate, τ_b , the buffer time desired by local authorities before starting the evacuation, and τ_a , the buffer time desired by local authorities

after the end of the evacuation. The window starts at the time of τ_b^c and ends at τ_a^c . The function is equal to 1 during the time periods within the time window and is equal to 0 for the time periods outside of the time window.

In this work, T is 72 hours. We obtain the τ_s^{evac} from the previous work of Jones (2021). Here, we assume authorities do not make decisions on a community-by-community basis, and set τ_s^{evac} equal to the total clearance time for all communities, or 14 hours when all bridges are available (Jones 2021). We estimate τ_b and τ_a based on average evacuation times provided in HURREVAC for emergency managers (Hurricane 2022). Specifically, we set $\tau_b = 6$ hours and $\tau_a = 7$ hours. This assumes a moderate time to call an evacuation and a 13-hour evacuation call window. Thus, the evacuation window is from $\tau_b^c = 52$ to $\tau_a^c = 65$ hours, which allows $D_{s\tau}$ to take on values greater than 0 for $53 \leq \tau \leq 66$ due to a one hour lag in decision-making. Figure 3.16 and Figure 3.17 show the probability of strike function within the credible evacuation window for the different tracks for Hurricane Bob and Gloria and indicate if the probability of strike reaches 1 within the window.

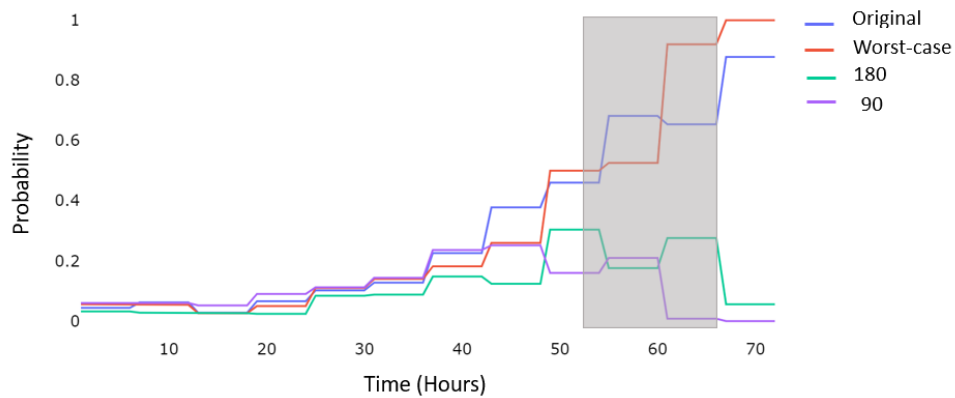


Figure 3.16. Visualization of Credibility Function and Probability of Strikes for Hurricane Bob. The probability of strike for the original tracks is displayed in blue, the worst-case track is displayed in red, the 180° track is displayed in green, and the 90° track is displayed in purple. The credible evacuation time window starts at $\tau = 53$ and ends at $\tau = 66$ and is displayed in the grey box.

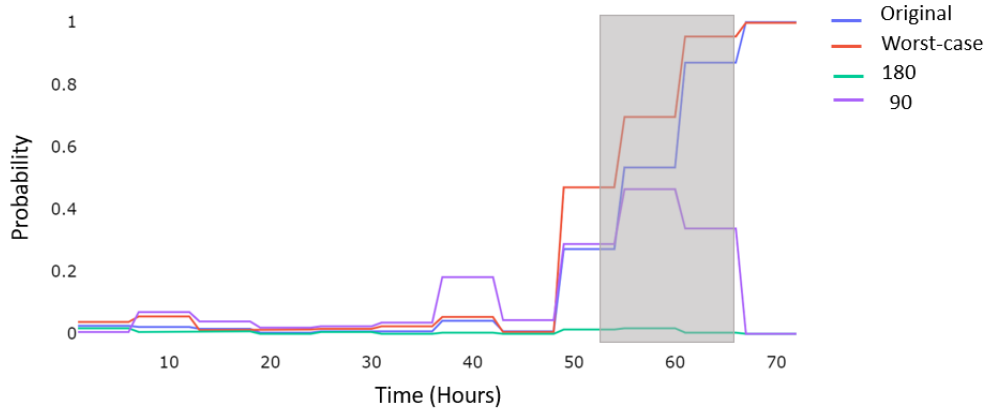


Figure 3.17. Visualization of Credibility Function and Probability of Strikes for Hurricane Gloria. The probability of strike for the original tracks is displayed in blue, the worst-case track is displayed in red, the 180° track is displayed in green, and the 90° track is displayed in purple. The credible evacuation time window starts at $\tau = 53$ and ends at $\tau = 66$ and is displayed in the grey box.

3.4.4 Interpretation

While each part of Eq. 3.2 on its own may be simple, their combined interpretation is meaningful to capture complex evacuation demands and phenomena. The decision for any one household to evacuate is a combination of the anticipated consequences of an oncoming storm, the risk tolerance of emergency managers who call evacuations, the risk tolerance of local communities, trust between communities and emergency managers, and the capacity for all parties to coordinate decisions. We choose to represent Eqs. 3.3-3.5 to use the simplest model possible while capturing some of these tensions. We choose Eq. 3.3 to allow for evacuation demands that continue to occur over time periods with the same probability of strike, but with a decreasing number of vehicles. This form also allows any time period where $hit(\tau) = C(\tau) = 1$ to set evacuation demands equal to all remaining vehicles on Aquidneck Island. Eq. 3.4 is chosen to be conservative, such that any likelihood of strike has the potential to cause some amount of evacuation. It also assumes that the number of vehicles choosing to evacuate is scaled by the probability of strike and remaining demands calculated with $Veh(D_{s\tau})$. Eq. 3.5 is set based on the way HURREVAC is used by emergency managers.

It is worth noting that each equation can be represented by much more complicated models to capture decision-making phenomena. For example, Eq. 3.3 can be represented by a Poisson distribution representing expected demands as in Lee and Kockelman (2021). Eq. 3.4 can be dependent on the probability of strike from previous time periods and/or dependent on the change in strike probability across time periods (e.g., new evacuation demands only occur if strike probability increases). And, Eq 3.5 can be shifted earlier or later relative to the risk tolerance of emergency managers, can take on values in between 0 and 1 representing uncertainty or coordination difficult in evacuation decisions, or can change over the evacuation time period representing priorities for when vehicles should be allowed to evacuate. While each of these more complicated models have merits, each introduces additional complexity while not necessarily changing the accuracy of results to represent real decisions and evacuation needs.

Overall, Eq. 3.2 allows us to compute the number of vehicles expected to evacuate from all community nodes ($s \in S$) for all time periods ($\tau \in T$) for a given hurricane track. Thus, even though $D_{s\tau}$ is based on stochastic models and their expectations, its pre-processing allows us to determine optimal routing and clearance times using a deterministic model for a given forecast track.

3.5 Optimal Evacuation Routing Model Formulation

We develop a modified formulation of Jones (2021) that determines optimal evacuation routing and clearance times given expected demands $D_{s\tau}$. The updated formulation still uses a network optimization model, but the formulation also employs constraints that will account for the uncertainty and vary the number of vehicles that should evacuate in each time period.

Indices and Sets

$n \in N$	nodes (alias i, j)
$s \in S \subset N$	set of all source nodes
$e \in E \subset N$	set of all evacuation destination nodes
$(i, j) \in A \subseteq N \times N$	arcs
$\tau \in T$	number of time steps [0,72] ($\bar{\tau}$ = total time period)

$k \in K_s$ set of all evacuation paths starting at given source node $s \in S$

Data [units]

- $c_{ij\tau}$ capacity of arc (i, j) in time period τ [vehicles per hour (VPH)]
- $d_{ij\tau}$ distance of arc (i, j) in time period τ [miles]
- $\rho_{ij\tau}$ speed of arc (i, j) in time period τ [mph]
- z_s number of evacuating vehicles (i.e., supply) at source node s
- v_e shelter capacity for evacuees at node e
- λ_{sek} = 1 if evacuation node e is included in path k for source node s , 0 otherwise [Binary]
- w_{sijk} = 1 if arc i, j is included in path k for source node s , 0 otherwise [Binary]
- $D_{s\tau}$ number of required evacuating vehicles at source node s in time period τ
- $hit(\tau)$ probability of hurricane strike in time period τ
- $C(\tau)$ credibility of local decision-makers in time period τ

Decision Variables [units]

- σ_{sk} = 1 if path $k \in K_s$ chosen for source node $s \in S$; 0 otherwise [Binary]
- $\beta_{s\tau k}$ flow rate of evacuating vehicles leaving node s in time period τ along path k [VPH]
- $\mu_{s\tau}$ the number of evacuating vehicles remaining at node s in time period τ [VPH]

Formulation

$$\min_{\sigma, \beta, \mu} \sum_s \sum_{\tau} \mu_{s\tau} \quad (3.8)$$

$$\text{s.t. } \sum_s \sum_k \beta_{s\tau k} w_{sijk} \leq \left(\frac{60 \cdot d_{ij\tau}}{\rho_{ij\tau}} c_{ij\tau} \right) \quad \forall (i, j) \in A, \forall \tau \in T \quad (3.9)$$

$$\sum_k \sigma_{sk} = 1 \quad \forall s \in S \quad (3.10)$$

$$\sum_{\tau} \beta_{s\tau k} \leq \sigma_{sk} z_s \quad \forall s \in S, \forall k \in K_s \quad (3.11)$$

$$\mu_{s0} = D_{s0} \quad \forall s \in S \quad (3.12)$$

$$\mu_{s,\tau+1} = \mu_{s\tau} - \sum_k \beta_{s\tau k} + D_{s\tau} \quad \forall s \in S, \forall \tau \in T - 1 \quad (3.13)$$

$$\sum_s z_s \left[\sum_k \sigma_{sk} \lambda_{sek} \right] \leq v_e \quad \forall e \in E \quad (3.14)$$

$$\sigma_{sk} \in \{0, 1\} \quad \forall s \in S, k \in K_s \quad (3.15)$$

$$\beta_{s\tau} \geq 0 \quad \forall s \in S, \tau \in T \quad (3.16)$$

$$\mu_{s\tau} \geq 0 \quad \forall s \in S, \tau \in T \quad (3.17)$$

$$(3.18)$$

Discussion

For simplicity, we reproduce the explanation of the model as presented in Jones (2021) with slight changes to explain modification for uncertain demands.

“This model analyzes the flow of evacuating vehicles departing from source nodes located within flooding regions toward inland shelters and off-island evacuation points. The model assumes that evacuees will depart from their source nodes at the earliest time period based on available road capacity within their assigned route to their assigned destination. Additional model assumptions are that each source node will be assigned one route and one destination node. This assigned route and destination will be utilized by all of the population evacuees throughout the entire duration of their trip” (Jones 2021).

These assumptions remain true for the updated formulation, however, the updated model

does not aim to evacuate everyone in all time periods. The model aims to balance the number of evacuees and the number of the population that will shelter in place instead, depending on the time of landfall of the hurricane and if it will strike the area. This formulation assumes that local authorities have the information on the length of time needed for a population at a source node to fully evacuate and the lead time before the hurricane makes landfall.

As explained by Jones (2021): “The objective function value (3.8) of the formulation minimizes the number of vehicles waiting to depart, summed over each time period. This creates an incentive for vehicles to leave as soon as possible. Constraint (3.9) enforces the capacity on each arc (i,j) given nonlinear congestion. Constraint (3.10) enforces that only one evacuation path is selected for each source nodes. Constraint (3.11) enforces the total flow of vehicles out of source node s along the selected evacuation path to be less than or equal to the number of evacuees initially at that node. Constraint (3.14) enforces that the total number of evacuees from all source nodes that arrive at a destination node e be less than or equal to its total shelter capacity. Stipulations (3.15), (3.16) and (3.17) enforce the binary and non-negativity requirements for the decision variables” (Jones 2021).

In the new formulation, we adjust constraint (3.12) to enforce that at time period $\tau = 0$, the initial number of evacuees at each source node s is D_{s0} . Since the credible evacuation period is 0 for the initial time step ($C(0) = 0$), by convention $\mu_{s0} = 0$ in our model for all scenarios. The constraint (3.13) “calculates the number of evacuees remaining at source node s for all remaining time periods τ and is equal to the prior time period’s number of evacuees remaining minus the number of vehicles that were able to evacuate during that prior time period τ ” (Jones 2021). We modify (3.13) to include $D_{s\tau}$ such that at any time period τ new evacuation demand may be added into the network at a source node s . Thus, for time periods before any $D_{s\tau} > 0$, $\mu_{s\tau} = \beta_{s\tau k} = 0$. For time periods after demand $D_{s\tau} > 0$, $\mu_{s\tau}$ and $\beta_{s\tau k}$ take on values to evacuate as many vehicles as possible over selected route $k \in K_s$ within road capacity constraints.

3.6 Summary

Taken together, our methods enable study of optimal evacuation routes and clearance times given synthetic hurricane tracks, uncertain hurricane impacts, and evacuation decisions. We summarize the methods presented in this chapter in Figure 3.18.

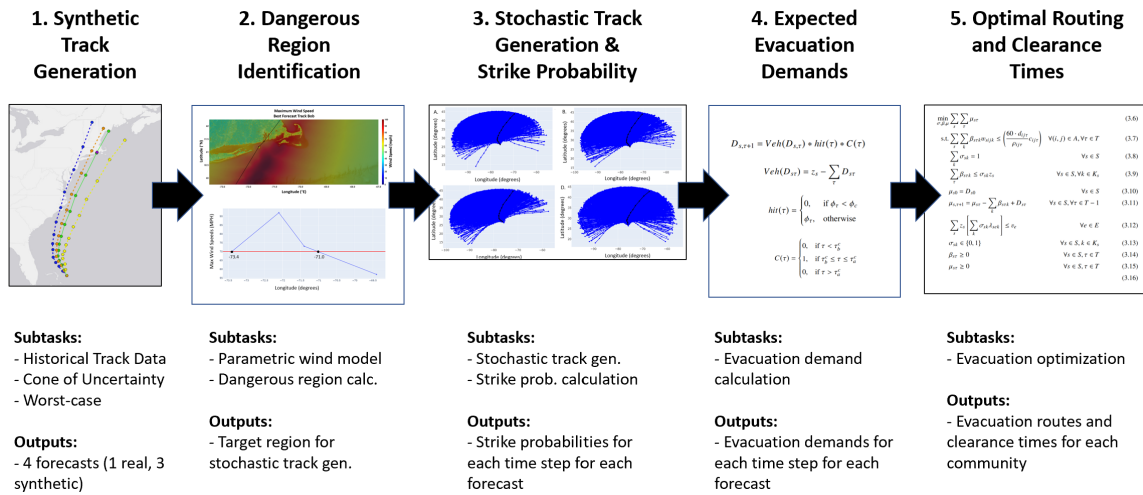


Figure 3.18. Summary of Methods for Evacuation Modeling. This thesis completes five analysis tasks, each with distinct subtasks and methods. The overall goal is to study evacuation routing and clearance times given uncertain historical storm scenarios.

Tasks 1-4 are pre-processing tasks, with results presented in the sections above. Only Task 5 (optimal routing and clearance times) involves results of an optimization model. Results from this task are presented in the next chapter.

CHAPTER 4: Analysis

In this chapter, we use the model formulated in Chapter 3 to study evacuation routing and clearance times for Aquidneck Island if it were to be hit today by the 1991 Hurricane Bob or the 1985 Hurricane Gloria. We analyze how the combination of a predicted hurricane track, its probability of striking the most dangerous region near Newport Bridge, and the time range for evacuation influence the number of residents that should evacuate at each time period, the routes they take, and their total clearance times.

For our analysis, we use the Aquidneck Island network model developed by Jones (2021) (Figure 4.1). This network includes 11 destination nodes and 55 community source nodes. The destination nodes in this model included three inland locations of safety accessed by evacuating over bridges and eight evacuation shelters on Aquidneck Island. However, only one on-island location — Gaudet Middle School — is an official evacuation shelter for Aquidneck Island. Thus, we consider only four destination nodes representing real evacuation destinations: Newport Bridge, Mt. Hope Bridge, Sakonnet River Bridge, and Gaudet Middle School.

The network connecting communities to evacuation destinations includes 2477 edges representing roads connected by 1058 nodes representing intersections. The travel time and capacity of roads are estimated using parameters from official sources in Rhode Island. For additional information on the data and network, we refer the reader to Jones (2021).

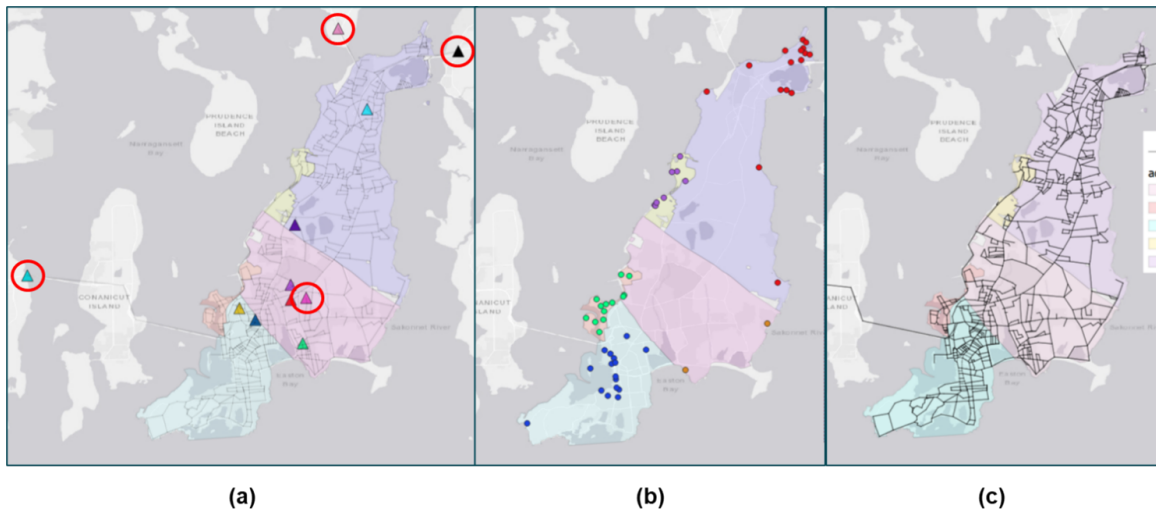


Figure 4.1. Aquidneck Island Evacuation Model Data. We use data from Jones (2021) to model evacuation of Aquidneck Island. This includes: (a) evacuation destinations, (b) community source nodes representing vulnerable populations, and (c) the island road network. In each subplot, each Aquidneck Island community is color coded — Newport: light blue; NAVSTA Newport: red; Middletown: pink; NUWC: yellow; and, Portsmouth: purple. *Note:* Only destination nodes highlighted in red are used in this study (subplot a). All community source nodes and roads are used in our analysis. Figure adapted from Jones (2021).

4.1 Analysis of Hurricane Bob (1991)

We study evacuation routing and clearance times for the original, worst-case, 180°, and 90° hurricane tracks.

4.1.1 Evacuation from Original Track

We begin with the original track for Hurricane Bob (see Ch. 3, Figure 3.6, green line). Figure 4.2 shows the total number of vehicles required to evacuate for each community due to expected evacuation demand. We find that all the communities evacuate the maximum number of vehicles by the end of the credible evacuation period, meaning that all vehicles evacuate in this scenario. However, the municipalities fulfill the evacuation demands at different times. Specifically, Middletown and NUWC evacuate all the vehicles by hour

$\tau = 58$, Portsmouth evacuates all the vehicles by hour $\tau = 60$, Newport and NAVSTA Newport evacuate all the vehicles by hour $\tau = 66$. Because there is no point at which the probability of strike (Eq. 3.4) reaches 1 during the credible evacuation period window (Eq. 3.5), there is not a time period where all demand enters the network (see Ch. 3, Figure 3.16, blue line). Hence, larger evacuation demands require longer credible evacuation periods to ensure full evacuation is met.

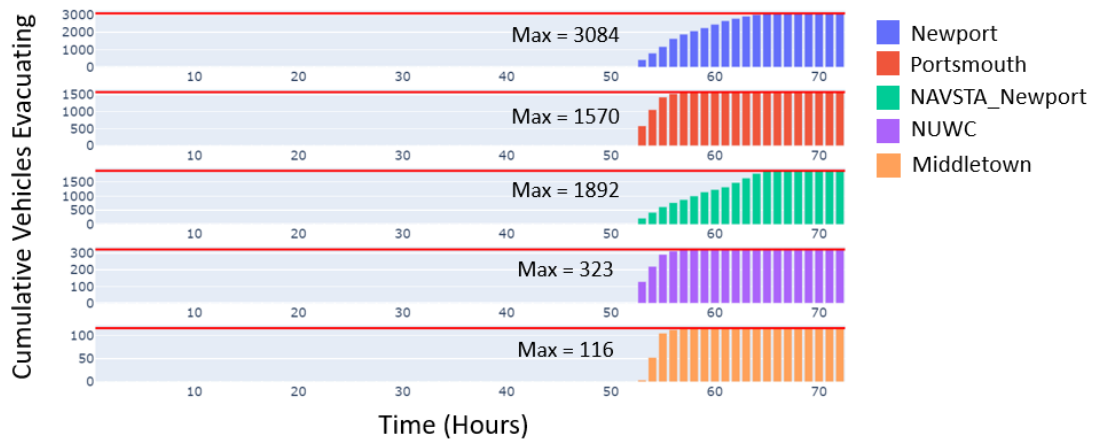


Figure 4.2. Cumulative Vehicles Evacuating from Each Community given the Original Hurricane Bob Track. For each community, we calculate the total evacuation vehicle demand added to the network up to that time period ($\sum_{\tau} D_{st}$). The number of vehicles that can evacuate from each community is indicated with a red line. For this scenario, we find all evacuation demands are added to the network for Portsmouth by hour $\tau = 60$, Middletown and NUWC by hour $\tau = 58$, Newport and NAVSTA Newport by hour $\tau = 66$.

Figure 4.3 shows the number of vehicles needing to evacuate during each time period for each community ($\mu_{s\tau}$). The change between time steps is a combination of both vehicles evacuating from the network ($\beta_{s\tau k}$) and new evacuation demands entering the network ($D_{s\tau}$). Once a line plot declines to 0, it means evacuation is complete for that community. Newport and NAVSTA Newport evacuate vehicles for 13 hours whereas Portsmouth, Middletown, and NUWC evacuate vehicles for three hours. Portsmouth evacuates a larger number of

vehicles in less time than Newport and NAVSTA Newport.

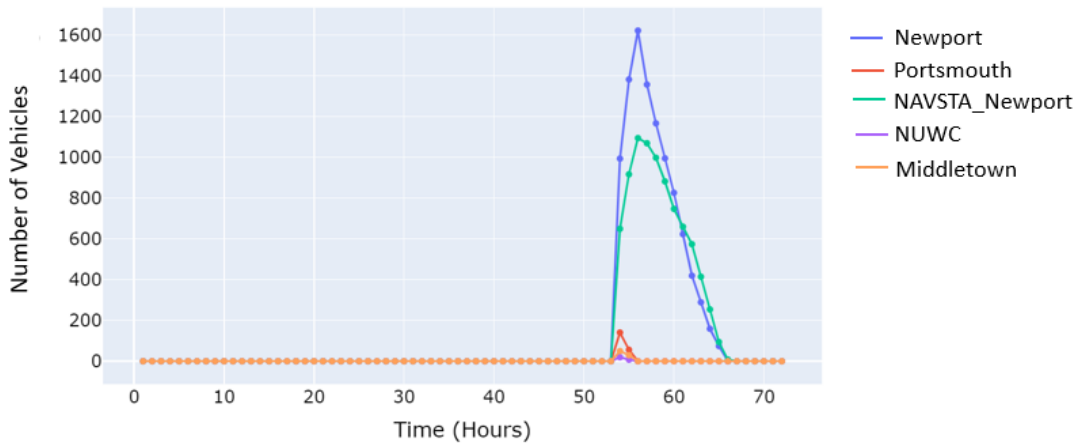


Figure 4.3. Number of Vehicles Waiting to Evacuate at Each Time Period for the Original Hurricane Bob Track ($\mu_{s\tau}$). The total time period is 72 hours. The evacuation starts at $\tau = 53$ for all municipalities and ends at $\tau = 66$ for NAVSTA and Newport, $\tau = 56$ for Portsmouth, $\tau = 56$ for NUWC, and $\tau = 56$ for Middletown. The total evacuation lasts for the entire 13-hour credible evacuation period.

For the municipalities with higher vehicle demands, there are a significant number of vehicles waiting to evacuate across time periods. The time period with the greatest number of vehicles waiting is $\tau = 56$, with 2717 vehicles trying to evacuate but waiting at source nodes. The community with the greatest number of vehicles waiting at any point in the evacuation is Newport, with 1622 vehicles waiting at $\tau = 56$. Yet, the community with the greatest number of vehicles waiting changes throughout the evacuation process. For the first seven hours of evacuation, Newport has more vehicles waiting to evacuate. Then, for the last six hours of evacuation, NAVSTA Newport has more vehicles waiting to evacuate.

4.1.2 Evacuation from Worst-case Track

Figure 4.4 shows the total number of vehicles required to evacuate for each community due to expected evacuation demand for the worst-case track (see Ch. 3, Figure 3.6, orange

line). In this scenario, we find all vehicles evacuate via the network. However, the timing at which communities reach full evacuation is different from the best-track scenario. As the values for $Veh(D_{st})$ (Eq. 3.3) and $C(\tau)$ (Eq. 3.5) are held constant between scenarios, this difference in demand is driven by hurricane strike probability, $hit(\tau)$ (Eq. 3.4). Here, full evacuation demands are reached for Portsmouth by hour $\tau = 61$, Middletown by hour $\tau = 59$, NUWC by hour $\tau = 60$, Newport by hour $\tau = 64$, and NAVSTA Newport by hour $\tau = 66$.

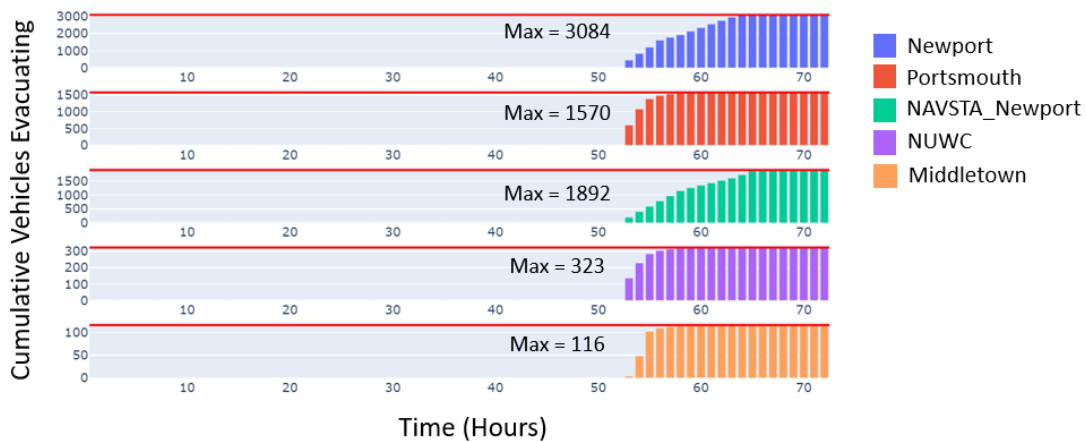


Figure 4.4. Cumulative Vehicles Evacuating from Each Community in the Worst-Case Hurricane Bob Track. For each community, we calculate the total evacuation vehicle demand added to the network up to that time period ($\sum_{\tau} D_{st}$). The maximum number of vehicles that can evacuate from each community is indicated with a red line. For this scenario, we find all evacuation demands added to the network for Portsmouth by hour $\tau = 61$, Middletown by hour $\tau = 59$, NUWC by hour $\tau = 60$, Newport by hour $\tau = 64$, and NAVSTA Newport by hour $\tau = 66$.

Differences in when demands are added to the network changes the rate of evacuation for some municipalities. The Figure 4.5 shows the number of vehicles waiting to evacuate (μ_{st}) across all time periods. For the worst-case track, we find an increase in the vehicles waiting at source nodes in Portsmouth and a decrease in the vehicles waiting to evacuate from Newport. For this scenario, Portsmouth, NUWC, and Middletown evacuate in three

hours, Newport evacuates for 12 hours, and NAVSTA Newport evacuates for 13 hours. In this case, Newport accomplishes full evacuation an hour earlier than the best track. On the other hand, NAVSTA Newport takes longer to evacuate all vehicles.

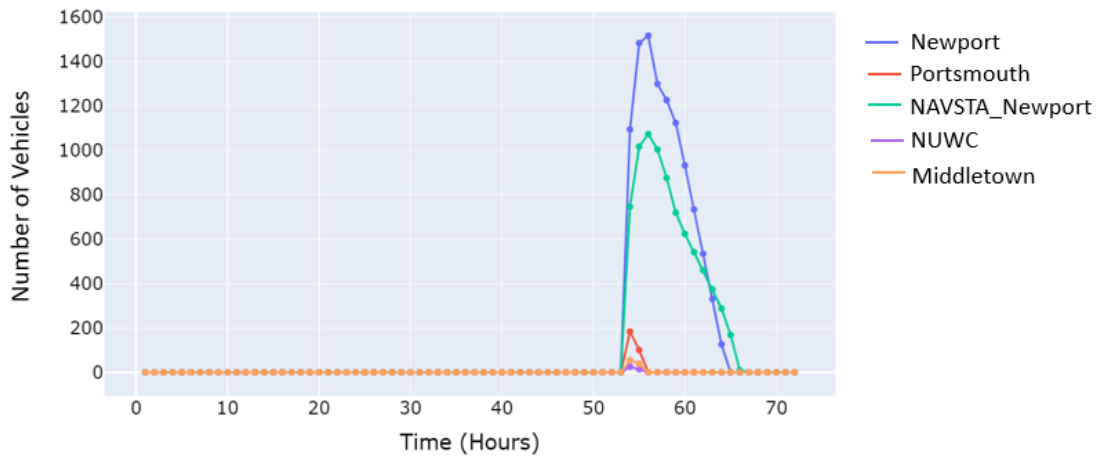


Figure 4.5. Number of Vehicles Waiting to Evacuate at Each Time Period for the Worst-case Hurricane Bob Track (μ_{ST}). The total time period is 72 hours. The evacuation starts at $\tau = 53$ for all municipalities and ends at $\tau = 66$ for Newport, $\tau = 66$ for NAVSTA, $\tau = 56$ for Portsmouth, $\tau = 56$ for NUWC, and $\tau = 56$ for Middletown. The total evacuation period for Aquidneck Island lasts the entire 13-hour credible evacuation period.

For the worst-case scenario, the time period with the greatest number of vehicles waiting is $\tau = 55$, but only 2600 vehicles are trying to evacuate, which is fewer than the best-case track. The community with the greatest number of vehicles waiting at any point in the evacuation is Newport, with 1516 vehicles waiting at $\tau = 56$. Again, the community with the greatest number of vehicles waiting changes throughout the evacuation process. For the first nine hours of evacuation, Newport has more vehicles waiting to evacuate. Then, for the last four hours of evacuation, NAVSTA Newport has more vehicles waiting to evacuate.

4.1.3 Evacuation from 180° Track

We continue the analysis for the 180° (left) edge of the cone of uncertainty track (see Ch. 3, Figure 3.6, blue line). Figure 4.6 shows the total number of vehicles required to evacuate for each community due to expected evacuation demand for the 180° track. Unlike previous scenarios, the maximum evacuation demand for all five of the communities is not met. Newport evacuates 2839 vehicles, Portsmouth evacuates 1445 vehicles, NAVSTA Newport evacuates 1742 vehicles, NUWC evacuates 298 vehicles, and Middletown evacuates 107 vehicles. In this case, a full-scale evacuation is not necessary but a large-scale evacuation still occurs.

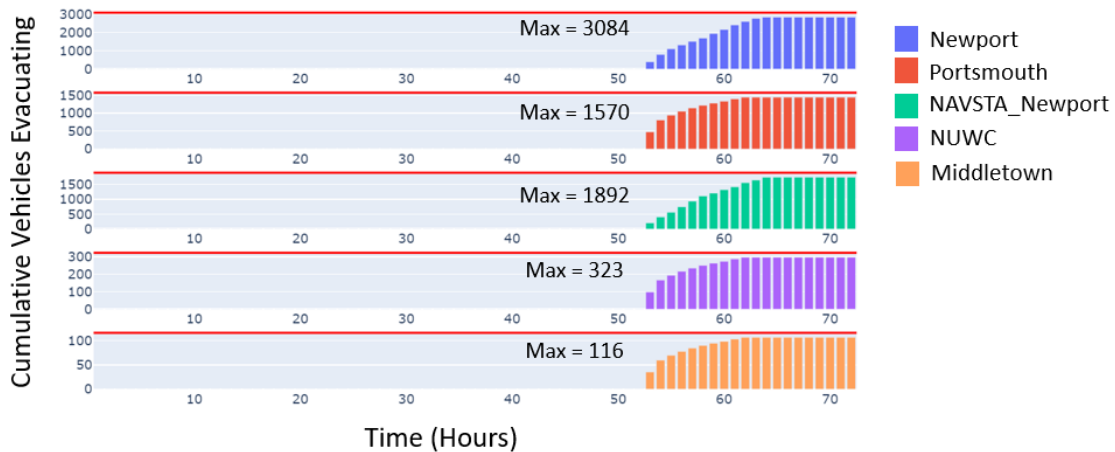


Figure 4.6. Cumulative Vehicles Evacuating from Each Community in the 180° Hurricane Bob Track. For each community, we calculate the total evacuation vehicle demand added to the network up to that time period ($\sum_{\tau} D_{st}$). The maximum number of vehicles that can evacuate from each community is indicated with a red line. For this scenario, no municipality reaches full evacuation demands. The evacuation demands added to the network for Portsmouth, Middletown, and NUWC peak by hour $\tau = 62$. The evacuation demands for Newport peak by hour $\tau = 64$ and for NAVSTA Newport peak by hour $\tau = 65$.

We also find the rate vehicles are added to the network is spread more evenly across time periods for all communities. In the best track and worst-case scenarios, Portsmouth, NUWC, and Middleton all reach full evacuation demands in five or less hours. Instead, for

this scenario, we find Portsmouth, Middletown, and NUWC peak by hour $\tau = 62$ (or nine hours after evacuation starts). This is due to low but present strike probabilities across the credible evacuation period that lead to a gradual increase in evacuees (see Ch. 3, Figure 3.16, green line).

Figure 4.7 shows the number of vehicles waiting to evacuate ($\mu_{s\tau}$) across all time periods for the 180° track. Unlike previous scenarios, Figure 4.7 shows fewer vehicles waiting to evacuate. All demands originating at Portsmouth, NUWC, and Middletown can immediately evacuate without waiting ($\beta_{s\tau k} = D_{s\tau}$). Only Newport and NAVSTA Newport have high enough demands that vehicles will need to wait to evacuate. Here, the total evacuation still takes the same amount of time as previous scenarios, yet Newport and NAVSTA evacuate for the same length of time (13 hours). The greatest number of vehicles waiting is lower than previous scenarios: 1366 vehicles at $\tau = 55$. The community with the greatest number of vehicles waiting at any point in the evacuation is Newport, with 797 vehicles waiting at $\tau = 55$. The community with the greatest number of vehicles waiting changes throughout the evacuation process. For the first 11 hours of evacuation, Newport has more vehicles waiting to evacuate. Then, for the last two hours of evacuation, NAVSTA Newport has more vehicles waiting to evacuate.

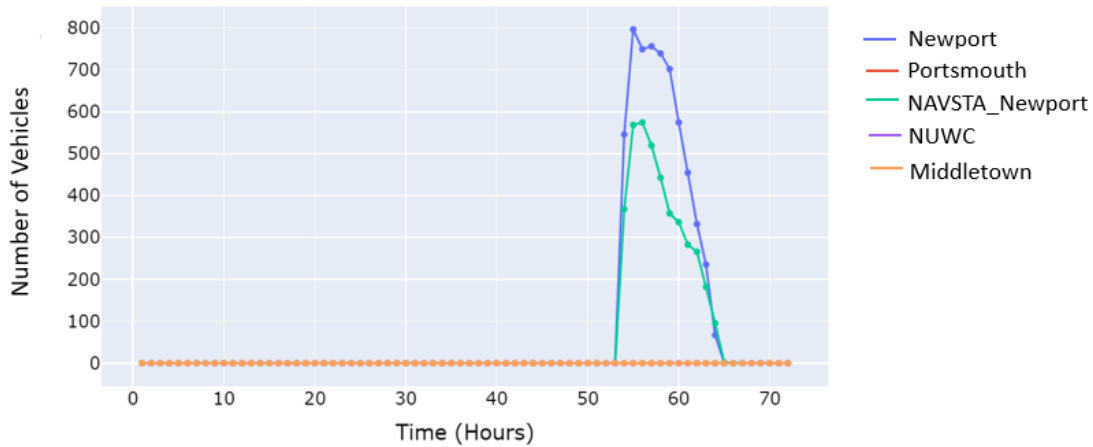


Figure 4.7. Number of Vehicles Waiting to Evacuate at Each Time Period for the 180° Hurricane Bob Track ($\mu_{s\tau}$). The total time period is 72 hours. The evacuation starts at $\tau = 53$ for Newport and NAVSTA only and ends at $\tau = 66$ for Newport and $\tau = 66$ for NAVSTA. The total evacuation period for Aquidneck Island lasts the entire 13-hour credible evacuation window.

4.1.4 Evacuation from 90° Track

Finally, we study the 90° (right) edge of the cone of uncertainty track (see Ch. 3, Figure 3.6, yellow line). Figure 4.8 shows the total number of vehicles required to evacuate for each community due to expected evacuation demand for the 90° track. Similar to the 180° scenario, the maximum evacuation demand for all five of the communities is not met. Newport evacuates 2564 vehicles, NUWC evacuates 269 vehicles, Portsmouth evacuates 1305 vehicles, NAVSTA Newport evacuates 1573 vehicles, and Middletown evacuates 97 vehicles. Also similar to the 180° scenario, we find the rate of vehicles entering the network to be spread out over a longer time period. Newport, NUWC, Portsmouth, and Middletown peak by hour $\tau = 62$ and NAVSTA Newport peaks by hour $\tau = 63$.

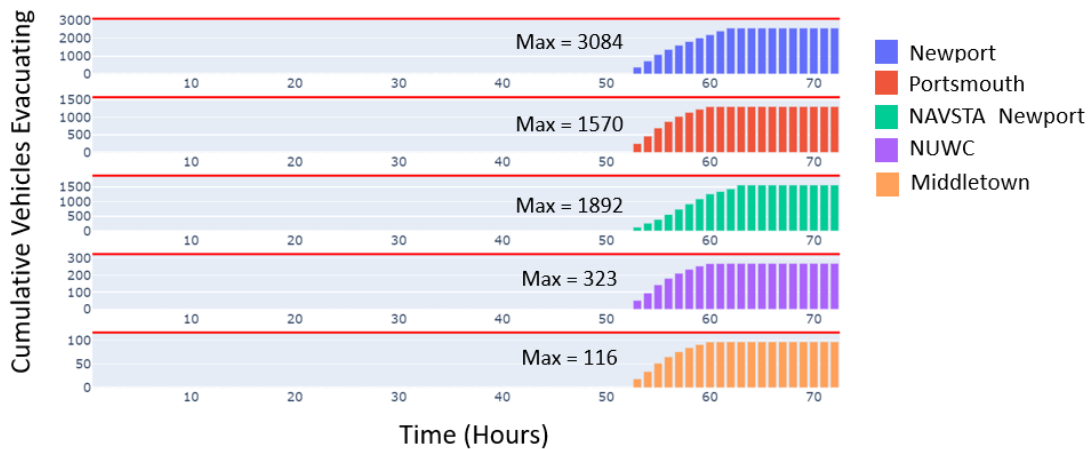


Figure 4.8. Cumulative Vehicles Evacuating from Each Community in the 90° Hurricane Bob Track. For each community, we calculate the total evacuation vehicle demand added to the network up to that time period ($\sum_{\tau} D_{st}$). The maximum number of vehicles that can evacuate from each community is indicated with a red line. For this scenario, no municipality reaches full evacuation demands. The evacuation demands added to the network for Portsmouth, Middletown, NUWC, and Newport peak by hour $\tau = 62$, and NAVSTA Newport peak by hour $\tau = 63$.

Figure 4.9 shows the number of vehicles waiting to evacuate ($\mu_{s\tau}$) across all time periods for the 90° track. The results are similar to the 180° track as few evacuees are waiting to evacuate across all time steps. Again, Middletown, Portsmouth, and NUWC meet the vehicle demand in each time period — only Newport and NAVSTA Newport have vehicles waiting to evacuate. Unlike other scenarios, NAVSTA Newport has more vehicles needing to evacuate than Newport. The maximum number of vehicles waiting occurs later in the evacuation than other scenarios with 902 at $\tau = 58$. Moreover, Newport has an evacuation period of 12 hours and NAVSTA has an evacuation period of 13 hours, meaning it has the greatest number of waiting vehicles and takes the longest to clear.

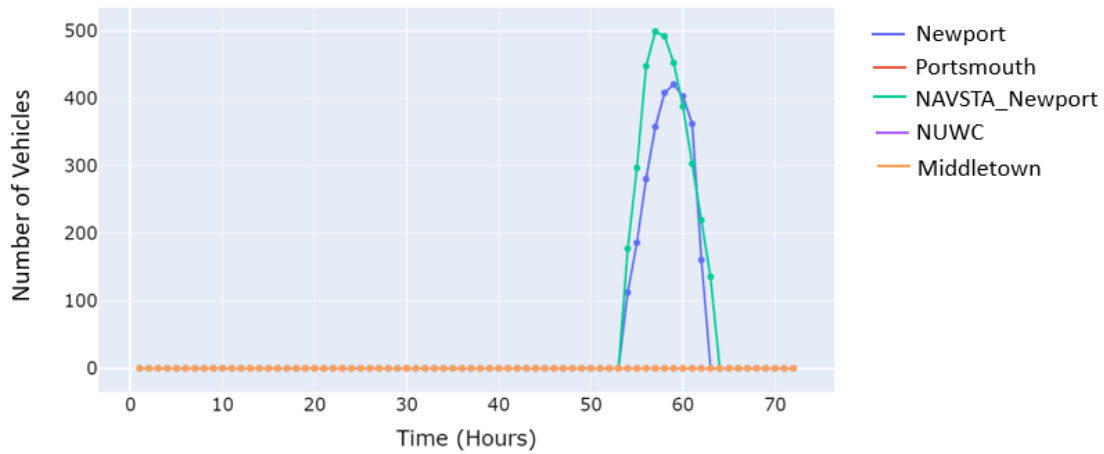


Figure 4.9. Number of Vehicles Waiting to Evacuate at Each Time Period for the 90° Hurricane Bob Track ($\mu_{s\tau}$). The total time period is 72 hours. The evacuation starts at $\tau = 53$ for Newport and $\tau = 53$ for NAVSTA and ends at $\tau = 65$ for Newport and $\tau = 66$ for NAVSTA Newport. The total evacuation period for Aquidneck Island lasts 13 hours.

4.1.5 Comparison Across Scenarios

We summarize in Table 4.1 the total number of vehicles that traveled to each evacuation point and the number of vehicles that did not evacuate (i.e., shelter-in-place) for each scenario. For the purposes of our work, we consider an effective evacuation plan as one that evacuates all vulnerable populations for storms that strike the most dangerous region or one that evacuates as few populations as possible for a storm that does not strike. For Hurricane Bob, the original track and worst-case tracks are scenarios that strike, where the 180° and 90° do not. Hence, we want to maximize evacuation (i.e., Total Evacuation = 6985) for the best and worst-case tracks and we want to maximize the shelter-in-place for 180° and 90° tracks (i.e., Total Not Evacuated = 6985).

Table 4.1. Total Number of Vehicles Evacuating via Each Route for Hurricane Bob Scenarios.

Track	Mt. Hope Bridge	Newport Bridge	Sakonnet Bridge	Gaudet Middle School	Total Evacuated	Total Not Evacuated
Original	1283	2878	2718	106	6985	-
Worst-Case	836	2970	3073	106	6985	-
180°	1274	2243	2819	95	6431	554
90°	1690	2433	1578	107	5808	1177

The maximum number of vehicles that can evacuate is 6,985. The capacity of Gaudet Middle School is 138 vehicles.

The original and worst-case tracks result in a full evacuation, which is ideal given they will strike Aquidneck Island. However, the model also recommends that there should be an evacuation during the 180° and 90° scenarios, which do not strike. Only 554 vehicles will be expected to shelter in-place for the 180° track, where 1177 vehicles will similarly not evacuate for the 90° track. This means storms with a best track and physical characteristics like Hurricane Bob may be more difficult to plan for if they veer west rather than east. Moreover, this means Aquidneck Island would face high evacuation costs for threatening, but non-striking storms like Hurricane Bob due to the disruption cause by evacuation and possible risk for vehicles evacuating into more dangerous areas that experience landfall.

Furthermore, the optimal evacuation route changes for each scenario. While the original and worst-case track produce full evacuation, they achieve evacuation via different routes. A total of 447 more vehicles would travel over the Mt. Hope Bridge (north) given the original track. Instead, the worst-case track would send 355 more vehicles over the Sakonnet Bridge (east) and 92 more vehicles over the Newport Bridge (west). Interestingly, the 90° track sends the most vehicles across the Mt. Hope Bridge (north) than all other scenarios and, proportionally, under utilizes the Sakonnet Bridge compared to other scenarios.

Results indicate that track direction influences bridge utilization. Storms tracking towards Aquidneck Island and East (original, 90°) produce more evacuation across Mt. Hope Bridge and less across Sakonnet Bridge. In contrast, storms tracking west (worst-case, 180°) produce

more eastern evacuation across Sakonnet Bridge. Although all model runs can utilize all bridges equally, this result produces an unexpected safety maneuver, forcing more vehicles east to avoid western storms. This may suggest interactions between the target chosen for the most dangerous region (Newport Bridge), the distribution of vulnerable populations across the island, and the optimal timing of evacuations given expected demands.

We also note that Gaudet Middle School is under-utilized for all hurricane scenarios. The maximum number of vehicles arrive at Gaudet Middle school is 107 (90° track), which is 21 vehicles short of its capacity. This is largely due to the choice of possible evacuation route ($k \in K_s$) requires the final destination to have capacity for all vehicles from a given community. Due to the small capacity of Guadet Middle School, it is not recommended to send many communities. Hence, results the model favors sending evacuees to the bridges instead of on island shelters. While this emphasizes evacuating as many people as possible, it introduces additional risk when sending evacuees over bridges during threatening, non-striking storms.

4.2 Analysis of Hurricane Gloria (1985)

We study evacuation routing and clearance times for the original, worst-case, 180°, and 90° hurricane tracks as described previously in Figure 3.7. The credible evacuation window for these tracks is the same as the window used for the Hurricane Bob tracks.

4.2.1 Evacuation from Original Track

Starting with the original track for Hurricane Gloria (see Ch. 3, Figure 3.7, green line), Figure 4.10 shows the total number of vehicles required to evacuate for each community due to expected evacuation demand. We find that all vehicles evacuate, meaning that all vehicles enter the network, however, the rate of the vehicles entering the network is spread out over the credible evacuation period. In this case, Middletown peaks by hour $\tau = 60$, NUWC peaks by hour $\tau = 61$, Portsmouth peaks by hour $\tau = 62$, Newport peaks by hour $\tau = 64$ and NAVSTA Newport peaks by hour $\tau = 66$.

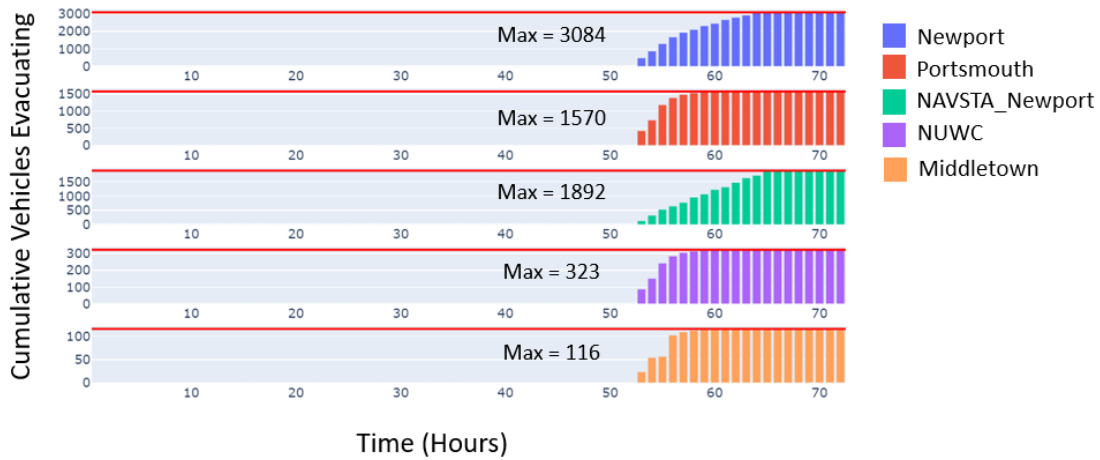


Figure 4.10. Cumulative Vehicles Evacuating from Each Community in the Original Hurricane Gloria Track. For each community, we calculate the total evacuation vehicle demand added to the network up to that time period ($\sum_{\tau} D_{st}$). The maximum number of vehicles that can evacuate from each community is indicated with a red line. For this scenario, the evacuation demands added to the network for Middletown peaks by hour $\tau = 60$, NUWC peaks by hour $\tau = 61$, Portsmouth peaks by hour $\tau = 62$, Newport peaks by hour $\tau = 64$ and NAVSTA Newport peaks by hour $\tau = 66$.

Figure 4.11 shows the number of vehicles waiting to evacuate ($\mu_{s\tau}$) across all time periods. Portsmouth and NUWC are the only communities that meet the vehicle demand in each time period. The time period with the maximum number of vehicles waiting is $\tau = 57$, with 2080 vehicles waiting at source nodes. Newport has the greatest number of vehicles waiting to evacuate, with 1055 vehicles waiting at $\tau = 57$. Newport and NAVSTA Newport have similar numbers of vehicles waiting to evacuate across time periods for the first seven hours. However, the evacuation period for NAVSTA Newport is longer and the installation has more vehicles waiting to evacuate for the last six hours of evacuation. Specifically, Newport evacuates for 12 hours, NAVSTA Newport evacuates vehicles for 13 hours, and Middletown evacuates for four hours.

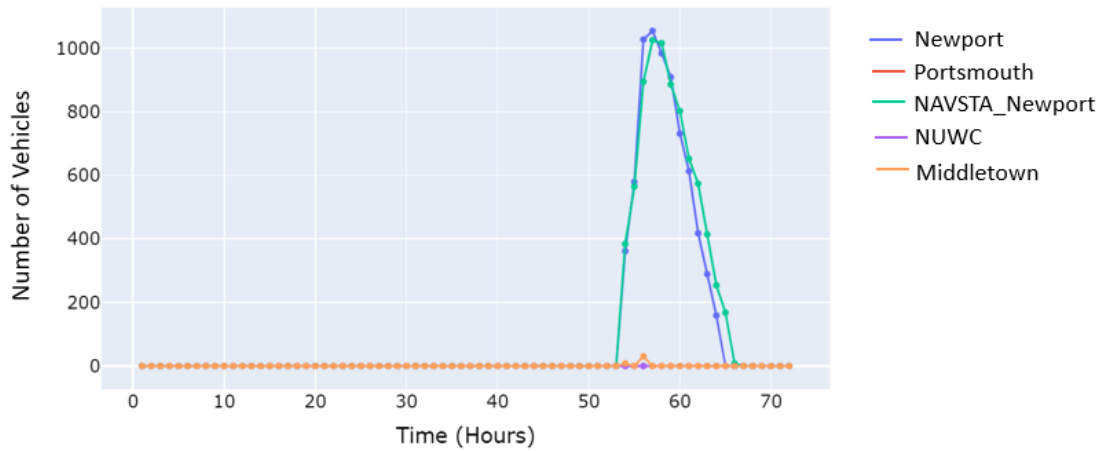


Figure 4.11. Number of Vehicles Waiting to Evacuate at Each Time Period for the Original Hurricane Gloria Track ($\mu_{s\tau}$). The total time period is 72 hours. The evacuation starts at $\tau = 53$ for Newport, NAVSTA, and Middletown and ends at $\tau = 66$ for NAVSTA, $\tau = 65$ for Newport, and $\tau = 57$ for Middletown. The total evacuation period for Aquidneck Island lasts 13 hours.

4.2.2 Evacuation from Worst-case Track

Figure 4.12 shows the total number of vehicles required to evacuate for each community due to expected evacuation demand for the worst-case track (see Ch. 3, Figure 3.7, orange line). In this scenario, a full-scale evacuation is necessary, but unlike the best track, full evacuation for all five of the communities is not met. While Newport, NAVSTA Newport, and Middletown evacuate the maximum evacuation demands, Portsmouth evacuates 1508 of 1570 vehicles and NUWC evacuates 303 of 323 vehicles.

The rate vehicles are added to the network is not as evenly spread across time periods for all communities as it was in the best track. In this case, we find a larger demand added earlier in the evacuation. Evacuation demands reach their peak for Middletown by hour $\tau = 57$, Portsmouth and NUWC by hour $\tau = 57$, Newport by hour $\tau = 64$ and NAVSTA Newport by hour $\tau = 65$. NAVSTA Newport peaks earlier in this scenario than in the best track scenario.

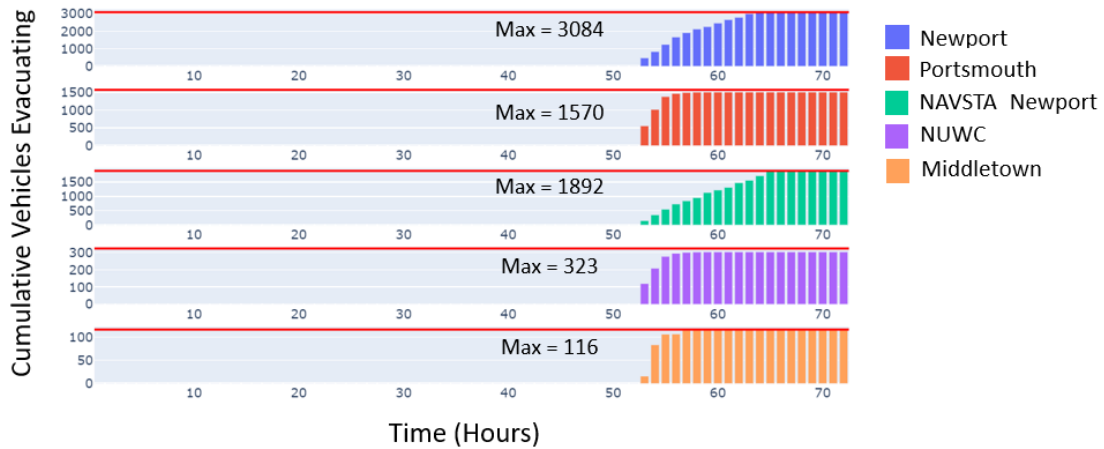


Figure 4.12. Cumulative Vehicles Evacuating from Each Community in the Worst-Case Hurricane Gloria Track. For each community, we calculate the total evacuation vehicle demand added to the network up to that time period ($\sum_{\tau} D_{st}$). The maximum number of vehicles that can evacuate from each community is indicated with a red line. For this scenario, the evacuation demands added to the network for Portsmouth, Middletown, and NUWC peak by hour $\tau = 57$, Newport by hour $\tau = 64$ and NAVSTA Newport by hour $\tau = 65$.

Figure 4.13 shows the total number of vehicles required (μ_{st}) to evacuate for each community due to expected evacuation demand for the worst-case track. In this instance, there are a greater number of vehicles waiting to evacuate from Newport, NAVSTA Newport, and Portsmouth than the best track. The maximum number of vehicles waiting is 2680 at hour $\tau = 56$. Newport has the largest number of vehicles waiting to evacuate, with 1572 vehicles at hour $\tau = 56$. Newport has more vehicles waiting to evacuate for the first seven hours of the evacuation period, and NAVSTA Newport surpasses Newport with the number of vehicles needing to evacuate in the last six hours of the evacuation. Additionally, Portsmouth has more vehicles waiting to evacuate than Middletown and NUWC. Newport evacuates for 12 hours, NAVSTA Newport evacuates vehicles for 13 hours, and Middletown, NUWC, and Portsmouth evacuate vehicles for three hours.

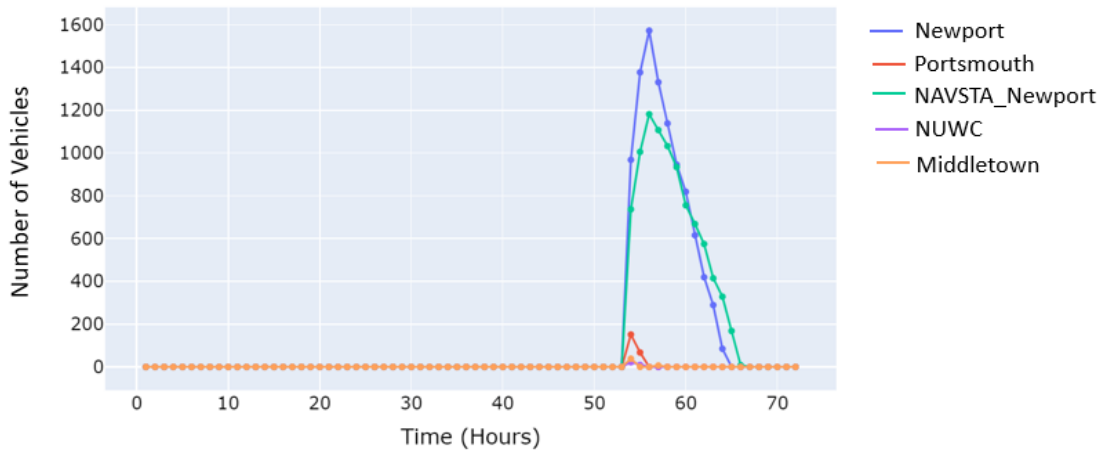


Figure 4.13. Number of Vehicles Waiting to Evacuate at Each Time Period for the Worst-case Hurricane Gloria Track (μ_{ST}). The total time period is 72 hours. The evacuation starts at $\tau = 53$ for the municipalities and ends at $\tau = 66$ for NAVSTA, $\tau = 65$ for Newport, and $\tau = 57$ for Middletown, Portsmouth, and NUWC. The total evacuation period for Aquidneck Island lasts 13 hours.

4.2.3 Evacuation from 180° Track

For the 180° track (see Ch. 3, Figure 3.7, blue line), Figure 4.14 shows the total number of vehicles required to evacuate for each community due to expected evacuation demand. This case is the least threatening storm of all scenarios studied for either hurricane. Accordingly, there are significantly fewer evacuees expected from all communities. Newport evacuates 417 vehicles, NAVSTA Newport evacuates 256 vehicles, Portsmouth evacuates 212 vehicles, Middletown evacuates 16 vehicles, and NUWC evacuates 44 vehicles.

Even with less overall evacuees, we find that the rate vehicles are added to the system are spread more evenly across the time periods. Middletown peaks by hour $\tau = 61$, and NUWC, Portsmouth, Newport, and NAVSTA Newport peak by hour $\tau = 62$. This is due to the low strike probabilities throughout the credible evacuation period, which leads to low numbers of evacuees.

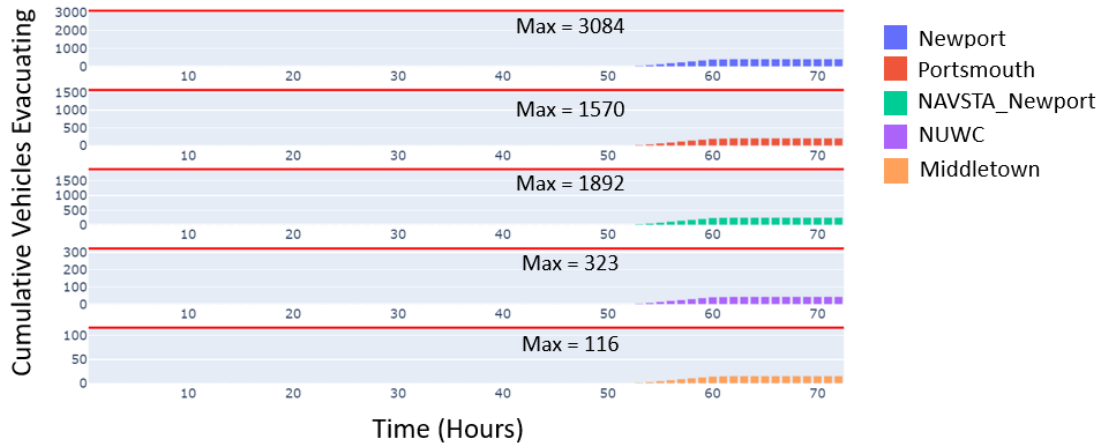


Figure 4.14. Cumulative Vehicles Evacuating from Each Community in the 180° Hurricane Gloria Track. For each community, we calculate the total evacuation vehicle demand added to the network up to that time period ($\sum_{\tau} D_{st}$). The maximum number of vehicles that can evacuate from each community is indicated with a red line. For this scenario, the evacuation demands added to the network for NUWC, Portsmouth, Newport, and NAVSTA Newport peak by hour $\tau = 62$ while Middletown peak by hour $\tau = 61$.

The Figure 4.15 shows the number of vehicles waiting to evacuate ($\mu_{s\tau}$) across all time periods for the 180° track. The results show that there are few vehicles waiting to evacuate. Portsmouth is the only community where there are vehicles waiting to evacuate across the evacuation period – Newport, NAVSTA Newport, NUWC, and Middletown evacuation demands are met for all time periods. The maximum number of vehicles waiting at Portsmouth is 5 at hour $\tau = 63$. Furthermore, Portsmouth evacuates vehicles for two hours instead of 12 hours as seen in the previous scenarios. In this event, decision-makers would most likely not call any evacuation.

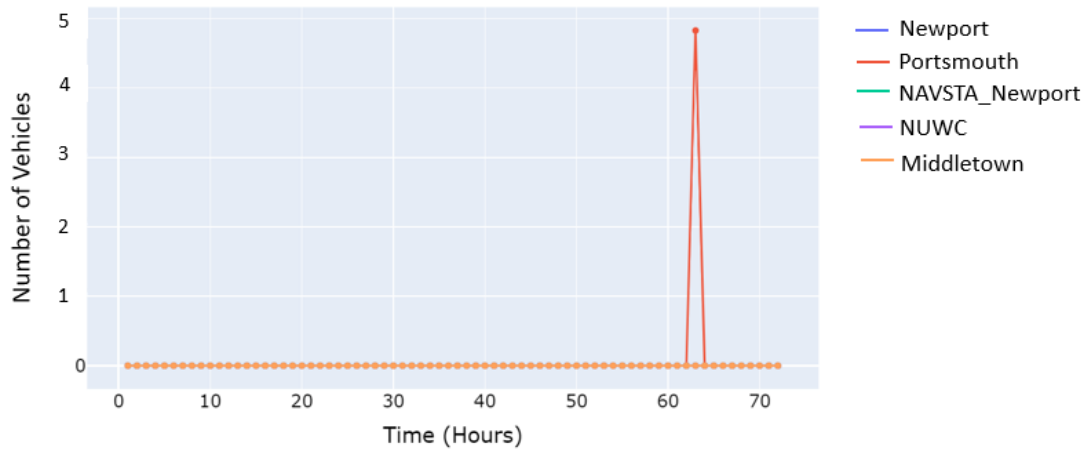


Figure 4.15. Number of Vehicles Waiting to Evacuate at Each Time Period for the 180° Hurricane Gloria Track ($\mu_{s\tau}$). The total time period is 72 hours. The evacuation starts at $\tau = 62$ and ends at $\tau = 64$ for Portsmouth. The total evacuation period for Aquidneck Island lasts two hours.

4.2.4 Evacuation from 90° Track

Lastly, Figure 4.16 shows the total number of vehicles due to expected evacuation demand for the 90° track (see Ch. 3, Figure 3.7, yellow line). In this scenario, a large-scale evacuation occurs, yet the storm is threatening and non-striking. Newport evacuates 3068 vehicles, NAVSTA Newport evacuates 1882 vehicles, Portsmouth evacuates 1562, Middletown evacuates 116 vehicles, and NUWC evacuates 322 vehicles. Middletown is the only community to evacuate the maximum evacuation demand. We also find that the rate of vehicles entering the network is spread out over longer periods of time. Middletown reaches full evacuation demands by $\tau = 62$, Portsmouth and NUWC peak by hour $\tau = 62$, and Newport and NAVSTA Newport peak by hour $\tau = 65$.

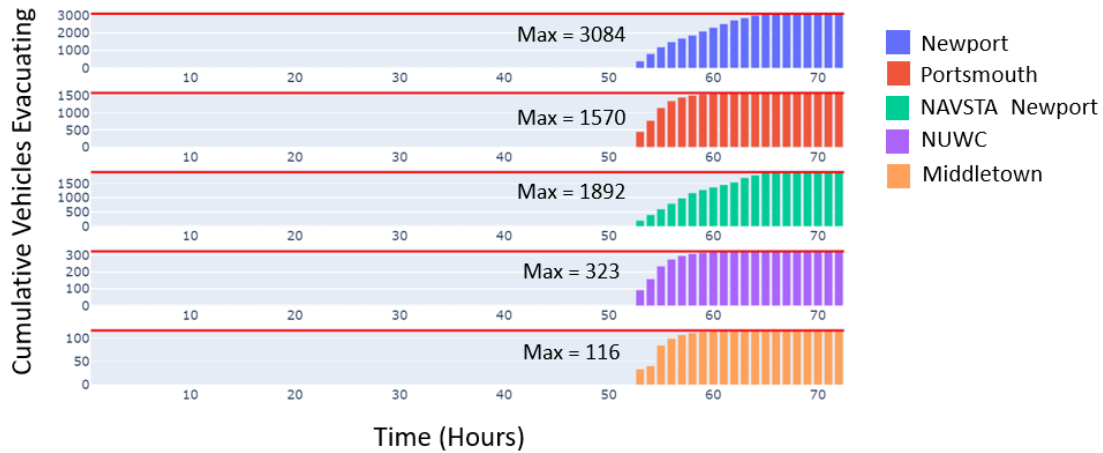


Figure 4.16. Cumulative Vehicles Evacuating from Each Community in the 90° Hurricane Gloria Track. For each community, we calculate the total evacuation vehicle demand added to the network up to that time period ($\sum_{\tau} D_{st}$). The maximum number of vehicles that can evacuate from each community is indicated with a red line. For this scenario, the evacuation demands added to the network for Portsmouth, Middletown and NUWC peak by hour $\tau = 62$, and Newport and NAVSTA Newport peak by hour $\tau = 65$.

Figure 4.17 shows the number of vehicles waiting to evacuate ($\mu_{s\tau}$) across all time periods for the 90° track. Generally, there are more vehicles waiting to evacuate from Newport in this case than in the best track, but there are fewer vehicles waiting from NAVSTA Newport. Middletown, has fewer vehicles waiting to evacuate than the best track. Portsmouth and NUWC have no vehicles waiting across the evacuation period. The greatest number of vehicles waiting to evacuate across all time periods is 1966 vehicles at hour $\tau = 57$. Newport is the community that has the largest number of vehicles needing to evacuate, which is 1149 vehicles at $\tau = 58$. Throughout the 13 hour evacuation period, Newport consistently has more vehicles waiting to evacuate than NAVSTA Newport. For Middletown, the evacuation period is three hours, but there are vehicles waiting to evacuate at hour $\tau = 55$ only.

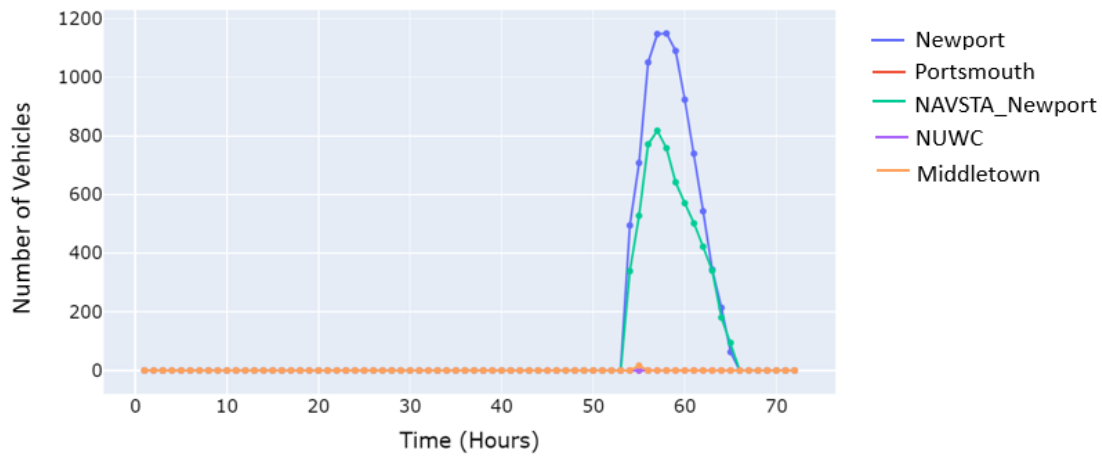


Figure 4.17. Number of Vehicles Waiting to Evacuate at Each Time Period for the 90° Hurricane Gloria Track ($\mu_{s\tau}$). The total time period is 72 hours. The evacuation starts at $\tau = 53$ and ends at $\tau = 66$ for Newport and NAVSTA. Middletown starts evacuation at $\tau = 53$ and ends evacuation at $\tau = 56$. The total evacuation period for Aquidneck Island lasts 13 hours.

4.2.5 Comparison of Gloria Results

Table 4.2 summarizes the total number of vehicles that traveled to each evacuation point and the number of vehicles that did not evacuate (i.e., shelter-in-place) for each scenario. For Hurricane Gloria, the original best track and worst-case tracks are scenarios that strike, where the 180° and 90° do not. Again, we want to maximize evacuation for the best and worst-case tracks and maximize the shelter-in-place for the 180° and 90° tracks.

Table 4.2. Total Number of Vehicles Evacuating via Each Route for Hurricane Gloria Scenarios.

Track	Mt. Hope Bridge	Newport Bridge	Sakonnet Bridge	Gaudet Middle School	Total Evacuated	Total Not Evacuated
Original	1334	2920	2612	119	6985	-
Worst-Case	846	3035	2968	54	6903	82
180°	0	926	19	0	945	6040
90°	636	2907	3323	84	6950	35

The maximum number of vehicles that can evacuate is 6,985. The capacity of Gaudet Middle School is 138 vehicles.

For this hurricane, we find that the original track results in a full-scale evacuation, which is preferred, while the worst-case scenario, a striking track, does not. Moreover, we find the 90° track, a non-striking track, would produce a large-scale evacuation. Specifically, there are 82 vehicles expected to shelter-in-place for the worst-case track and 35 vehicles for the 90° track. This means that the model recommends to evacuate more vehicles for the 90° scenario over the worst-case. This is not an ideal outcome, considering that the populations sheltering-in-place for the worst-case are put at risk. Likewise, vehicles evacuating the 90° track would be put at risk.

On the other hand, the model recommends the majority of vulnerable populations to not evacuate and shelter-in-place for the 180° track. In fact, this is the best result for a non-striking track of all studied in this thesis with only 945 vehicles not sheltering-in-place. Overall, the model produces good results for the original track and the 180°, but poor results for the worst-case and 90° tracks.

Again, we find that the optimal evacuation route changes for each scenario. The original track results in a full evacuation while the 90° track evacuates the next highest number of vehicles. The original track sends 698 more vehicles over the Mt. Hope Bridge (north), 7 more vehicles over the Newport Bridge (west), and 35 more vehicles to the Gaudet Middle School shelter than the 90° track. The 90° track sends 711 more vehicles to the Sakonnet Bridge (east) than the original track. The 180° track does not send any vehicles over the Mt.

Hope Bridge (north) or to Gaudet Middle School. Also, significantly more vehicles are sent to the Newport Bridge (west) than the Sakonnet Bridge (east) for the 180° track.

The results suggest that track direction influences bridge utilization. The storms that track towards the West (180°) result in less evacuation across Mt. Hope Bridge and Sakonnet Bridge. The worst-case, 90°, and original track all track towards Aquidneck Island and East, increasing evacuation across Sakonnet Bridge.

Once more, we find that Gaudet Middle School is under-utilized for all hurricane scenarios. The original track has the maximum number of vehicles that arrive at Gaudet Middle School, which is 119 and is 19 vehicles under its capacity. The other 180° scenario does not use the shelter at all. Although the 90° track still has 54 vehicles that can be sent to the shelter, the model recommends an almost full evacuation for this storm. This suggests that the shelter may not be necessary to include in evacuation plans since a full evacuation could be completed without it.

4.3 Comparison Across Hurricanes

We compare results across hurricanes to determine the implications of our model for evacuation planning. We consider how well our approach estimates when go/no-go decisions should happen (related to expected demands) and how well the model supports evacuation for a given scenario (related to network optimization).

4.3.1 Expected Demands

Table 4.3 shows the number of evacuating or non-evacuating vehicles across all scenarios. For both Hurricane Bob and Gloria, full evacuation for the original and worst-case track is preferred as these storms strike the most dangerous region, where full shelter-in-place is preferred for the 180° and 90° tracks as they are threatening, but non-striking.

We find that our model has moderate performance in resulting in the preferred evacuation plan for each track. Our model produces full evacuation for 3 of 4 striking scenarios, and leaves fewer than 2% of vehicles sheltering-in-place for the worst-case Gloria scenario. In contrast, our model has poor performance for threatening, non-striking tracks. For the 180° and 90° tracks, 3 of 4 scenarios lead to large-scale evacuation. Fewer than 17% of vehicles

sheltering-in-place for the 90° Bob track, and the other two perform even worse. In contrast, the 180° Gloria track produces a good outcome of moderate evacuation with less than 14% of vehicles evacuating.

Table 4.3. Comparison of Evacuation Totals for Hurricanes Bob and Gloria.

Track	Bob Total Evacuated	Bob Total Not Evacuated	Gloria Total Evacuated	Gloria Total Not Evacuated
Original	6985	-	6985	-
Worst-Case	6985	-	6903	82
180°	6431	554	945	6040
90°	5808	1177	6950	35

The maximum number of vehicles that can evacuate is 6,985.

Interestingly, our results match realistic expectations for evacuation decisions suggesting our model may reproduce realistic evacuation phenomena. As presented in Ch. 2, Section 2.2.1, Lindell and Prater (2007) observe a binary decision tree for evacuations (see Figure 2.1). The decision tree shows that emergency managers are likely to choose to evacuate often for threatening, non-striking storms to avoid situations of high cost (i.e., no evacuation for threatening, striking storms). Our methods produce expected demands that fit this paradigm. However, in an ideal case, the appropriate go/no-go decision will be made to minimize loss of life. This means the model may be more useful to estimate what the costs of poor decisions might be, rather than directly support an evacuation plan.

4.3.2 Evacuation Optimization Efficacy

We compare key metrics for the efficacy of the evacuation routing and clearance times produced with our optimization model. Table 4.4 (for Hurricane Bob) and Table 4.5 (for Hurricane Gloria) present the maximum number of vehicles waiting to evacuate, key evacuation times, evacuation length, and communities most impacted by evacuation routing decisions. In general, we prefer the following outcomes:

- The number of vehicles waiting to evacuate to be low across all time steps (i.e., $\beta_{s\tau k} = D_{s\tau}$; $\forall s \in S, \forall \tau \in T$). This ensures vulnerable populations are not trying

to leave simultaneously and cause unexpected traffic. Moreover, managing larger simultaneous demands puts larger burden on emergency managers.

- The time step τ with peak waiting to be early in evacuation to avoid large numbers of vehicles trying to evacuate near storm landfall.
- The evacuation length to be as short as possible. This avoids unnecessary risk caused when unforeseen circumstances (e.g., traffic, road closure) extends evacuation times.
- Shared risk across the island. We prefer that no one community is prioritized for evacuation over others, or more importantly, no one community is always last to evacuate. When certain communities are always last, this creates an unintended risk for those populations that follow emergency management plans.

Table 4.4. Hurricane Bob Vehicle Waiting and Evacuation Times.

Track	Max Num Vehicles Waiting ($\mu_{s\tau}$)	Time of Max Waiting (τ)	Community with Most Waiting	Evacuation Length (hrs)	Last to Evacuate
Original	2717	56	Newport	13	Tie*
Worst-Case	2600	55	Newport	13	NAVSTA
180°	1366	55	Newport	13	Tie*
90°	902	58	NAVSTA	13	NAVSTA

NAVSTA is short for NAVSTA Newport. Tie means both Newport and NAVSTA Newport took the same amount of time.

Table 4.5. Hurricane Gloria Vehicle Waiting and Evacuation Times.

Track	Max Num Vehicles Waiting ($\mu_{s\tau}$)	Time of Max Waiting (τ)	Community with Most Waiting	Evacuation Length (hrs)	Last to Evacuate
Original	2080	57	Newport	13	NAVSTA
Worst-Case	2754	56	Newport	13	NAVSTA
180°	5	63	Portsmouth	2	Portsmouth
90°	1966	57	Newport	13	Tie*

NAVSTA is short for NAVSTA Newport. Tie means both Newport and NAVSTA Newport took the same amount of time.

The model performs well at reducing the maximum number of vehicles for non-threatening storms (180°, 90°) for both hurricanes and the original track for Hurricane Gloria. In the original track for Hurricane Gloria, the maximum number of vehicles decreased from the original Hurricane Bob track by 637 vehicles. The non-threatening storms also reduced the maximum number of vehicles waiting from the threatening storms for each hurricane. In all the cases, the time of the maximum vehicles waiting occurred at an earlier τ , except for the Hurricane Gloria 180° track. By minimizing the peak, especially for the situations such as the original Gloria track, there is less buildup of traffic which allows for a safer and more efficient evacuation.

The model performs moderately for the majority of scenarios as they have high, early peaking demands that are difficult for egress. In these scenarios, a large number of vehicles can evacuate throughout the entire evacuation period. In contrast, the model does not perform well in scenarios such as the 180° track for Hurricane Gloria. Due to the low evacuation demands for this scenario, the results are difficult to interpret. The 180° track is the only track out of all the scenarios where the maximum number vehicles waiting occurs at a τ near the end of the credible evacuation period.

Across all scenarios, NAVSTA Newport is the last community to evacuate and is at most risk using this approach to routing and clearance. Newport almost always has the largest number of vehicles waiting to evacuate. On the other hand, Middletown and NUWC never have the largest number of vehicles waiting to evacuate and are never the last community to evacuate.

The model is effective at minimizing evacuation period. The evacuation length is 13 hours for all evacuations, except for the scenarios with few evacuees. This makes sense, as in many scenarios the last evacuees are added to the network at hour 13. Therefore, there are not vehicles waiting past the last time period for planned evacuation. Additionally, the time that the maximum number of vehicles are waiting happens early on in the credible evacuation period, such as within the first five hours of starting an evacuation.

Overall, it appears the model produces the best results for the original track for Hurricane Gloria. In this case, a full evacuation is achieved and the maximum number of vehicles waiting is less than all other threatening and striking storms. For this hurricane, vehicle demand is added to Newport more gradually across the credible evacuation period. This is

the ideal outcome from this model since we maximize the total number of evacuees and minimize the number of vulnerable evacuees that are waiting to evacuate.

4.4 Discussion

Results presented in this thesis suggest that our model is helpful for evacuation planning. In a basic sense, for an evacuation model to support an evacuation plan no vehicles should be on roads when a hurricane strikes to avoid loss of life. Go/no-go decisions should be made early enough and routing should ensure egress completes well before strike. Using our approach, go/no-go decisions were made within the determined time frame and evacuation ended before a hurricane would strike. This indicates the potential benefits of using our model to guide future evacuation plans and egress.

Still, there are possible issues with our model that require additional analysis prior to use for real evacuation. This is because our optimal evacuation decisions are sensitive to the approach of a storm. The more aligned a storm is with making a direct hit with the most dangerous region, the easier the evacuation decision becomes. Storms that fall near the dangerous region, but are non-striking, may induce large evacuations when they ideally would not. Our model produces results that match current realistic decision uncertainties and sub-optimal actions. Ultimately, we expect evacuees to over-utilize the bridge routes and under-utilize shelters.

We also identify several interdependent relationships not fully supported by our model. The recommended number of evacuees depends on the storm track, and we expect that there will be a higher number of evacuees for more threatening and striking storms. When there are more evacuees, the maximum number of vehicles waiting to evacuate increases. Ideally, the model would attempt to manage demands to allow them to be more gradual to minimize this peak. Still, the maximum number of vehicles waiting to evacuate also occurs earlier in the evacuation period, which is preferred.

Routing is also sensitive to hurricane scenario. Across our study, we find the optimal routing for each municipality and the number of evacuees from each municipality crossing each bridge depends on the hurricane track. This may be related to the size and location of the most dangerous region for bridge closure. For Hurricane Bob and Gloria, the location of

the most dangerous regions are the same size, yet shifted in space. Disentangling these relationships between evacuation route, storm track, and dangerous region would improve the efficacy of using our model for real evacuation planning.

CHAPTER 5: Conclusions

Aquidneck Island is vulnerable to future storms that will impact both military and civilian communities. Past work identified the need for coordinated evacuation plans across vulnerable communities in Newport, Portsmouth, and Middletown alongside military communities from NAVSTA Newport and NUWC (Jones 2021). However, previous studies only estimate optimal vehicle routing and clearance times, and ignore uncertainty in go/no-go decisions to evacuate or shelter-in-place as a hurricane approaches. This thesis builds on past work to study how a storm's approach may influence go/no-go decisions.

If an evacuation is necessary due to high winds, storm surge, and flooding, the majority of evacuees will need to cross bridges to egress off Aquidneck Island to safety. However, it is unsafe to traverse bridges after winds exceed 70 mph, which will happen as a storm approaches. Uncertainty in whether an oncoming storm will strike Aquidneck Island (requiring evacuation) or not strike (requiring sheltering-in-place) is high when the storm is far from landfall. This uncertainty decreases the closer a storm is to landfall. Thus, go/no-go decisions involve a time-dependent process based on storm approach that will affect the number of vehicles evacuating and when they are likely to be driving on roads. Accordingly, this time-dependent process will affect optimal evacuation routing and clearance times.

We establish a model to estimate go/no-go decisions for Aquidneck Island given an oncoming storm. We summarize the main results of this work, discuss its limitations, and the potential future applications.

5.1 Summary

The primary contribution of this work is a model for go/no-go decisions and results given two historical storms: Hurricane Bob from 1991 and Hurricane Gloria from 1985.

5.1.1 Model

Our model is the result of several data pre-processing and analysis steps. First, we chose historical hurricanes that have available data for their track and wind field characteristics (i.e., Hurricane Bob and Gloria for this work). We created three synthetic hurricane tracks for each storm, two based on the NHC cone of uncertainty and one worst-case track for Aquidneck Island.

Using real and synthetic tracks, we establish the most dangerous region for hurricane strike by measuring maximum wind speeds with a PWM. We define the most dangerous region as a physical region in space where, if the historical storm made landfall, it would shut down bridges and require evacuation. Based on the PWM, we find that there are two scenarios each for Hurricane Bob and Gloria that end in strike (i.e., the original best track and worst-case track) and two that end in no strike (i.e., 180° and 90° tracks).

We estimate the probability of strike at each point in the approach of a historical storm towards Aquidneck Island using a stochastic track generation procedure. Our procedure takes a starting point, bearing, and forward speed for a storm, and then progresses a stochastic track forward in space based on NHC track uncertainties. With this procedure, we produced thousands of stochastic tracks to estimate the likelihood that a storm would strike the most dangerous region given a lead time before strike.

Finally, we estimate the expected evacuation vehicle demand given a particular track and determine optimal routing and clearance times. We estimate evacuation demands using three interrelated functions: (1) time-dependent vehicle demands based on population data and the number of evacuees remaining in a community, (2) the probability of strike as a storm approaches, and (3) a credible evacuation period in which vehicles are allowed to evacuate. We adapt the optimal evacuation routing and clearance model from Jones (2021) to incorporate resulting time-dependent demands. We solve the model to determine an optimal evacuation plan given expected demands to real and synthetic storm tracks.

5.1.2 Results

We study evacuation for each real and synthetic track produced for Hurricanes Bob and Gloria. We determine the efficacy of our model to produce evacuation demands and routing recommendations.

For evacuation demands, we prefer full evacuation for storms that strike the most dangerous region (i.e., original and worst-case tracks) and no evacuation for storms that do not strike (i.e., 180° and 90° tracks). We find our model produces mixed results meeting these criteria. In general, our model produces complete evacuation for striking storms, with only a single scenario leaving some vehicles in communities to shelter-in-place. In contrast, we find our model produces high evacuation demands for threatening, non-striking storms. Only a single scenario achieved minimal evacuation for a non-striking storm (i.e., Hurricane Gloria, 180°).

Despite these results being non-ideal for go/no-go decisions, they suggest that our model does reproduce realistic evacuation phenomena. Due to the expected costs of go/no-go decisions, there is a tendency to evacuate a larger number of vehicles for non-striking storms, than evacuate a smaller number of vehicles for striking storms.

For routing recommendations, we compare several key metrics, including: the peak number of vehicles waiting to evacuate, the time waiting occurs across the evacuation period, the length of the evacuation period, the communities that experience the greatest number of vehicles waiting, and the communities that are last to evacuate. Emergency managers prefer results that have a smaller peak number of vehicles waiting to evacuate, an earlier time period for the waiting peak number of vehicles, and a short evacuation period. The emergency managers also want to avoid singling out a particular community to always be the last to egress.

Again, we find our model produces mixed results across these criteria. Our model performs poorly with regard to minimizing the peak number of vehicles waiting in communities by creating and adding large evacuation demands to the network early in the evacuation period. A more ideal situation would be to gradually increase demands to ensure that few vehicles are waiting to evacuate. However, this can be hard to coordinate and can cause unexpected traffic. We also find our model performs poorly with respect to failing to evacuate a community that is vulnerable, as NAVSTA Newport is always either last to fully evacuate or tied for last. Similarly, Newport city almost exclusively experiences the largest number of vehicles waiting to evacuate. This suggests that our model does not produce shared risk across communities, and might unintentionally put NAVSTA Newport evacuees at greater risk and put greater emergency coordination burden on Newport than other municipalities.

In contrast, we find our model produces preferred results for waiting times and evacuation period length. Across all scenarios, our model shifts peak waiting times early in the evacuation period, which is important to manage potential issues with coordination with as much lead time as possible. Moreover, routing chosen by the model ensures that all evacuees are able to egress off the island with several hours before predicted landfall. This allows a buffer time to manage possible issues that can arise during an emergency and to redistribute emergency resources from evacuation to sheltering-in-place.

Overall, we find our model performs moderately across all storms, but we cannot recommend its use for evacuation planning without further development. Based on all metrics, our model performed best for the original track for Hurricane Gloria and worst for the 90° track for the same storm. Both the track and location of landfall of Gloria (i.e., west of Aquidneck Island) make it more straightforward to produce appropriate evacuation demands for striking scenarios. However, its original track with westward landfall also meant that the 90° track appears to have a high strike probability as it approaches, yet veers further east and avoids strike. In contrast, the model performs moderately well for all Hurricane Bob scenarios. These discrepancies suggests that there are additional factors dictating preferred go/no-go decisions and evacuation routing that are ignored in the current model.

5.2 Limitations

There are many assumptions made throughout this thesis that deserve further development and analysis. Several assumptions are embedded in the optimization model and are outlined in previous work (see: Jones 2021, Chapter 5). We summarize assumptions that impact expected demands, which include the design of the stochastic track generation model and the expected demand estimation function.

Assumptions in our estimation of expected demands limit the efficacy of results. With respect to the stochastic storm generation procedure, our current model produces many storm tracks that are highly unlikely based on hurricane physics. Specifically, hurricanes far from landfall can take tracks that are widely off target and do not land within the NHC cone of uncertainty. An improved model might produce more realistic probabilities of strike, and by construction, more accurate estimates of evacuation demands.

One key assumption is the use of a credible evacuation time window for when evacuees are allowed to be added as demands on the road network. We estimated our time window based on HURREVAC tools (Hurricane 2022). Although this time window was effective for providing one realistic view of when evacuations might happen, this time range will vary depending on the attitude of local authorities on hurricane risk. A more conservative local authority may choose a larger time window, while a less conservative local authority may choose a smaller time window. Moreover, we assume that local authorities will have at least a 72-hour lead time before the hurricane makes landfall. However, local authorities may have more or less time available depending on the hurricane track and warning. The actual time window used might be dependent on the track a hurricane follows.

The current evacuation demand function also assumes that the number of evacuees entering the network is proportional to the probability of strike. In reality, this number is unknown by normal citizens and might not be a useful estimate for how many additional evacuees are likely to begin evacuation. For example, the expected evacuation demands can consider strike probability in many ways, such as weighting future evacuation demands (e.g., in time step $\tau + 1$) on previous strike probabilities (e.g., in time step τ). For example, there is often a minimum likelihood of strike that would generate demands. We provide a mathematical form of the $hit(\tau)$ function that supports this formalism (see Chapter 3, Eq. 3.4), yet assume any possible strike will induce evacuation demands ($\phi_c = 0$). Given our version of $hit(\tau)$, there may be an optimal ϕ_c to ensure threatening, non-striking storms do not lead to large evacuations. Moreover, evacuation calls will have decreasing likelihood as a storm gets very close to strike to avoid sending vehicles on roads into dangerous situations. This suggests that there several different variations of $hit(\tau)$ that may appropriately capture real evacuation decisions. Future analysis of this function should support more nuanced, and possibly better model results.

5.3 Future Work

There exists several ways to improve upon the results in this thesis. First, more analysis of the existing results would benefit decision-makers. We recommend conducting the same analysis for Hurricanes Bob and Gloria given a bridge is unavailable for evacuation. In particular, the Mt. Hope Bridge is not officially on evacuation routes used by Aquidneck Island emergency managers. Studying the same results with and without Mt. Hope Bridge

will determine the additional benefits in terms of routing and clearance time when the bridge is available.

Another improvement would be using a more realistic stochastic track generation procedure. While some of the stochastic tracks we generate are similar to the synthetic tracks, there are many that extend below the starting point and have no resemblance to a real storm. This is because the headings in our current model can be greater than 180° degrees, which can cause a hurricane to turn directions. One way to ensure stochastic tracks are more accurate would be restricting the heading in between time steps. We anticipate this control to generate tracks that better resemble the synthetic tracks and produce more realistic strike probabilities. Additionally, we assume an error distance of 23.73 kilometers is Gaussian distributed across east-west bearings. In reality, hurricanes may be more or less likely to veer in a particular direction due to weather physics. Improving the model to weight one direction over another may also produce more realistic tracks. Ultimately, there should be further research into the error distances and the heading restrictions to improve the stochastic track generation process.

More detail can be included into the expected demand function to determine whether go/no-go decisions should be made. Importantly, we do not consider hurricane damage in our model, just if bridges will close. A damage function, which can be obtained from various standard software and modeling approaches, could be used in conjunction with vehicle demands, strike probability, and credible evacuation period. However, this effort requires significantly more data and data processing than what is currently used in this thesis, including building stock and wind speed vulnerability curves.

Finally, building on this work to produce a full, multistage stochastic program that incorporates all track uncertainties and evacuation demands would benefit stakeholders. One approach to do this would be to weight the expected demands across tracks based on their overall probability and include additional decision variables for evacuation period start and end times. The goal of this model would be to determine optimal first stage decisions (i.e., evacuation decision time frames and routing) before second stage decisions (volume of vehicles leaving each vulnerable community). This would also support a robust optimization model to meet specific levels of risk either through a cardinal robust approach or via chance constraints. This analysis assumes that the communities on Aquidneck Island are the only

ones that are potentially going to evacuate. However, all of the surrounding communities potentially face the same decision. Therefore, understanding the ways in which the evacuation decisions and behavior of one community impact another is an important topic for future research.

To conclude, we recommend that future work build on our model to support Aquidneck Island communities. While our approach establishes a procedure to determine useful (and possibly realistic) evacuation scenarios, it requires improvements prior to use by real decision-makers.

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