Optimization Modeling Approaches to Evacuations of Isolated Communities

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Abstract

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Isolated communities are particularly vulnerable to disasters caused by natural hazards. In many cases, evacuation is the only option to ensure the population's safety. Isolated communities are becoming increasingly aware of this threat and demand solutions to this problem. However, the large body of existing research on evacuation modeling usually considers environments where populations can evacuate via private vehicles and by using an existing road infrastructure. These models are often not applicable to remote valleys and islands, where road connections can be disrupted or do not exist at all. The use of external resources is therefore essential to evacuate the population. How to systematically evacuate an isolated community through a coordinated fleet of resources has not yet been researched. This dissertation thesis addresses this knowledge gap by designing a new routing problem called the Isolated Community Evacuation Problem (ICEP) that optimally routes recovery resources between evacuation pick-up points and shelter locations to minimize the total evacuation time. The research presents derivations of the initial model for (a) emergency planning and (b) response purposes to give emergency planners and researchers tools to prepare for and react to an evacuation of an isolated community. For (a), a scenario-based two-stage stochastic program with recourse considers different emergency scenarios to select the optimal set of

recovery resources to hold available for any evacuation emergency. Furthermore, the dissertation explores efficient structure-based heuristics to solve the problem quickly. For (b), the assumption of certainty over the size of the affected population at the time of evacuation is relaxed. Approaches from robust and rolling-horizon optimization are presented to solve this problem. Moreover, meta-heuristics are explored to solve the problem to optimality while overcoming the complexity of the problem formulation. Finally, an in-depth, real-world case study that was conducted in collaboration with first responders and emergency authorities on Bowen Island in Canada is presented to test and evaluate the applicability of the proposed models. This case study further informed the official evacuation plan of the island. This collaboration demonstrates the potential of full integration of the research approach with local emergency expertise from the affected area and highlights the data requirements that need to be met to maximize the use of the model.

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GLOSSARY

Abbreviations

ANOVA	Analysis of Variance
BC	British Columbia
BEP	Bus Evacuation Problem
BIM	Bowen Island Municipality
BRKGA	Biased Random Key Genetic Algorithm
CPU	Central Processing Unit
CTM	Cell-Transmission Model
CWPP	Community Wildfire Protection Plan
DARP	Dial-a-Ride-Problem
DCR	Demand-Capacity-Ratio
DTA	Dynamic Traffic Assignment
D-ICEP	Deterministic Isolated Community Evacuation Problem
DVF	Demand Variance Factor
EOC	Emergency Operation Center
FEMA	Federal Emergency Management Agency
GB	Gigabyte
GHz	Gigahertz
HRVA	Hazard Risk and Vulnerabiltiy Assessment
ICBC	Insurance Corporation of British Columbia
ICEP	Isolated Community Evacuation Problem
LRP	Location Routing Problem
MEOPAR	Marine Observation, Prediction, and Response
MIP	Mixed Integer Program
MLE	Maximum-Likelihood Estimator
MOTI	Ministry of Transportation and Infrastructure
MP-BRKGA	Multi-Parent Biased Random Key Genetic Algorithm
MVRP	Multi-trip Vehicle Routing Problem

NCE	Network of Centres of Excellence
NP	Nondeterministic Polynomial Time
RAM	Random-Access Memory
RBEP	Robust Bus Evacuation Problem
R-ICEP	Robust Isolated Community Evacuation Problem
RSH	Resource Set Heterogeneity
RH-ICEP	Rolling Horizon Isolated Community Evacuation Problem
RKGA	Random Key Genetic Algorithm
SAR	Search and Rescue
S-ICEP	Stochastic Isolated Community Evacuation Problem
SIREN	Strategic Planning for Coastal Community Resilience to Marine Transportation Risk
TSP	Traveling Salesman Problem
UBCM	Union of British Columbia Municipalities
VRP	Vehicle Routing Problem
VRP-TW	Vehicle Routing Problem with Time Windows

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DEDICATION

Für Mama.

Danke für Alles.

Chapter 1

INTRODUCTION

1.1 Motivation

Large-scale emergency evacuations can become necessary for a variety of reasons. One possible reason for an evacuation is an industrial accident like a chemical spill, a fire, or a nuclear accident. Further, militarized conflicts can cause large-scale evacuations. Alternatively, natural hazards, such as a wildfire, storm, volcanic eruption, flood, earthquake, or tsunami, can create the need for an evacuation of a population. The increasing frequency of disasters caused by natural hazards has repeatedly been connected to changing climate patterns [114, 115, 144]. Evidence has further been found that extreme natural disasters are causing increases in economic damages [48]. In particular, with rising temperatures, wildfires are becoming an increasingly high threat to societies around the world [85]. These threats lead to rising importance of disaster planning and evacuation preparedness for urban and rural environments. Therefore, an important research question is how to evacuate a population quickly and efficiently?

Evacuations are a prevalent problem in research and emergency evacuation planning [101] has received a lot of attention in the research community over the last years as numerous literature surveys show [5, 12, 56, 57, 83, 100, 123, 153, 154]. Researchers and professionals equipped with a wide range of subject matter expertise have come up with different approaches to planning and executing emergency evacuations under different circumstances. The vast majority of research has focused on the evacuation of highly populated areas, such as urban centers and cities since the most significant populations live in these areas [12]. This focus is motivated by the fact that evacuating a large population through a limited infrastructure in a short amount of time seems to be a more challenging problem than a rural area, where congestion and maximum infrastructure capacities are less of a concern.

Recently though, disasters caused by natural hazards have shown that some communities can be complicated to evacuate due to a lack of available evacuation routes. Some examples are the seasonal wildfires in California from 2017 to 2020 [1, 3, 149], the 2020 bush fires in Australia, which required a marine and air evacuation of Mallacoota in Victoria [2] by marine resources, or the evacuation of Samos Island in Greece during the wildfires of 2019 [44]. Storms can also require the evacuation of isolated communities, such as in the Bahamas after Hurricane Dorian in 2019 [125]. Furthermore, volcanic eruptions led to the evacuation of Vulcano Island in Italy in 2021 [111], the evacuation of St. Vincent in 2021 [55], and the evacuation of some islands in Tonga in 2022 [110]. Another example was the 9/11 terrorist attack in Manhattan in 2001 [87] that resulted in a large-scale evacuation of Manhattan. Communities with geographically vulnerable characteristics are not uncommon. A geo-spatial data analysis conducted by StreetLight Data [138] has highlighted the 100 most difficult to evacuate communities in the United States, most of which are either located in remote areas in the mountains or in coastal communities such as communities on islands or peninsulas. This research shows that, while the affected populations in these areas are small compared to the populations of large urban centers, it can be challenging to evacuate these areas if necessary. This problem has received attention recently as more geographically isolated communities aim to plan for developing robust and quick evacuation plans [36].

From an engineering perspective, optimization and simulation models come to mind as suitable tools to solve the coordination of this problem, as they have been used frequently as methods to solve evacuation problems [56, 57, 154]. However, most of the existing research focuses on road-based evacuations, where the population evacuates with private vehicles [12, 57]. In contrast to this, isolated communities, such as the ones presented by StreetLight Data [138], may not be possible to evacuate using private vehicles. This can be the case if no road connection exists or if one of the few existing roads is disrupted. As a result, evacuation has to be executed through a coordinated effort of resources to transport the population to safety, for example, air or marine transport. The research question emerging from this problem is, how to evacuate an isolated community as quickly as possible, where the population cannot self-evacuate since it does not have a reliable road connection? This question is not discussed in existing research. This problem is denoted as the Isolated Community Evacuation Problem (ICEP), and it will be referred to as that throughout this proposal. The research in this dissertation thesis addresses the need for solution approaches for the evacuation of isolated communities using optimization. Therefore, the main research goal of this thesis is to develop a modeling framework that can give decision support on how to plan and execute the evacuation of an isolated area with recovery resources.

1.2 Research Objectives

This dissertation presents answers to three research objectives, which focus on optimizing the planning for the evacuation of isolated communities with heterogeneous resources, and the execution of the evacuation plan. Furthermore, the dissertation focuses on finding efficient ways to solve these problems promptly. The research objectives are the following:

Objective 1: Develop a new optimization formulation that optimally routes resources to evacuate an isolated community as quickly as possible.

This research objective aims to formulate a model that incorporates the unique circumstances of evacuating isolated communities and produces an efficient route plan to evacuate the community quickly. The research results presented in Chapter 3 show an optimization formulation that models these particular aspects and presents a deterministic version of this problem in section 3.3, denoted D-ICEP. This formulation minimizes the total evacuation time of the isolated community. In addition, section 3.4 presents a structure-based local-search heuristic that solves this problem quickly.

Objective 2: Adapt the optimization formulation to develop a planning tool that identifies the right set of recovery resources to be prepared for a variety of disasters.

The second objective aims to take a planning perspective on the problem to make sure that a community can prepare for various disaster scenarios that are likely to occur in the area of interest. Chapter 4 shows that a promising approach to this problem can be to build a two-stage stochastic recourse model framework. This model uses a modified version of the deterministic formulation of D-ICEP as the scenario-dependent second stage and identifies the right set of evacuation resources in the scenario-independent first stage. This problem is denoted the S-ICEP. A multi-objective function complements this approach by balancing the time minimization objective against the cost of the evacuation fleet, and multiple objective functions are provided in section 4.3. Also, for this formulation, a structure-based local-search heuristic is provided to solve the problem quicker than a commercial solver in Section 4.4. The challenges in finding the global optimum of the S-ICEP with this heuristic are more significant than for the D-ICEP. Therefore, Chapter 7 presents a meta-heuristic approach to solve the problem. The presented solution method consists of a customized decoder function that can be used in the Multi-Parent Biased Random Key Genetic Algorithm (MP-BRKGA) framework to solve the S-ICEP more efficiently than a commercial solver and more accurately than the previously presented structure-based heuristic for larger problem instances. The differences in performance are demonstrated through experiments. In Chapter 6 the S-ICEP model formulation is applied to a real-world case study that demonstrates the validity of the approach in practice for emergency planning. The chapter also stretches the importance of an integrated end-to-end approach to data aggregation and collection, which involves a broad set of stakeholders in the data acquisition process. This effort included local residents and volunteer groups, agencies from all levels of government, and the private sector. Due to the high level of attention to data collection requirements, guidance and interpretations of the results, this research can be used as a template for future evacuation planning studies for isolated communities. The validity of this approach is further confirmed by including the analysis results in the official evacuation plan of Bowen Island.

Objective 3: Adapt the optimization formulation to develop a response tool that makes near-optimal routing decisions during an emergency when demand information is uncertain.

The third objective aims to take an emergency response management perspective on the ICEP. Chapter 5 shows versions of the model formulation that can be used during an evacuation to make quick decisions on routing when information about the number of evacuees is not available, uncertain or changes over time with the arrival of additional evacuees or better information. For that, the assumption that the number of evacuees at each evacuation location is certain needs to be relaxed. The presented formulations are based on the D-ICEP formulation. The first formulation is based on the concept of cardinality-constrained robust optimization for mixed-integer programs [20, 23]. The second approach is based on rolling-horizon optimization [41, 146] and updates the evacuation plan over time. Computational experiments demonstrate that both the R-ICEP and the RH-ICEP represent a substantial improvement over using the regular D-ICEP during response situations across all simulations. The RH-ICEP further was shown to be capable of outperforming the R-ICEP consistently.

1.3 Contributions

The research presented in this dissertation is novel since it is the first research line that attempts to find a mathematical formulation specifically for optimizing the evacuation of isolated communities where road-based evacuation is not possible. Extending this formulation, this research provides both a planning and a response tool to manage such evacuations and provides the first systematic application of this framework to a real-world case. In detail, the contributions are:

1. This is the first research that models the evacuation of isolated communities as a routing problem and takes into account the specific constraints of isolated communities, whose self-evacuation is difficult and where evacuation resources are mostly heterogeneous in their capabilities, capacities, and compatibilities with potential pick-up and shelter locations (D-ICEP) so that it can realistically represent the evacuation of an isolated community;
2. The expansion of the ICEP to a two-stage stochastic model with recourse presented in Chapter 4 allows planning for emergency evacuations by incorporating uncertainty based on different emergency scenarios (S-ICEP). In combination with a variety of objective functions to select from, this allows decision-makers to prioritize between time and cost efficiency and makes the model framework useful for evacuation planning

in practice;

3. The case study presented in Chapter 6 represents the first reported attempt to systematically plan the evacuation of an island by marine resources beyond regular ferry operations based on an integrated approach of data collection, surveying, stakeholder management, and mathematical modeling. The strength of this data-backed approach is the collaboration and integration of knowledge from the modeling expertise of academic researchers with the inputs and experience of emergency authorities and the process knowledge of municipal emergency managers. This leads to significant insights for evacuation planning on the island of interest that are manifested in the inclusion in the official evacuation plan [30]. The process followed in the case study can be used as a template for future evacuation studies and for planning for the evacuation of similarly geographically challenged communities.
4. Constructive local search heuristics (Chapter 3 and Chapter 4) and meta-heuristic solution approaches (Chapter 7) allow the ICEP formulations to be solved efficiently with a limited penalty on the optimality of the results and thus makes it practical to solve larger problem instances more quickly than implementations with a commercial solver would take;
5. The reformulation of the ICEP model into robust (R-ICEP) and rolling-horizon (RH-ICEP) optimization frameworks (Chapter 5) improves the capability of the ICEP to be used for response purposes when the exact number of evacuees at each affected location is unknown. Using historical knowledge through uncertainty sets or updating route plans when evacuee numbers become more certain during evacuation execution is valuable during emergency response. It makes the ICEP a useful tool to respond quickly to an evacuation notice and ensure that people are brought to safety as quickly as possible.

Chapter 2
LITERATURE BACKGROUND

2.1 Introduction

The following chapter provides an introduction to the general framework of evacuation modeling. It further presents different modeling approaches for the subset of evacuation studies for emergency response and planning that have been proposed in previous research and evaluates them regarding their application potential for the ICEP. Lastly, it focuses on related routing problems from other application areas and highlights the current gaps in the existing research compared to requirements for the ICEP. Specific literature that relates directly to the research objectives presented in Chapter 1 is presented in the corresponding chapters.

2.2 General Evacuation Framework

To assess where the ICEP falls in a general evacuation framework, Tüydeş [142] provided multiple components of a general evacuation study. The first components are a hazard analysis, which investigates the severity of the event, and a vulnerability analysis, which identifies the population at risk. On the basis of the outcome of these components, disaster response actions can be defined [142]. These include emergency operations and evacuation coordination, which both involve the aspect of traffic management and coordination. Southworth [135] further mentioned the necessity to conduct a behavior analysis to predict the behavior of the population during an evacuation and a shelter analysis to identify where and how many shelters would be needed [135]. The ICEP falls into the response action component of evacuation analysis, which includes the coordination of evacuation resources. At the same time, the ICEP requires inputs from other evacuation study components to ensure meaningful outputs of the modeling effort. The resulting classification of evacuation studies

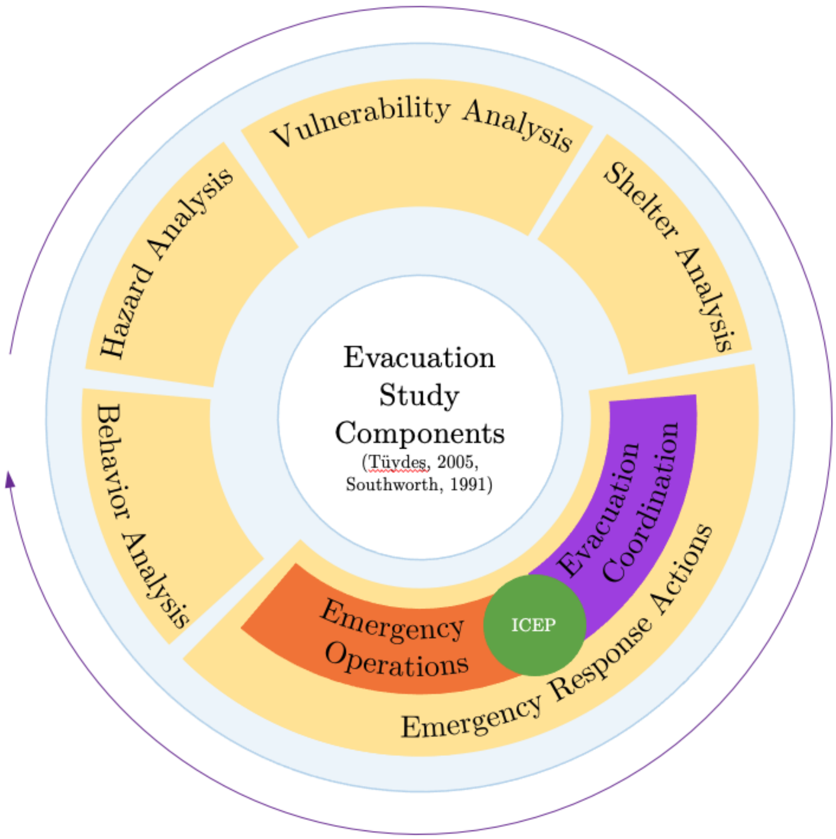

Figure 2.1: Classification of evacuation studies, modeled after [135, 142]

is illustrated in Figure 2.1.

For the ICEP, it can be assumed that sufficient information can be collected about the vulnerability of the population, shelters and that different realistic disaster scenarios can be mapped. While consideration of evacuation behavior is important if the population can self evacuate [140], the ICEP does not provide the population with much flexibility to leave the area on their own, which influences how evacuation behavior can be incorporated in the modeling effort.

2.3 Evacuation Planning and Response Modeling

In considering modeling approaches for the response action component of the evacuation study, Bayram's literature review [11] provided a comprehensive field survey regarding the optimization of emergency planning. Evacuation models can be classified on the basis of their modeling approach, whether they are static or dynamic, whether they contain multiple levels, whether they are of stochastic or deterministic nature, whether shelter location decisions are included, and the modes of transportation used. The full body of literature on evacuation modeling is extensive. For a full review of modeling techniques and available literature on evacuation modeling using optimization and simulation techniques, the reader is therefore referred to the large number of literature surveys in the field [5,12,56,57,83,100,123,153,154]. Instead, this chapter focuses on a general classification of modeling techniques for evacuation optimization to identify appropriate modeling approaches for the ICEP.

The review by Bayram [12] shows that many methods developed on evacuation modeling use traffic assignment models or routing models that focus on finding either the user equilibrium or the overall system optimum [82, 132]. Furthermore, it can be distinguished between static or dynamic modeling approaches. The majority of static models are derived from the static traffic assignment models introduced by Beckmann [15], and de Palma and Nesterov [54], the static network flow problem [66], and classic routing problems [53]. Dynamic models can be categorized into microscopic traffic assignment simulation models and macroscopic route schedule optimization models [102]. Dynamic schedule optimization models can be further categorized to be based on either dynamic traffic assignments (DTA) models as first introduced by Merchant and Nemhauser [106], which form a dynamic extension of the Beckmann formulation [15], the cell-transmission model (CTM) developed by Daganzo [51, 52, 156], dynamic network flow models based on the ideas from the linear dynamic network flow problem [67], or dynamic routing problems [96].

Simulation models are suitable to capture large complexity and randomness and are well suited to model individual behavior of people during a disaster. Particularly, evacuation behavior, which has been a frequently researched topic in previous research [140, 141], can be modeled on a microscopic scale using simulation models. Hence, simulations are useful to investigate elements of an evacuation that rely heavily on behavioral and stochastic aspects and can further be used to identify bottlenecks in evacuation routes. Some examples are the studies conducted by Cova and Johnson [49], and Belogzalov et al. [18] for wildfire evacuations as well as Chen [42] for hurricane evacuations.

However, while simulations can be informative, they do not guarantee optimal solutions and are difficult to convert into a usable plan for the emergency manager. Optimization models in contrast are mostly of macroscopic nature [82] and have the advantage that they provide optimal policies, which is particularly useful for both planning and execution. Provided that sufficient effort has been spent on ensuring the accuracy of the formulation and the provided parameters, optimization models can be used to make decisions with high confidence over the quality of the solution. Since the research presented in this dissertation focuses on providing a transportation plan to optimally route first response resources to solve the ICEP, reviewing research that focuses specifically on optimization models is valuable.

2.4 Related Traffic Assignment Models

Static and dynamic traffic assignment (DTA) models such as [26, 43, 113, 152] follow the idea to optimally allocate traffic flows to each route, such that either a user equilibrium is reached (user-optimal) or that the overall capacity of the system is optimally exploited (system-optimal), assuming that there is a finite number of routes and that every unit of flow added to a route causes increased congestion [106]. The subset of CTM-based DTA models are generally link based [51] instead of path based, and are thus not suitable for generating paths for optimal routing. Further, the non-convexity of these problems can lead to large problem sizes [88], which can make the models impractical as a real time response tool due to computational expense. Furthermore, evacuation flows in DTA models usually consider vehicles as unit flows, and thus only consider one transportation mode and treat them as equivalents in the model, which usually represents private vehicles.

2.5 Related Network Flow Problems

Many studies have made use of variations of the classic network flow problem classic network flow problem [66] to optimize evacuation plans [11]. In particular, its dynamic expansion can be useful for evacuation studies as it allows travel times on a path to depend on the time of execution. The main idea behind the dynamic network flow model is to describe the dynamic problem as an expanded static network with sub-nodes for different points in time. Thus, a larger time-expanded version of the network flow model is generated, where the static nodes are copied for every time instance [67]. For example, the models developed by [34,35,99,118] all consider the time-expanded modeling technique to model adaptations of the dynamic network flow model. Like DTA models, dynamic network flow problems are computationally expensive, and since routing decisions mostly require integer variables, mostly NP-complete and can either only solve smaller sized networks or require heuristic solution approaches.

Furthermore, network flow problems that aim to minimize the total route completion time are particularly relevant for the ICEP, because planners want to minimize the total evacuation time. The simplest network flow model that describes this problem is the quickest flow model [37]. Building on this, Lu et al. [102] have used the time-expanded network flow model as a base line for a new heuristic to achieve sub-optimal solutions for the network clearance time for evacuations. Furthermore, Lim et al. [98] considered network clearance time in the context of reliability-based evacuation routing that included uncertainty in the link capacities caused by congestion. Pillac et al. [120] developed a column generation-based two-level evacuating algorithm in which the sub-problem generates an evacuation path for each evacuation area, while the master problem resolves conflicts between the paths. Karabuk and Mansour [86] have developed a multi-stage stochastic program for tornado evacuation management that considers the path uncertainty of a tornado to make evacuation decisions as the weather event evolves.

Given the above, the vast majority of network flow models that minimize network clearance time focus on land-based evacuation routing. These models use existing road networks and usually model private vehicle traffic. Because these models represent single vehicles as unit flows, their application potential to the ICEP is limited. The ICEP requires complex routing extensions to model the resource routing element.

Considering that the ICEP aims to optimally route a heterogeneous fleet of recovery resources to enable efficient evacuation flows of the population through these resources, routing decisions and path generation become a necessary additional component of the model. Further, the recovery resources considered in this research problem, such as marine vessels and aircraft, do not rely on existing road networks. Thus, they are less restricted in their path choices and it would require a high volume of traffic to actually generate congestion and require time dependent travel times. Considering the high complexity resulting from time-expanded networks, the benefits of using this modeling technique do not seem to outweigh its disadvantages in the context of the ICEP.

2.6 Related Routing Problems

It is worth exploring related problem types that are not as frequently applied to evacuation studies. Considering the goals of the ICEP, routing problems are relevant. The general vehicle routing problem (VRP) [53], and its dynamic expansion [96] (both generalizations of the Traveling Salesman Problem (TSP) [65]), are well-studied problems with a vast literature [95, 119]. Similarities to the ICEP can be found with the VRP with time windows (VRP-TW) [128], a generalization of the VRP. Another related problem class is the location-routing problem (LRP), which considers both the optimization of the vehicle routes and depot locations, see for example [16]. This is particularly the case if shelter location considerations are part of the problem. Another related problem class is that of the multi-trip vehicle routing problem (MVRP), where vehicles can perform multiple round-trips and visit nodes multiple times to fulfill their orders [32,39]. As a variant of the MVRP, the VRP with satellite depots can also be considered. In this problem, vehicles can take on additional orders at satellite facilities and do not have to go all the way back to the depot to take on additional orders [50]. Another related problem that is derived from the VRP-TW is the Dial-a-Ride-

Problem (DARP) [46], where the vehicles share their capacity between multiple customers to transport customers from requested pick-up to requested drop-off points. However, this problem is strongly constrained by the time windows and maximum duration constraints for customers and therefore difficult to solve efficiently.

2.7 Related Evacuation Transit Routing Problems

No previous research has developed optimization models for non-road-based evacuations. Hence, structurally related network models for the evacuation of populations through the use of buses, trains, or other public transit vehicles [123] are reviewed. Mass transportation models optimize the routing of vehicles to evacuate an otherwise immobile population through a set of nodes representing evacuation area pick-up points and shelters. These models require routing decisions for the recovery resources, which makes them difficult to solve, but they enable exact modeling of the resource usage. However, only a few applicable papers on mass transit evacuation have been published.

Song et al. [134] presented a location-routing problem (LRP) that models evacuations from an urban city network via transit vehicles and uses different heuristic and algorithmic approaches to solve the problem. Sayyady and Eksioglu [127] provided a mixed-integer linear program (MILP) that optimizes the total evacuation time in urban areas for no-notice evacuation by using buses that collect passengers from multiple pick-up locations until the bus capacity has been reached. An et al. [6] expanded the bus evacuation idea and integrated it with decisions on the design of evacuation pick-up locations and furthermore considered service availability. Abdelgawad and Abdulhai [4] developed a large-scale multi-modal evacuation model that combines a private vehicle evacuation model with a VRP-based mass transit evacuation model to obtain a holistic evacuation plan for large cities (NETDC). Kulshrestha et al. [94] expanded this problem by considering pick-up location decisions and incorporating demand uncertainty through a robust optimization formulation. An additional study by Wu et al. [151] considers evacuation by barges (BEPP) ahead of storm events.

Bish [25] presented a bus-based evacuation model as a variant of the general VRP, called the bus evacuation problem (BEP). The BEP requires a significantly different formulation than the classic VRP, but it uses a network structure that is similar to that of the ICEP. It consists of initial bus depots, pick-up points, and shelter locations. Buses are routed from an initial depot to the pick-up points and then alternate between the pick-up points and shelter locations, sequentially evacuating the entire population. Multiple extensions to the BEP have been published. Pereira and Bish [117] expanded the BEP to consider the arrival rates of people at pick-up points. Zheng [155] provided a similar model to optimize mass transit evacuations of urban areas with different constraints on arrivals of evacuees, and solved it by using a Lagrangian relaxation-based algorithm. Goerigk et al. [73] introduced multiple solution approaches that use branch-and-bound procedures to solve the BEP efficiently, and presented a simplified robust optimization formulation of this problem (RBEP) with delayed scenario generation [72]. This formulation solves the RBEP for uncertain numbers of evacuees by using a linear and a tabu search to find near-optimal solutions. The search procedures take advantage of the problem's high symmetry, caused by identical buses and symmetric travel times. Goerigk et al. [71] further developed a way to solve the RBEP by using two stages that sequentially add new scenarios generated from uncertainty set, solving a much larger number of uncertain scenarios in a reasonable amount of time. Goerigk et al. [74] further improved the optimal evacuation time of the network by combining the BEP with decisions on pick-up locations. Lastly, Goerigk et al. [70] integrated the BEP into a comprehensive evacuation framework that not only considers the aspects of previous work [74], but introduces multi-modal commodity decisions and solves the problem by using a genetic algorithm.

Dikas and Minis [58] expanded the usage of the BEP to the recovery of casualties, such as in a ceasefire on a battlefield, and created a variant called the Casualty Evacuation Problem (CEP). They further provided a hybrid solution framework for the BEP that combines the BEP heuristic concepts [25] with column-generation [58]. Baou et al. [10] introduced a variant of the BEP that can consider heterogeneous bus capacity and take into account mobility impairments among some evacuees. The concept of using heterogeneous resources is relevant for solving the ICEP, though the stark differences between resources used for isolated communities come with further limitations as discussed previously in Chapter 1. Lastly, Wang and Wang [145] consider re-balancing both supply and demand across the evacuation locations in the BEP to reduce total evacuation time.

2.8 Gaps in Literature

No previous research has provided any solutions for optimizing the evacuation of isolated communities. Table 2.1 visualizes a comparison of selected related studies and structurally similar models evaluating them against the features that characterize the ICEP. Common routing problem formulations that are derived from the TSP and VRP do not contain the constraints required to model the network structure, the resource heterogeneity, and the objective functions that are needed for the ICEP. Furthermore, while structurally similar problems, particularly the BEP [25] and its variants [10, 58, 72, 74], are useful as a baseline for formulating and solving the ICEP, no other published research has focused on the specific circumstances of geographically isolated areas. This includes the partial incompatibility between resources and access points, multiple access point alternatives per location, asymmetric travel time matrices, heterogeneous speed and capacity capabilities of recovery resources, and, for the stochastic cases, the challenges to predict how a disaster will unfold. Neither has research been published about the practical implications of the evacuation of isolated communities. The research presented in this dissertation thesis aims to fill these gaps through new formulations, tailored solution methods and application studies.

Table 2.1: Feature Evaluation of Selected Related Models and Studies

		Selected Relevant Features												
Study	**Model**	**Multiple Resources**	**Routing element**	**Flow element**	**Different node classes**	**Individual routes per resource**	**Limited compatibility**	**Multiple trips per resource**	**Different routes per trip**	**Heterogeneous fleets**	**Partial self-evacuation**	**Asymmetric travel times**	**Minimizing total duration of route plan**	**Demand uncertainty**
Flood [65]	TSP		✓			(✓)						(✓)		
Dantzig and Ramser [53]	VRP(-TW)	✓	✓			✓						(✓)		
Belenguer et al. [16], Song et al. [134]	LRP	✓	✓		✓	✓								
Cattaruzza et al. [39]	MVRP	✓	✓			✓		✓	✓					
Cordeau [46]	DARP	✓	✓		✓									
Sayyady and Eksioglu [127]	NETDC	✓		✓	✓			✓						
Wu et al. [151]	BEPP	✓	✓		✓	✓		✓	✓	✓			✓	
Bish [25]	BEP	✓	✓	✓	✓	✓		✓	✓				✓	
Goerigk and Grün [72]	RBEP	✓	✓	✓	✓	✓		✓	✓				✓	✓
Dikas and Minis [58]	CEP	✓	✓	✓	✓	✓		✓	✓					

Chapter 3

THE DETERMINISTIC ISOLATED COMMUNITY EVACUATION PROBLEM

The work presented in this chapter represents the first half of a research manuscript that has been published under the title ”The Isolated Community Problem with Mixed Integer Programming” in *Transportation Research Part E: Logistics & Transportation Review* and is co-authored with Dr. Anne V. Goodchild [91]. This chapter is not the copy of record and may not exactly replicate the authoritative document that was published.

3.1 Abstract

As awareness of the vulnerability of isolated regions to natural disasters grows, the demand for efficient evacuation plans is increasing. However, isolated areas, such as islands, often have characteristics that make conventional methods, such as evacuation by private vehicle, impractical to infeasible. Mathematical models are conventional tools for evacuation planning. Most previous models have focused on densely populated areas, and are inapplicable to isolated communities that are dependent on marine vessels or aircraft to evacuate. This chapter introduces the Isolated Community Evacuation Problem (ICEP) and a corresponding mixed integer programming formulation that aims to minimize the evacuation time of an isolated community through optimally routing a coordinated fleet of heterogeneous recovery resources. ICEP differs from previous models on resource-based evacuation in that it is highly asymmetric and incorporates compatibility issues between resources and access points. To increase efficiency, structure-based heuristics are introduced and evaluated through computational experiments. The results give researchers and emergency planners in remote areas a tool to build optimal evacuation plans given the heterogeneous resource fleets available,

which is something they have not been previously able to do.

3.2 Introduction

3.2.1 Motivation

The new model formulation presented in this chapter was motivated by the rising need to prepare for and mitigate the effects of disasters caused by natural hazards on the populations in remote communities. Particularly, small inhabited islands and similarly isolated communities such as coastal communities, remote valley hamlets, and mountain towns are vulnerable to the effects of natural disasters because of their dependence on waterways or limited and vulnerable roads. These conditions often do not allow the affected population to evacuate in private vehicles. Therefore, emergency management authorities often need to coordinate a highly heterogeneous set of recovery resources that have to alternate between the disaster area and shelter locations to evacuate the entire population. Some disasters that require such actions are wildfires, such as the Australian bushfires, which required a marine and air evacuation of Mallacoota in Victoria, Australia in 2020 [2], and the evacuation of Samos Island in Greece during the wildfires of 2019 [44]. Storms can also require such an evacuation, such as in the the Bahamas after Hurricane Dorian in 2019 [125]. Volcanic eruptions led to the evacuation of Vulcano Island in Italy in 2021 [111], the evacuation of St. Vincent in 2021 [55], and the evacuation of some islands in Tonga in 2022 [110]. These events increased awareness of threats and caused remote communities to recognize the need to develop robust and quick evacuation plans [36] at a time when climate change is increasing the risk of many natural disasters [114]. Furthermore, communities with geographically vulnerable characteristics are not uncommon. In fact, a geospatial data analysis conducted by StreetLight Data [138] has highlighted the 100 most difficult to evacuate communities in the United States, most of which are either in remote areas in the mountains or in coastal settings such as islands or peninsulas, where road-based evacuation is not possible. No existing formulation is capable of capturing this exact problem, and thus, a new formulation is required. This problem can be expressed through a concise research questions:

1. *How can resources be optimally routed to evacuate the entire community as quickly as*

possible?

To answer this question, the compatibility between recovery resources and landing locations needs to be considered. This problem is complex when multiple pick up locations are considered. Considering the literature review presented in Chapter 2, a routing optimization model is a suitable approach.

This chapter refers to the problem that poses the research question above as the Isolated Community Evacuation Problem (ICEP). The chapter provides a deterministic mixed-integer programming formulation (D-ICEP) to model the problem. The D-ICEP can be used for optimizing the evacuation plan for an isolated community, where all parameter and set data is known in advance. The recovery resources under consideration can be, depending on the environment to which the model is applied, a heterogeneous fleet of marine vessels, aircraft or land vehicles. The D-ICEP can therefore be used to help decision makers and emergency managers to make decisions on how to effectively allocate available recovery resources to different parts of the disaster area and how to evacuate the affected population in the fastest possible way. It will also give insights into which part of the area will be most difficult to evacuate and where more resources can potentially help reduce the evacuation time further. In addition to introducing the model formulation, bounds are established on some key parameters that illustrate the model dynamics of the formulation, and some numerical experiments are provided. For an alternative efficient solution process, a structure-based heuristic is presented and evaluated numerically.

3.2.2 Contributions

Despite the increased demand for evacuation plans for vulnerable isolated communities, the literature review in Chapter 2 has shown that existing work on optimal evacuation modeling has focused primarily on urban evacuations on road networks. Bayram [11] further found that most researchers have considered the management of emergency response resources and the evacuation of the affected populations as separate problems. This differs from the reality that emergency managers face when having to evacuate an isolated area, since these problems interact with each other. Furthermore, the solution methods presented to solve related previously developed problems cannot simply be re-used and therefore required the design of new solution approaches. Considering the research gaps mentioned in the previous section, and the need for solutions to evacuate isolated communities, the formulation presented in this chapter is novel and highly relevant. The contributions of this chapter to the research body are as follows.

1. The ICEP is the first study that uses a resource-routing approach to model the evacuation of communities without road-based evacuation routes. It takes into account the specific constraints of isolated communities, where self-evacuation is difficult and where evacuation resources are mostly heterogeneous in their capabilities, capacities, and compatibility with potential pick-up and shelter locations;
2. The structure-based local search heuristics presented for the D-ICEP allows the problem to be solved efficiently despite their heterogeneous structure with limited penalty on the optimality of the results.

The remainder of this chapter is structured as follows: Section 3.3 provides assumptions about the ICEP. Following that, the deterministic version of the ICEP (D-ICEP) is constructed through a step-wise creation of the required network components in Section 3.3.2 and its mathematical formulation is introduced in Section 3.3.3. The D-ICEP is then further analyzed for parameter choices. Section 3.4 presents a structure-based, two-phase heuristic to solve the D-ICEP, including the results of numerical experiments benchmarking the heuristic against a commercial solver. Lastly, Section 3.5 provides conclusions and future directions for research.

3.3 Problem Formulation

3.3.1 Assumptions

The following assumptions were made to formulate the D-ICEP model.

1. All road connections out of the disaster area are considered disrupted. Therefore, the

ability of people to self-evacuate is limited to using private vehicles that do not rely on roads such as aircraft or boats. However, since the majority of people do not own such resources, the majority share of the evacuation requires the use of external resources.

2. The evacuee populations are distributed in between different locations of the affected area.
3. The evacuee population is considered large enough to require a significant amount of resources and/or multiple trips to evacuate.
4. A central planning entity has full authority over planning and coordination of a fleet of recovery resources, except for private modes of transportation.
5. The central planning entity aims to minimize the total evacuation time.
6. All recovery resources considered are located within reasonable distance to the affected area and may differ in their capabilities in terms of their contracting cost, variable operating cost, carrying capacity, loaded and unloaded travel speeds, loading times, time to availability, initial locations, and their compatibility with potential pick-up and drop-off points in the affected area.
7. All recovery resources start from their initial positions once they have been staffed, and travel to a pick-up location in the affected area, and they alternate in between pick-up locations and shelter locations until the number of evacuees is zero, ending at a shelter location.
8. For model simplicity, recovery resources visit only one evacuation pick-up point and one drop-off point per trip.
9. The sets of initial resource positions, evacuation pick-up points, and shelters are known. Shelter and pick-up point identification is thus not part of this problem.
10. The population of evacuees will be at the pick-up locations upon arrival of resources, such that arrival rates of evacuees do not have to be considered. This entails that the evacuees travel to the pick-up locations either by foot or other modes of transport. It should be noted that at this point the transportation of evacuees to the pick-up points is out of scope of this model and needs to be considered separately in future work.

11. Evacuees are considered safe once they have been dropped off at a shelter location.
12. Recovery resources are operating continuously without downtime.
13. Recovery resources are accessible and prepared for all types of evacuees, including children and mobility impaired populations.
14. The capacity of pick-up locations and shelter locations is considered infinite.

3.3.2 Model Design

The D-ICEP minimizes the total evacuation time of a given disaster with fixed evacuee numbers and a fixed set of recovery resources. The network presented in Figure 3.1 illustrates the physical flows of evacuees. Let s denote the source node, representing the entire isolated community. The as denote geographically separated evacuation areas, the bs denote the evacuation pick-up points,the cs denote the shelters, and t denotes the sink node. Green arcs indicate routes on which passengers can be transported. Blue arcs show the routes of people who decide to self-evacuate using private vehicles. If it was easy to determine the capacities and transit times for all arcs, the minimal evacuation time could be found through a quickest flow formulation [37].

However, the capacities and time parameters for the arcs between pick-up points and shelter locations are non-linear because for the ICEP, these depend on which resources are used on a route and how many round trips are made to evacuate the area. Furthermore, resources each have different starting points and may not be compatible with every evacuation pick-up point. For example, a ferry that is in regular service between an island and the mainland might be nearby, but it will only be able to dock at a specifically designed ferry dock. This requires individual routing decisions for each resource and therefore the introduction of binary variables for routing choices, making the problem a mixed-integer formulation. Figure 3.2 illustrates the resource routing problem for a single resource. Let h denote the initial resource location. The bs and cs denote the evacuation pick-up points and shelters respectively, as in Figure 3.1. A resource travels from its initial location h to a pick-up point b and transports evacuees to a shelter c and returns to one of the compatible

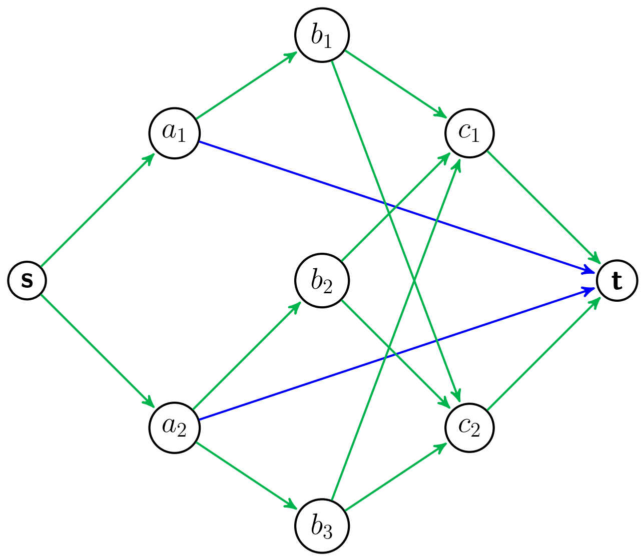

Figure 3.1: Illustration of population flows from evacuated to safe locations for two evacuated areas, three evacuation pick-up points, and two shelters

evacuation pick-up points b (not necessarily the same as the one it served in the previous trip) for another trip. The left part of Figure 3.2 illustrates this problem for a routing problem with one round trip back to the evacuation location and back to the safe location. Breaking down the bs and cs into sub-nodes for each round trip, as illustrated in the right part of Figure 3.2, expands the model structure into a trip-expanded structure, which follows a logic similar to that of the time-expansion presented by Ford and Fulkerson [67].

With the network presented in Figure 3.2, resource routes can be optimized, provided that a separate routing scheme is in place for every considered resource, as the arc capacities and costs in this network still depend on which resource is used on each route. Using this network structure, the arcs can determine the travel time as a function of distance in between nodes and resource speed, while the arcs from b to c also maintain flow capacity according to the corresponding resource carrying capacity. The h nodes further determine the time to availability of a resource, and the nodes b and c, the passenger loading and unloading time respectively. Optimizing this sub-network as a shortest path problem would provide

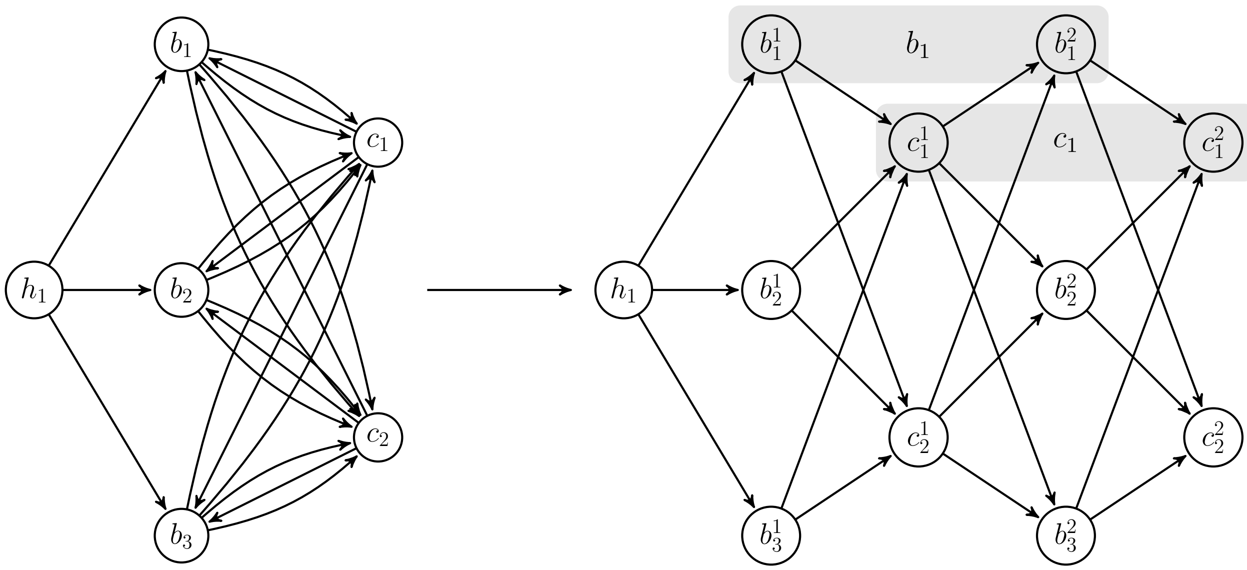

Figure 3.2: Illustration of a route network among initial resource location, evacuation areas, and safe areas for two trips to the evacuation location, three evacuation pick-up points, two shelters and two initial resource locations

the path with the lowest time consumption.

Integrating the passenger flows from Figure 3.1 with the routing network from Figure 3.2 for multiple resources produces the network visualized in Figure 3.3. Arcs with no flows are visualized in black, arcs with finite capacity in blue, and arcs with infinite capacity in green. Each node corresponding to a specific resource is illustrated in a different color and the boxes show the frame of a round trip for a resource. The remaining parts of the network work as described previously in Figures 3.1 and 3.2. Note that the network as illustrated in Figure 3.3 assumes full compatibility between resources and evacuation pick-up points and shelters. For limited compatibility, arcs in between nodes and resources that are incompatible have to be removed from the network. This network defines D-ICEP, and solving it with the objective of minimal route completion time generates an optimal evacuation route plan for the isolated community the provided data represents.

The D-ICEP can be considered a trip-expanded heterogeneous fleet variant of the location routing problem (LRP) with multiple node visits, where the total route plan length is minimized. Since the LRP, a generalization of the VRP, is NP-hard, so is the D-ICEP. The problem size and the required computational run time to find an optimal solution therefore increase exponentially when instances are added to the problem sets. A particular structural challenge in solving this problem is the heterogeneity and limited compatibility of the resource set. This makes the solution space more complex than for a symmetric resource set, leading to a higher risk of difficulties in solution discrimination for the solver. It also makes it more difficult to modify an existing solution through existing local search methods, as the routes in between different resources are not fully interchangeable. These challenges are also heavily influenced by the provided data set. Depending on how compatible the resources considered are with the pick-up and drop-off points, the number of route options varies a lot. A fully compatible resource set therefore has a lot more flexibility than a set with limited compatibility in choosing routes, but also requires higher computational effort. The following section describes the D-ICEP in mathematical terms. Table 3.1 introduces the notation for the formulation, followed by the problem formulation.

3.3.3 Deterministic Problem Formulation (D-ICEP)

Mathematical Formulation

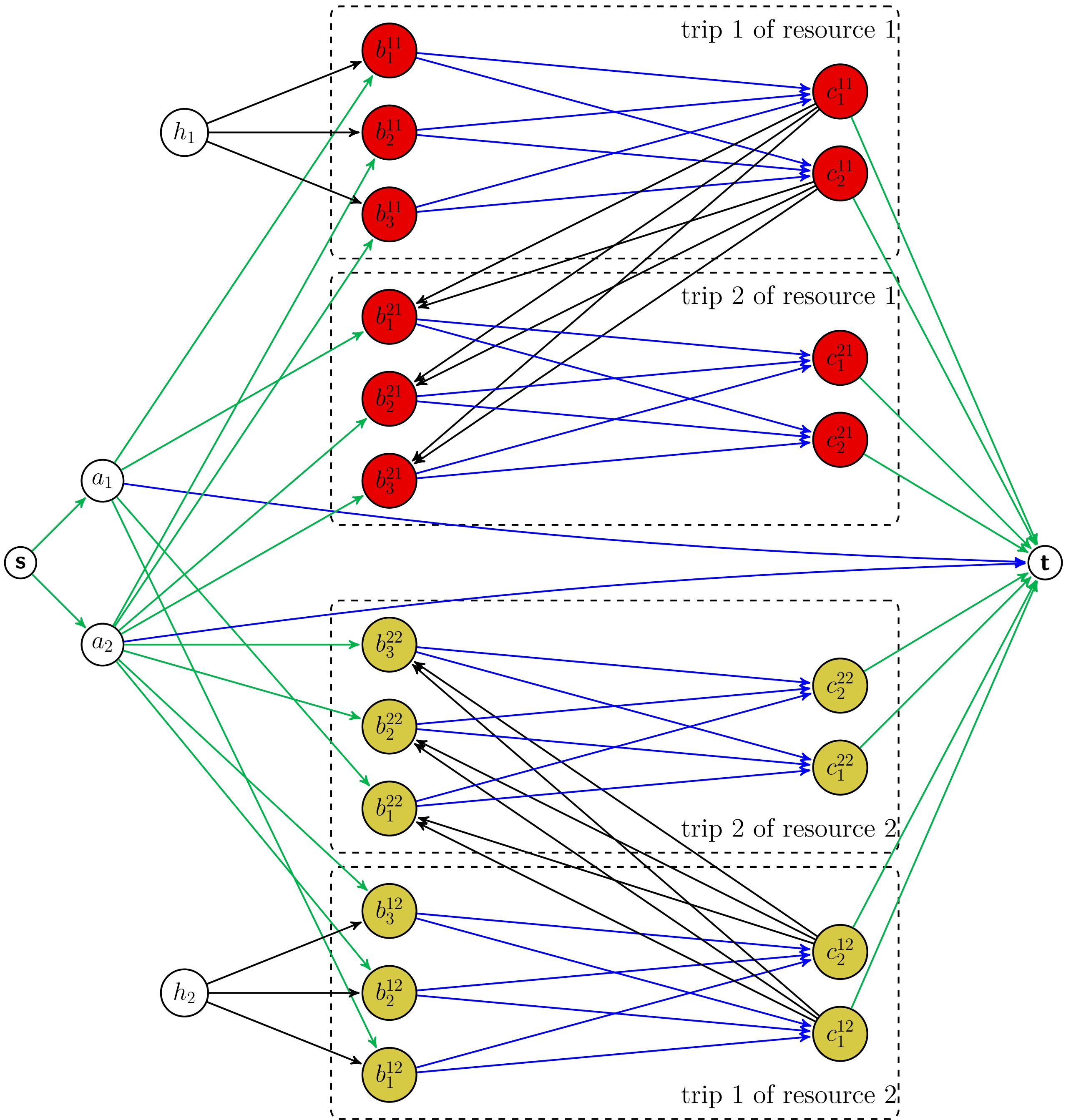

Figure 3.3: Illustration of a combined max-flow and routing problem for two trips per resource with three pick-up points, two shelters, and two fully compatible resources.

Table 3.1: Notation Key for D-ICEP

Sets	**Set Description**	**Parameters**	**Parameter Description**
$i \in I$	recovery resources	q_i	passenger capacity of resource i
$k \in K$	potential round trips per resource	u_i	time to availability of resource i
s	source node	o_i	loading time of resource i
$a \in A$	evacuation areas	p_i	unloading time of resource i
$b \in B$	pick-up points in evacuation area	d_a	evacuation demand at location a
$c \in C$	drop-off points in safe locations	g_a	max. no. of self-evacuations from area a
t	sink node	t^i_{hb}	$\frac{distance(h \to b)}{\text{empty travel speed of resource } i}$: cost of arc ζ^{1i}_{hb}
$h \in H$	initial resource locations	t^i_{bc}	$\frac{distance(b \to c)}{\text{loaded travel speed of resource } i}$: cost of arc γ^{ki}_{bc}
		t^i_{cb}	$\frac{distance(c \to b)}{\text{empty travel speed of resource } i}$: cost of arc δ^{ki}_{cb}, only $k = 1, ..., K-1$
Arcs	**Arc Description**	**Variables**	**Variable Description**
$\alpha_{sa} \in \bar{A}$	source s to area a	fl_{at}	flow on arc λ_{at}
$\beta^{ki}_{ab} \in \bar{B}$	area a to pick-up b of trip k for resource i	fl^{ki}_{ab}	flow on arc β^{ki}_{ab}
$\gamma^{ki}_{bc} \in \bar{\Gamma}$	pick-up b to drop-off c of trip k for resource i	fl^{ki}_{bc}	flow on arc γ^{ki}_{bc}
$\delta^{ki}_{cb} \in \bar{\Delta}$	drop-off c to pick-up b of trip k to trip $k+1$	fl^{ki}_{ct}	flow on arc ϵ^{ki}_{ct}
	for resource i, for $k = 1, ..., K-1$	w^{1i}_{hb}	$\{$**1**: if route on ζ^{1i}_{hb} selected, **0**: otherwise$\}$
$\epsilon_{ct} \in \bar{E}$	drop-off c to sink node t	x^{ki}_{bc}	$\{$**1**: if route on γ^{ki}_{bc} selected, **0**: otherwise$\}$
$\zeta^{1i}_{hb} \in \bar{Z}$	initial resource location h to pick-up b	y^{ki}_{cb}	$\{$**1**: if route on δ^{ki}_{cb} selected, **0**: otherwise$\}$
	for resource i, on trip 1	r	total evacuation time
$\lambda_{at} \in \bar{\Lambda}$	area a to sink node t, for private evacuations	s_i	route completion time of resource i

$$\min \quad r \tag{3.1}$$

$$s.t. \quad r \geq s_i \qquad \forall i \in I \tag{3.2}$$

$$\begin{aligned} s_i = & \sum_{\zeta_{hb}^{1i} \in \bar{Z}} \left(t_{hb}^{i} w_{hb}^{1i}\right) + \sum_{\gamma_{bc}^{ki} \in \bar{\Gamma}} \left(t_{bc}^{i} x_{bc}^{ki}\right) + \sum_{\delta_{cb}^{ki} \in \bar{\Delta}} \left(t_{cb}^{i} y_{cb}^{ki}\right) + \\ & \sum_{\zeta_{hb}^{1i} \in \bar{Z}} \left(u_i w_{hb}^{1i}\right) + \sum_{\zeta_{hb}^{1i} \in \bar{Z}} \left(o_i w_{hb}^{1i}\right) + \\ & \sum_{\delta_{cb}^{ki} \in \bar{\Delta}} \left(o_i y_{cb}^{ki}\right) + \sum_{\gamma_{bc}^{ki} \in \bar{\Gamma}} \left(p_i x_{bc}^{ki}\right) \qquad \forall i \in I \end{aligned} \tag{3.3}$$

$$fl_{at} \leq g_a \qquad \forall \lambda_{at} \in \bar{\Lambda} \tag{3.4}$$

$$fl_{bc}^{ki} \leq q_i(x_{bc}^{ki}) \qquad \forall \gamma_{bc}^{ki} \in \bar{\Gamma} \tag{3.5}$$

$$d_a = fl_{at} + \sum_{\beta_{jb}^{ki} \in \bar{B}: j=a} fl_{ab}^{ki} \qquad \forall a \in A \tag{3.6}$$

$$\sum_{\beta_{aj}^{ki} \in \bar{B}: j=b} fl_{ab}^{ki} = \sum_{\gamma_{jc}^{ki} \in \bar{\Gamma}: j=b} fl_{bc}^{ki} \qquad \forall b \in B, \forall k \in K, \forall i \in I \tag{3.7}$$

$$\sum_{\gamma_{bj}^{ki} \in \bar{\Gamma}: j=c} fl_{bc}^{ki} = fl_{ct}^{ki} \qquad \forall c \in C, \forall k \in K, \forall i \in I \tag{3.8}$$

$$\sum_{\zeta_{hb}^{1i} \in \bar{Z}} w_{hb}^{1i} \leq 1 \qquad \forall i \in I \tag{3.9}$$

$$\sum_{\gamma_{bc}^{ki} \in \bar{\Gamma}} x_{bc}^{ki} \leq 1 \qquad \forall i \in I, k \in K \tag{3.10}$$

$$\sum_{\delta_{cb}^{ki} \in \bar{\Delta}} y_{cb}^{ki} \leq 1 \qquad \forall i \in I, k \in K \setminus \{k = K\} \tag{3.11}$$

$$\sum_{h \in H} w_{hb}^{1i} = \sum_{c \in C} x_{bc}^{1i} \qquad \forall b \in B, \forall i \in I \tag{3.12}$$

$$\sum_{c \in C} y_{cb}^{(k-1)i} = \sum_{c \in C} x_{bc}^{ki} \qquad \forall b \in B, \forall i \in I, \forall k \in K \setminus \{k = 1\} \tag{3.13}$$

$$\sum_{b \in B} x_{bc}^{ki} \geq \sum_{b \in B} y_{cb}^{ki} \qquad \forall c \in C, \forall i \in I, \forall k \in K \setminus \{k = K\} \tag{3.14}$$

$$fl_{at} \geq 0 \qquad \forall \lambda_{at} \in \bar{\Lambda} \quad (3.15)$$

$$fl_{ab}^{ki} \geq 0 \qquad \forall \beta_{ab}^{ki} \in \bar{B} \quad (3.16)$$

$$fl_{bc}^{ki} \geq 0 \qquad \forall \gamma_{bc}^{ki} \in \bar{\Gamma} \quad (3.17)$$

$$fl_{ct}^{ki} \geq 0 \qquad \forall \epsilon_{ct}^{ki} \in \bar{E} \quad (3.18)$$

$$s_i \geq 0 \qquad \forall i \in I \quad (3.19)$$

$$r \geq 0 \qquad (3.20)$$

$$w_{hb}^{1i} \in \{0,1\} \qquad \forall \zeta_{hb}^{1i} \in \bar{Z} \quad (3.21)$$

$$x_{bc}^{ki} \in \{0,1\} \qquad \forall \gamma_{bc}^{ki} \in \bar{\Gamma} \quad (3.22)$$

$$y_{cb}^{ki} \in \{0,1\} \qquad \forall \delta_{cb}^{ki} \in \bar{\Delta} \quad (3.23)$$

The D-ICEP minimizes the total evacuation time r. The time constraint (3.2) lower bounds r with the highest route completion time of any resource, which is defined in (3.3). Capacity constraint (3.4) ensures that no more private self-evacuations can occur than denoted per location a. (3.5) ensures that the arc capacity is limited by the capacity of the corresponding resource, if the arc is selected as part of the resource route, and if no resource is selected, to be zero. Flow conservation constraints are (3.6) through (3.8), which ensure that the inflow of evacuees equals the outflows at every node except the source, sink and initial resource location nodes. Constraints (3.9) through (3.11) ensure that a maximum of one connection per route segment can be selected for each resource at a time. Route adjacency constraints (3.12) through (3.14) ensure that on every leg of a trip, the resources depart from the same node they arrived at on the previous leg. Route adjacency constraint (3.12) secures this for the arrival from the initial resource location and constraint (3.13) does this for all other round trips. Ultimately, route adjacency constraint (3.14) ensures that a resource does not have to return to an evacuation location if no potential evacuees are left. Lastly, variables (3.15) through (3.18) define all flows as non-negative continuous variables, variables (3.19) and (3.20) define the time-related variables as non-negative continuous, variables (3.21) through (3.23) define all route selections as binary variables.

Considerations on the Number of Round Trips

The resource set I, the number of evacuation areas A, pick-up points B, shelter drop-offs C, and initial resource locations H are usually fixed. Because of the heterogeneity of the resources, increasing the maximum number of round trips K per resource i by one trip, increases the size of the problem by the sum of pick-up and drop-off points multiplied by the number of resources. Therefore, choosing arbitrarily large sets will inflate the size of the problem and the computational effort, while not improving the results. However, if the resource and round trip sets are unreasonably small, the problem will cause a penalty for D-ICEP, since only a part of the population can be evacuated. A lower bound to the required size of the resource set I and the number of round trips K can be found if the requirement presented in (3.24) is met.

$$K \sum_{i \in I} q_i \geq \sum_{a \in A} d_a \tag{3.24}$$

This requirement is simple to obtain. However, it would only work for a single solution that does evacuate the entire population, that is only if every resource i would do exactly K round trips and if the full capacity of every resource i can be used on every trip k. This can be far from optimal and may not even be feasible in reality. However, it is not possible to determine by how much to increase K exactly without solving the D-ICEP problem by itself. It is therefore recommended to choose the number of round trips with a good safety margin in the above equation on the right hand side of the equation (RHS), e.g. through $K \sum_{i \in I} q_i \geq 2 \sum_{a \in A} d_a$. On the other end of the spectrum, an upper bound for the number of round trips can be calculated through the formula presented in (3.25). The maximum number of trips can be determined by the entire evacuation demand divided by the capacity of the resource with the smallest capacity, which represents the case if only this resource would have to complete the entire population from the area.

$$\max \ K \leq \left\lceil \frac{\sum_{a \in A} d_a}{q_i} \right\rceil \ \{i = \arg\min q_i\} \tag{3.25}$$

3.4 Heuristic Solution Approaches

3.4.1 Heuristic for D-ICEP

As Section 3.3.2 already described, the D-ICEP is NP-hard. For that reason, commercial solvers are only able to solve relatively small instances in a reasonable amount of time. This chapter aims to provide a first attempt to solve this problem in a fast and efficient way by using a structure-based heuristic to solve the D-ICEP. This is motivated by the fact that, during an emergency situation, time is so valuable that it is crucial to obtain results quickly, and approximately optimal results are acceptable.

Bish [25] provided a problem for bus evacuation with two heuristics that aim to solve the BEP efficiently. To solve D-ICEP efficiently, it was first attempted to solve the problem using the heuristics for the BEP. However, significant modifications were necessary. The compatibility between recovery resources and pick-up and drop-off nodes needs to be modeled, as well as the heterogeneity of the fleet in terms of capability and capacity. However, even with these modifications, these heuristics did not deliver solutions in any way close to the optimum, because the heuristic for the BEP takes advantage of the symmetry of the resource fleet, where all resources are considered identical and direct route swaps between resources are possible.

For the D-ICEP, the heterogeneity of the fleet and limited compatibility between nodes and resources make the problem a lot more complex and therefore require a different algorithm structure. While a structure that first generates an initial feasible solution first and then applies a local search to improve this solution can still be used, every step needs to include a feasibility check. In contrast to the BEP, the number of movements per resource does not play a large role; because of the fleet heterogeneity, a movement by one resource does not necessarily have the same impact as a movement by another resource. Hence, the expected evacuation time of a resource, along with its passenger capacity, have to be used as an allocation argument. This requires an inherently different structure of the local search heuristic. Algorithm 1 is the first phase of the newly developed heuristic. It takes as inputs the fleet of resources, the evacuation locations, pick-up and drop-off nodes, number of evacuees, a travel distance matrix, and an upper bound to the evacuation time. It returns an evacuation plan that provides a good starting point for a local search that minimizes the total evacuation time.

Algorithm 1: D-ICEP Heuristic Phase 1: Initial Feasible Solution Generation

```
Result: A feasible evacuation route plan
initialize all resources n, evacuees m as the remaining evacuees, pick-up nodes j, drop-off nodes k;
set a maximum time for the route plan;
while remaining evacuees ¿ 0 do
    for n in resources do
        for j in pick-up nodes do
            Calculate the distance to the current location of n;
        end
        Select the closest pick-up node to n as the next potential pick-up node;
        for k in drop-off nodes do
            Calculate the distance to the next potential pick-up node of n;
        end
        Select the closest drop-off node to the next potential pick-up node of n as the next
          potential drop-off node;
        Expected route time [n] := current route time[n] + time to next potential pick-up node +
          load time + time to next potential drop-off node + unload time
    end
    Select the resource a with the lowest expected route time;
    if expected route time [a] ≤ max route time then
        Next pick-up node [a]:= Next potential pick-up node[a];
        Next drop-off node [a]:= Next potential drop-off node[a];
        if remaining demand at next pick-up node ¿ capacity of resource a then
            load evacuees according to max capacity;
        else
            load evacuees according to remaining demand;
        end
        Update current route time [a];
    else
        break and return incomplete route plan;
    end
end
```

Algorithm 1 uses a step-wise greedy structure that starts with the initial set-up at the beginning of an evacuation and greedily adds additional trips for each resource until all people are allocated to a trip to safety. It considers the initial time to availability of each resource in the initial route time of each resource. While there are still people left, the algorithm generates a potential next trip to the evacuation area and back for each resource, based on where there is demand, and which additional trip would result in the shortest expected total route time. The heuristic then selects the resource with the lowest expected total route time and makes the addition of this trip to its route permanent if its expected route time does not exceed the maximum evacuation time given as an input. The evacuees are then allocated based on the capacity of the resource. If the trip cannot be added without violating the maximum route time, then the while loop is interrupted and the route plan is returned without evacuating all the population. The provided route plan gives a feasible solution to the D-ICEP. The computational complexity can be identified as $O(mn(j+k))$ in the worst case, where m represents the number of evacuees, n represents the number of resources, j represents the number of pick-up nodes, and k represents the number of drop-off nodes. However, this worst case only applies if the capacity of a resource is 1. In the real world, resources can hold multiple passengers, so using a real-world data set reduces the time complexity significantly.

Because this first phase is a greedy algorithm, the solution is not guaranteed to be optimal. A local search heuristic was developed that tries to find better solutions by allocating remaining evacuees, reallocating evacuees to additional trips of other resources, and swapping entire trips between resources. Algorithm 2 describes this second phase of the heuristic. Algorithm 3, 4, and 5 describe auxiliary functions that describe the functionality of each step of Algorithm 2.

Algorithm 2 uses multiple strategies sequentially to improve the solution generated by Phase 1. It consists of a three-step structure that continues iterating through these steps until no improvement can be found. It considers the differences in speed profile, dock compatibility, and passenger capacity among resources to find solutions. The initialization starts with the route plan generated by algorithm 1 and the maximum time limit. If remaining evacuation demand exists that could not be accommodated with the route plan from Algorithm 1, then Algorithm 2 at first tries to allocate the remaining evacuees using auxiliary function 3. It does this by exploring, for every pick-up node with remaining evacuees, whether there is

Algorithm 2: D-ICEP Heuristic Phase 2: Improvement through Local Search

Result: An improved feasible evacuation route plan
Input a feasible route plan, max route time;
Initialize resources n and pick-up nodes j and drop-off nodes k accordingly;
Extra demand added := re-allocation added := swap added := True;
while *Extra demand added = True OR re-allocation added = True OR swap added = True* **do**
    1. Try allocating extra demand;
    feasible route plan, extra demand added := D-ICEP Heuristic Phase 2 Auxiliary function 1(feasible route plan, extra demand added);
    2. Try re-allocating passengers from the longest route;
    feasible route plan, re-allocation added := D-ICEP Heuristic Phase 2 Auxiliary Function 2(feasible route plan, re-allocation added);
    3. Try swapping routes between resources to decrease evacuation time;
    feasible route plan, swap added := D-ICEP Heuristic Phase 2 Auxiliary Function 3(feasible route plan, swap added)
end

Algorithm 3: D-ICEP Heuristic Phase 2 Auxiliary function 1: Extra demand allocation

Result: feasible route plan; Extra demand added
Input a feasible route plan, max route time;
Initialize resources n and pick-up nodes j and drop-off nodes k accordingly;
Extra demand added := False;
for *j in pick-up nodes with remaining demand* **do**
    Sort resources by current route time in ascending order; $n := 1$;
    while *extra demand left AND not all resources checked* **do**
        if *any trip of resource n serves j and has excess capacity* **then**
            Allocate extra demand until capacity of n is exhausted; Extra demand added := True;
        end
        $n := n + 1$;
    end
end

Algorithm 4: D-ICEP Heuristic Phase 2 Auxiliary Function 2: Re-allocate passengers from the longest route to existing routes of other resources

```
Result: feasible route plan; re-allocation added
Input a feasible route plan, max route time;
Initialize resources n and pick-up nodes j and drop-off nodes k accordingly;
Select the resource l with the longest evacuation time as the limiting resource;
Re-allocation added := False; n := 1; z := no. of trips on resource l;
while Re-allocation added = False AND z ≥ no. of trips on resource l do
    while Trip z of l has remaining passengers AND n ≤ no. of alternative resources do
        if any trip of alternative resource n serves j and has excess capacity then
            Re-allocate passengers; if no more passengers then break loop;
        end
        if Trip z of l has remaining passengers AND an additional trip of resource n serving
          pick-up node j and the closest drop-off node k can be added without exceeding the current
          evacuation time then
            Re-allocate passengers; if no more passengers then break loop;
        end
        n := n + 1;
    end
    if trip z of resource l has no more passengers AND the total route time through this change <
      current route time then
        Re-allocation added := True; make re-allocation permanent; break loop;
    else
        Reverse the re-allocation of trip z;
        z := z − 1;
    end
end
```

Algorithm 5: D-ICEP Heuristic Phase 2 Auxiliary Function 3: Swap routes in between resources and re-allocate passengers

```
Result: feasible route plan; swap added
Input a feasible route plan, max route time, re-allocation added;
Initialize resources n and pick-up nodes j and drop-off nodes k accordingly;
swap added := False;
if Re-allocation added = False then
    Swap added := False; n := 1; z := no. of trips on resource l;
    while Swap added = False AND z ≥ no. of trips on resource l do
        while n ≤ no. of alternative resources do
            if any trip of alternative resource n can be swapped with trip z of l then
                Perform the swap; Swap added := True; break loop;
            else
                n := n + 1;
            end
            z := z − 1;
        end
    end
end
```

extra capacity on other resources that visit this pick-up node and whether these remaining evacuees can be reallocated while the plan still conforms to the maximum time limit. In its second and third steps, the algorithm tries to shorten the total evacuation time. The second step (auxiliary function 4) starts with the last trip of the resource with the longest evacuation time, here called the limiting resource, and tries to reallocate its passengers. For the chosen trip of the limiting resource, it first tries to allocate the passengers to excess capacity on existing trips of alternative resources. If this is not sufficient, it checks whether an alternative resource can perform an additional trip to the corresponding location and pick up some of the passengers, if this will not increase the current evacuation time. The algorithm continues iterating through the alternative resources until all passengers have been reallocated and the total evacuation time has been improved. If this is not the case after checking all alternative resources, the reallocation is canceled, and step 2 is repeated on another trip of the limiting resource.

If the second step does not lead to an improvement, the third step (auxiliary function 4) tries to swap trips between the limiting resource and alternative resources to reduce the overall evacuation time. For example, if resource 1 was serving route $B1 \rightarrow C1 \rightarrow B1 \rightarrow C2$, and resource 2 was serving $B2 \rightarrow C2 \rightarrow B1 \rightarrow C3$, a successful trip switch of the first trip would result in resource 1 performing $B2 \rightarrow C2 \rightarrow B1 \rightarrow C2$ and resource 2 performing $B1 \rightarrow C1 \rightarrow B1 \rightarrow C3$. Again starting with the last trip of the limiting resource, the algorithm stops once an improvement is found or once all trips of all alternative resources have been tested.

After every iteration, the list of resources gets updated. If, after an improvement, a different resource contains the most time-consuming route, this one will become the limiting resource. The algorithm keeps iterating until none of the steps lead to an improvement of the solution. The theoretical run time complexity of this algorithm will be assessed for each step at first. For step 1, the worst case run-time complexity is $O(mnj)$, where m is the number of evacuees, n is the number of resources, and j the number of pick-up nodes. For step 2, the approximate worst case run-time complexity is $O(m^2nk)$, where k is the number of pick-up nodes. For the worst case, step 3 provides an approximate computational complexity of $O(m^2nj)$. This results in a run time of $O(m^2nj)$, or $O(m^2nk)$ per iteration of the outer while loop, depending on whether set j or set k is larger. Similarly to phase 1 of the heuristic, note that the algorithm does not scale 1:1 with the number of evacuees, since resources generally have more than a passenger capacity of 1 and thus the number of trips is a fraction of the evacuee number. Furthermore, the fact that each step stops as soon as a valid improvement has been found makes the algorithm much faster in the average case. It is also not trivial to determine the complexity of the outer while loop, since it iterates until no more improvements can be found. Because the run time complexity is difficult to estimate theoretically, the next section provides numerical experiments on some test data sets.

3.4.2 Numerical Experiments

The two-phase heuristic introduced in the previous section was benchmarked against an implementation of the D-ICEP in the Pyomo interface with the Gurobi 9.0 commercial solver. Table 3.2 illustrates some key characteristics that describe the size of the test data sets. A variety of small to medium-sized data examples that reflect realistic scenarios for emergency evacuations of isolated areas were chosen for the benchmark. Table 3.3 describes the results of the computational tests, and Figure 3.4 visualizes them in charts. To account for the effect of the local search in the second phase of the heuristic, separate tests were conducted using only phase 1 and using both phase 1 and 2. All computational runs were completed on a MacBook Pro with a 2.6 GHz Dual-Core Intel Core i5 CPU. A run time limit of 3600 seconds was enforced.

Table 3.3 shows that the presented D-ICEP heuristic was able to produce reasonable solutions for all but the smallest data sets, and, in several cases, also reached the optimal solution. Given that the presented heuristic is greedy, it could explore all areas of the solution space, and was not guaranteed to find the global optimum. In cases D4, D5, D6, D9, and D10, the first phase was able to reach the optimal solution. In cases D3 and D7, the first phase was not able to generate an optimal solution by itself, and the optimal solution could be

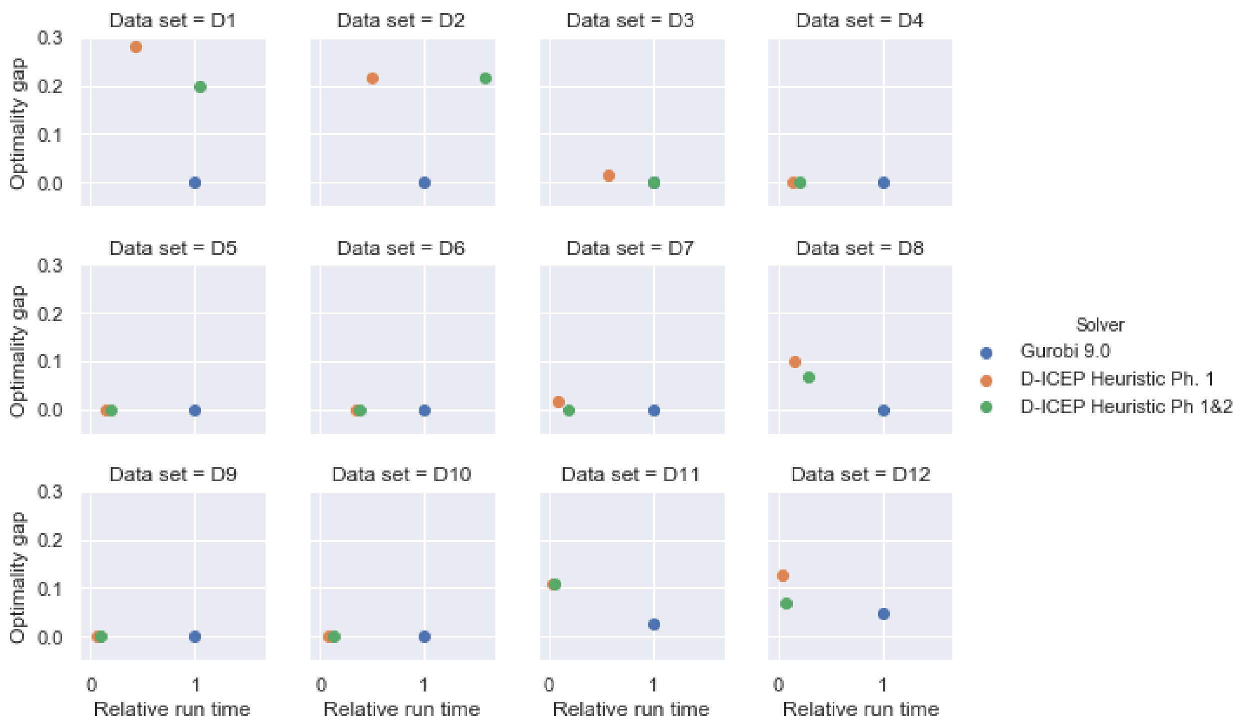

Figure 3.4: Test results for the D-ICEP: Run time of the D-ICEP phase 1 and both phase 1 and 2 relative to the Gurobi 9.0 run time vs. optimality gap of solution

Table 3.2: Test Data Sets for D-ICEP Heuristic Evaluation

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12
Sets							*Set size*					
Resources	6	6	6	6	8	8	20	20	20	20	20	20
Resource loc.	1	1	3	3	3	3	3	3	3	3	3	3
Evac. locations	2	2	2	2	3	3	2	2	1	1	5	5
Pick-up points	4	2	3	3	4	4	4	3	2	2	8	8
Drop-off points	2	2	3	3	3	3	3	3	3	3	3	3
Round trips	6	6	8	8	8	8	20	20	20	20	20	20
Parameters							*Setting*					
Penalty							5,000					
Max route time							600					
Variable Type							*Quantity*					
Continuous Var.	303	157	446	446	783	785	4,829	3,628	1,124	1,124	9,639	9,639
Binary Var.	312	156	450	450	800	800	4,880	3,660	1,220	1,220	9,760	9,760

found when the local search algorithm from phase 2 was also used. In cases D1, D8, D11, and D12, neither using only phase 1, nor both phase 1 and 2 was sufficient to reach the optimal solution, but phase 2 improved the solution quite significantly and reduced the optimality gap for D1, D8, and D12. Using only the first phase of the heuristic led to considerably faster run times, and, in many cases, better solutions. With regards to algorithm run time, observe that for most smaller problems (D1-D3), the heuristic did not lead to significant improvements in run time, and the desire for a good solution quality makes solving problems of this size with a commercial solver more attractive. However, the run time of Gurobi 9.0 increased significantly over a growing problem size, as the larger test cases showed. While the heuristic run time increased, too, its growth rate was much smaller in practice than the worst case theoretical run time from the previous section hinted. Note also that the experiment results show that the local search procedure only ran for a few iterations until it could not find a better solution, which demonstrated a problem from the previous question that the number of iterations of phase 2 of the heuristic was non-trivial to estimate. This showed that, for larger problem sizes, while the presented heuristic is not guaranteed to find a global optimum, it produces a solution much more quickly than a commercial solver does.

Table 3.3: Result Summary Data D-ICEP Heuristic Experiments

Data	Implementation	Objective	Runtime	Iterations	Opt. Gap	Runtime Gap
	Gurobi	72	2.24s	-	-	-
D1	Heuristic Phase 1	100	0.95s	-	28.00%	-57.49%
	Heuristic Phase 1&2	90	2.34s	1	20.00%	4.70%
	Gurobi	120	2.49s	-	-	-
D2	Heuristic Phase 1	153.33	1.24s	-	21.74%	-50.32%
	Heuristic Phase 1&2	153.33	3.92s	1	21.74%	57.43%
	Gurobi	131.66	3.17s	-	-	-
D3	Heuristic Phase 1	133.66	1.81s	-	1.50%	-42.90%
	Heuristic Phase 1&2	131.66	3.18s	2	-	0.32%
	Gurobi	81.67	4.38s	-	-	-
D4	Heuristic Phase 1	81.67	0.63s	-	-	-85.62%
	Heuristic Phase 1&2	81.67	0.89s	1	-	-79.68%
	Gurobi	88.33	7.35s	-	-	-
D5	Heuristic Phase 1	88.33	1.02s	-	-	-86.12%
	Heuristic Phase 1&2	88.33	1.48s	1	-	-79.86%
	Gurobi	93.6	5.32s	-	-	-
D6	Heuristic Phase 1	93.6	1.86s	-	-	-65.04%
	Heuristic Phase 1&2	93.6	2.07s	1	-	-61.09%
	Gurobi	96	98.27s	-	-	-
D7	Heuristic Phase 1	97.59	8.83s	-	1.63%	-91.01%
	Heuristic Phase 1&2	96	17.85s	2	-	-81.84%
	Gurobi	153.33	125.75s	-	-	-
D8	Heuristic Phase 1	170.33	20.24s	-	9.98%	-83.90%
	Heuristic Phase 1&2	164.24	17.85s	2	6.64%	-70.74%
	Gurobi	77.2	50.53s	-	-	-
D9	Heuristic Phase 1	77.2	2.96s	-	-	-94.14%
	Heuristic Phase 1&2	77.2	4.61s	2	-	-90.88%
	Gurobi	81.6	235.95s	-	-	-
D10	Heuristic Phase 1	81.6	20.44s	-	-	-91.34%
	Heuristic Phase 1&2	81.6	32.72s	2	-	-86.13%
	Gurobi	252.24*	3600s*	-	(lb 245.93) 2.64%	-
D11	Heuristic Phase 1	275.6	113.45s	-	10.7%**	-96.85%***
	Heuristic Phase 1&2	275.6	209.95s	1	10.7%**	-94.17%***
	Gurobi	276.24*	3600s*	-	(lb 262.99) 4.80%	-
D12	Heuristic Phase 1	300.66	134.83s	-	12.56%**	-96.25%***
	Heuristic Phase 1&2	282.56	249.42	3	6.95%**	-93.07%***

*Results were aborted after 3600s; the best available solution, optimality gap and lower bound are displayed.
**Optimality gap estimated based on lower bound provided by Gurobi 9.0.
***Run-time reduction compared to run time limit of 3600s.

Therefore, when solving a larger instance of the D-ICEP, the decision whether to use a commercial solver or the presented heuristic should be based on whether the solution quality or the run time is more important. In emergency situations having a good solution quickly is often preferable to waiting for a better solution. In the experiments, none of the steps in either phase 1 or phase 2 of the heuristic were parallelized in execution, but rather executed sequentially. Hence, there is still potential for improvement when using multi-core processors that can execute process steps in parallel. Nevertheless, it is not possible to establish a reliable bound on how close the heuristic will get to the optimal solution, because that is dependent on the exact problem instance and could only be approximated by conducting additional experiments with various data sets. When it tackles bigger problem sizes, the heuristic's run time increases, but it is able to handle larger problem sizes in reasonable time with the trade-off that the global optimal solution might not be found. Further expanding the heuristic to explore additional parts of the solution space might lead to a better solution quality, but will also increase the run time further, thus resulting in a trade-off. An alternative approach to finding the global optimum in approximation without increasing run time could be to use a metaheuristic.

3.5 Conclusions

This chapter introduced the D-ICEP, which aims to improve emergency planning by optimizing routing for the evacuation of isolated communities. The special considerations of D-ICEP on heterogeneous fleets, limited compatibility between nodes and resources, and alternative ways of evacuation make the D-ICEP more difficult to solve efficiently than previous models, but they enable emergency planners and researchers to develop an evacuation plan that is applicable to remote areas. This is the first routing model developed for planning the evacuation of isolated communities with a coordinated set of resources and therefore delivers an important contribution for research and practice on this topic. A two-phase structure-based greedy search heuristic was presented for the D-ICEP. Computational experiments showed that this heuristic is able to significantly reduce the run time of the algorithm and it found the optimal solution in some cases or got reasonably close, but this was not the case for all test data sets.

Future research could focus on the following model extensions:

- Relaxing the constraints that allow resources to visit only a single evacuation pick-up point per trip.
- A manual prioritization feature that allows the modeler to specify a specific region to be evacuated first. This can be helpful if a certain region is closer to the danger zone and needs to be prioritized during evacuation.
- Expanding the model to include the transportation of evacuees to the pick-up nodes.
- Expansion to a stochastic model to allow for scenario-based evacuation planning.

There are several possible strategies for modeling the movement of evacuees to pick-up locations. The D-ICEP could be integrated with a flow network that either reconfigures the demand at each location, similar to Wang and Wang [145], or simulates an arrival rate. Or, rolling horizon implementations of D-ICEP could be used that model the arrival of evacuees through sequential updates, resolving the remaining, not yet executed, part of the solution, every time new information is obtained. Robust optimization could be another approach. Chapter 5 provides a first attempt in this direction.

Moreover, the model could be expanded to a scenario-based planning model, such that uncertainties in the input data can be handled and incorporated into the outputs. This way, the model could be made more useful for long term evacuation planning. Chapter 4 expands the model formulation to a two-stage stochastic program with recourse to make it suitable for planning.

3.6 Acknowledgements

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Chapter 4

THE ISOLATED COMMUNITY EVACUATION PROBLEM FOR PLANNING PURPOSES

The work presented in this chapter represents the second half of a research manuscript that has been published under the title ”The Isolated Community Problem with Mixed Integer Programming” in *Transportation Research Part E: Logistics & Transportation Review* and is co-authored with Dr. Anne V. Goodchild [91]. This chapter is not the copy of record and may not exactly replicate the authoritative document that was published.

4.1 Abstract

With the introduction of the Deterministic Isolated Community Evacuation Problem (D-ICEP), a new model formulation was introduced to optimize the route plan for the evacuation of an isolated community. While this is a useful baseline tool, it requires emergency researchers and planners to have certain knowledge over the input data and parameters. Particularly during emergency planning this is often not a realistic assumption, as communities need to prepare for a variety of potential scenarios and need to make sure appropriate decisions are made regarding the selection of appropriate evacuation resources. For that reason, this chapter expands the D-ICEP into a two-stage stochastic problem that allows scenario-based optimal resource planning while also ensuring minimal evacuation time (S-ICEP). In addition, objective functions with a varying degree of risk are provided, and the sensitivity of the model to different objective functions and problem sizes is presented through numerical experiments. A structure-based heuristic for the S-ICEP, based on the previously presented D-ICEP heuristic is introduced and tested with experiments on synthetic data. The resulting planning model, provides emergency planners with a method to systematically plan for the

evacuation of a community under a variety of scenarios and to take actions to improve the resilience of their communities accordingly.

4.2 Introduction

4.2.1 Motivation

The development of the Deterministic Isolated Community Evacuation Problem (D-ICEP) introduced in Chapter 3 has provided emergency planners and researchers with a routing model that allows for route optimization of isolated community evacuation. The model is capable of providing an optimal route plan for a heterogeneous set of recovery resources with pick-ups and drop-offs in multiple, potentially disconnected locations. A key assumption of the D-ICEP is that the input data is certain. This includes the number of evacuees, the distribution of evacuees, and the location of the disaster. While planning for evacuations, however, emergency planners have to prepare communities for a variety of potential disasters, which could affect different locations and/or different populations. Therefore, the population size and distribution is usually highly uncertain and the assumption on certain evacuee numbers and locations is often unrealistic and requires special attention [135]. Furthermore, evacuation planning includes not only the creation of evacuation plans, but also preventive planning regarding the resources required to execute the evacuation to make communities more resilient [105]. Ideally this is achieved in a cost-efficient way. This results in a new research question:

1. *Which resources need to be secured to be prepared for quick evacuation over a variety of potential disaster scenarios?*

Any decision made to answer this research question has to be made without exact information about the nature of the disaster or evacuation demand patterns. To answer this question, a stochastic expansion of the D-ICEP was designed (S-ICEP), which adds a disaster-independent resource selection decision. A two-stage stochastic programming formulation with recourse makes it possible to separate the problem into two stages, separated by a probabilistic event: the disaster causing the evacuation. The S-ICEP therefore provides emergency planning teams with a way to plan for evacuations and to evaluate the community's level of preparedness for evacuation scenarios of different natures. Furthermore, decision makers can choose between multiple objective functions for the S-ICEP that balance the conflicting objectives of time and cost in different ways. An analysis with the S-ICEP can help communities decide whether the current infrastructure is sufficient to support a timely evacuation. For example, it will help to identify which areas are most vulnerable to disaster, and whether it could be helpful to reactivate a decommissioned air strip, upgrade docking infrastructure for vessels, or whether additional recovery resources need to be held available to be prepared for a disaster. It could also help identify which gathering points people should travel to, to ensure evacuation can be executed as quickly as possible. Investigating all potential managerial insights and the resulting requirements for data inputs and disaster scenario design in practice would go beyond the scope of this chapter and is instead addressed in Chapter 6 through a real-world case study. In addition to introducing the model formulations, bounds are established on some key parameters that illustrate the model dynamics of both formulations, and some numerical experiments are provided. Like for the D-ICEP in Chapter 3, a structure-based heuristic is introduced for the S-ICEP to solve the problem more efficiently.

4.2.2 Contributions

Expanding on the considerations on the D-ICEP in Chapter 3, the contributions of this chapter to research are the following.

1. The expansion of the D-ICEP to a two-stage stochastic program with recourse (S-ICEP) allows planning for emergency evacuations by incorporating uncertainty through a set of scenarios and thus makes it useful for emergency planners and researchers in practice;
2. A variety of objective functions for S-ICEP allow the decision makers to prioritize between time and cost efficiency in planning for emergency evacuations;
3. The introduction of a local search heuristic provides modelers and planners with an efficient solution approach that provides a faster alternative to the use of a commercial solver.

The remainder of this chapter covers the following topics: In Section 4.3.1 assumptions about the S-ICEP in addition to the D-ICEP are introduced. The mathematical formulation of the S-ICEP is introduced in Section 4.3.2. Different objective functions are also introduced that can be used for different policy implications and evaluated for their effects on the solution provided by the model. On the basis of the deterministic heuristic presented in Chapter 3, a heuristic to solve the S-ICEP is presented and numerical benchmarking experiments are shown in Section 4.4. Section 4.5 concludes the chapter with remarks on learnings and future directions for research.

4.3 Problem Formulation

4.3.1 Assumptions

The following assumptions in addition to the ones presented for D-ICEP in Chapter 3 have to be made for S-ICEP to support the desired behavior.

1. The exact disaster nature and time of occurrence is unknown.
2. The evacuation population in the area is uncertain because of seasonal fluctuation.
3. Weather conditions can influence travel times for resources.
4. The planning authority aims to select an optimal set of resources that minimizes expected evacuation time for a variety of disaster scenarios, while considering cost efficiency.

4.3.2 Expansion to a Stochastic Problem

During the planning stage, it is not possible to know how a disaster will turn out and where and how many people have to be evacuated. The underlying uncertainty affects a variety of factors: which resources are actually useful, the route choices the resources have to take, how many trips each of the resources have to complete, and ultimately what the resulting evacuation time is. Emergency planners want to optimally select a fleet of recovery resources that can handle a variety of evacuation scenarios, given the ability of a resource to reduce evacuation time and offer competitive cost structures. The model takes into account the costs of choosing a resource as part of the fleet, variable operating costs, such as labor and fuel, as well as the calculated cost of the loss of a human life. This needs to be considered to avoid minimizing evacuation time at the cost of not evacuating the entire population. Each evacuation resource needs to be determined before a disaster occurs based on its capabilities, given uncertainty about the location, number of evacuees, and the weather conditions at the time of the disaster. Typical optimization approaches to incorporate uncertainty are:

1. Evaluate the uncertainty by constructing an expected-value problem
2. (Multi-stage) stochastic dynamic programming
3. Robust optimization
4. Two-stage stochastic programs with recourse

The results from deterministic models oversimplify the model since they do not consider variety in the disaster nature. Further, the complexity of using stages of evolving knowledge that require stochastic dynamic programming solutions [17] is not considered to be necessary for the version of the S-ICEP presented in this chapter. Therefore, these two methods are not ideal for the S-ICEP. While robust optimization offers advantages by providing a robust solution [78,136], the high uncertainty over the disaster nature considered could lead to overly conservative solutions and thus lead to a much larger resource set than actually needed. Two-stage stochastic programs with recourse [131], on the other hand, offer the flexibility to design problems under uncertainty distributions. As an alternative to parameter distributions, two-stage stochastic programs also allow for the design of specific, probability-weighted scenarios. Scenario-based planning techniques can help first responders to clearly separate different disaster outcomes, for example between evacuations during different seasons of the year. With stochastic recourse models, differences among scenarios can be simply accounted for by using scenario specific travel distance and incidence matrices. Therefore, two-stage stochastic programs with recourse are a good fit for S-ICEP.

When expanding the D-ICEP into a two-stage stochastic programming framework, the resource fleet selection needs to be scenario-independent and, hence, needs to be decided in the first stage of the model. The second stage of the model must then find the optimal route plan for each scenario of interest, given the resource fleet selected in the first stage. Using the recourse component, the S-ICEP can select the resource fleet that provides minimal expected evacuation time over multiple scenarios, while considering cost imposed by the resource configuration. This results in a model structure that solves the D-ICEP in its second stage for each scenario of interest. Once the disaster happens, and the uncertainty is revealed, the D-ICEP has to be solved, with the resource set fixed to the decision made in the first stage of the problem. Since the S-ICEP contains the D-ICEP in its second stage, the challenges and parameter considerations of the D-ICEP also apply to the S-ICEP. This also applies to the complexity of the problem, which is therefore also NP-hard.

Section 4.3.3 introduces the S-ICEP as an expansion of the D-ICEP with the key notation for S-ICEP in Table 4.1.

4.3.3 Stochastic Problem Formulation (S-ICEP)

Mathematical Formulation

Table 4.1: Notation Key for S-ICEP

Sets	Set Description	Parameters	Parameter Description
$i \in I$	recovery resources	q_i	passenger capacity of resource i
$k \in K$	potential round trips per resource	u_i	time to availability of resource i
s	source node	o_i	loading time of resource i
$a \in A$	evacuation areas	p_i	unloading time of resource i
$b \in B$	pick-up points in evacuation area	d_a	evacuation demand at location a
$c \in C$	drop-off points in safe locations	g_a	max. no. of self-evacuations from area a
t	sink node	t^i_{hb}	$\frac{distance(h \to b)}{\text{empty travel speed of resource } i}$: cost of arc ζ^{1i}_{hb}
$h \in H$	initial resource staging locations	t^i_{bc}	$\frac{distance(b \to c)}{\text{loaded travel speed of resource } i}$: cost of arc γ^{ki}_{bc}
$\xi \in \Xi$	evacuation scenarios	t^i_{cb}	$\frac{distance(c \to b)}{\text{empty travel speed of resource } i}$: cost of arc δ^{ki}_{cb}, only $k = 1, ..., K-1$
		cf_i	fixed cost parameter of resource i
		cv_i	variable cost parameter of resource i
		T	upper time limit for r
		P	penalty cost for non-evacuated person

Arcs	Arc Description	Variables	Variable Description
$\alpha_{sa} \in \bar{A}$	source s to area a	fl_{at}	flow on arc λ_{at}
$\beta^{ki}_{ab} \in \bar{B}$	area a to pick-up b of trip k for resource i	fl^{ki}_{ab}	flow on arc β^{ki}_{ab}
$\gamma^{ki}_{bc} \in \bar{\Gamma}$	pick-up b to drop-off c of trip k for resource i	fl^{ki}_{bc}	flow on arc γ^{ki}_{bc}
$\delta^{ki}_{cb} \in \bar{\Delta}$	drop-off c to pick-up b of trip k to trip $k+1$	fl^{ki}_{ct}	flow on arc ϵ^{ki}_{ct}
	for resource i, for $k = 1, ..., K-1$	w^{1i}_{hb}	{**1**: if route on ζ^{1i}_{hb} selected, **0**: otherwise}
$\epsilon_{ct} \in \bar{E}$	drop-off c to sink node t	x^{ki}_{bc}	{**1**: if route on γ^{ki}_{bc} selected, **0**: otherwise}
$\zeta^{1i}_{hb} \in \bar{Z}$	initial resource location h to pick-up b	y^{ki}_{cb}	{**1**: if route on δ^{ki}_{cb} selected, **0**: otherwise}
	for resource i, on trip 1	r	total evacuation time
$\lambda_{at} \in \bar{\Lambda}$	area a to sink node t, for private evacuations	s_i	route completion time of resource i
		z_i	{**1**: if resource i selected, **0**: otherwise}
		n_a	number of non-evacuated people at area a

$$\min \quad \frac{\sum_{i\in I} cf_i(z_i)}{\sum_{i\in I}(cf_i + cv_i(T))} + \mathbb{E}[C(z,\xi)] \tag{4.1}$$

$$s.t. \quad z_i \in \{0,1\} \qquad \forall i \in I \tag{4.2}$$

where

$$C(z,\xi) := \min \quad r + \frac{\sum_{i\in I} cv_i(s_i)}{\sum_{i\in I}(cf_i + cv_i(T))} + P\sum_{a\in A} n_a \tag{4.3}$$

$$s.t. \quad r \geq s_i \qquad \forall i \in I \tag{4.4}$$

$$s_i = \sum_{\zeta^{1i}_{hb}\in\bar{Z}} \left(t^i_{hb} w^{1i}_{hb}\right) + \sum_{\gamma^{ki}_{bc}\in\bar{\Gamma}} \left(t^i_{bc} x^{ki}_{bc}\right) + \sum_{\delta^{ki}_{cb}\in\bar{\Delta}} \left(t^i_{cb} y^{ki}_{cb}\right) + \sum_{\zeta^{1i}_{hb}\in\bar{Z}} \left(u_i w^{1i}_{hb}\right) + \sum_{\zeta^{1i}_{hb}\in\bar{Z}} \left(o_i w^{1i}_{hb}\right) + \sum_{\delta^{ki}_{cb}\in\bar{\Delta}} \left(o_i y^{ki}_{cb}\right) + \sum_{\gamma^{ki}_{bc}\in\bar{\Gamma}} \left(p_i x^{ki}_{bc}\right) \qquad \forall i \in I \tag{4.5}$$

$$r \leq T \tag{4.6}$$

$$fl_{at} \leq g_a \qquad \forall \lambda_{at} \in \bar{\Lambda} \tag{4.7}$$

$$fl^{ki}_{bc} \leq q_i(x^{ki}_{bc}) \qquad \forall \gamma^{ki}_{bc} \in \bar{\Gamma} \tag{4.8}$$

$$fl^{ki}_{bc} \leq q_i(z_i) \qquad \forall \gamma^{ki}_{bc} \in \bar{\Gamma} \tag{4.9}$$

$$d_a(\xi) = fl_{at} + \sum_{\beta^{ki}_{jb}\in\bar{B}:j=a} fl^{ki}_{ab} + n_a \qquad \forall a \in A \tag{4.10}$$

$$\sum_{\beta^{ki}_{aj}\in\bar{B}:j=b} fl^{ki}_{ab} = \sum_{\gamma^{ki}_{jc}\in\bar{\Gamma}:j=b} fl^{ki}_{bc} \qquad \forall b \in B, \forall k \in K, \forall i \in I \tag{4.11}$$

$$\sum_{\gamma^{ki}_{bj}\in\bar{\Gamma}:j=c} fl^{ki}_{bc} = fl^{ki}_{ct} \qquad \forall c \in C, \forall k \in K, \forall i \in I \tag{4.12}$$

$$\sum_{\zeta^{1i}_{hb}\in\bar{Z}} w^{1i}_{hb} \leq z_i \qquad \forall i \in I \tag{4.13}$$

$$\sum_{\gamma^{ki}_{bc}\in\bar{\Gamma}} x^{ki}_{bc} \leq z_i \qquad \forall i \in I, k \in K \tag{4.14}$$

$$\sum_{\delta^{ki}_{cb}\in\bar{\Delta}} y^{ki}_{cb} \leq z_i \qquad \forall i \in I, k \in K \setminus \{k = K\} \tag{4.15}$$

$$\sum_{h\in H} w_{hb}^{1i} = \sum_{c\in C} x_{bc}^{1i} \qquad \forall b \in B, \forall i \in I \quad (4.16)$$

$$\sum_{c\in C} y_{cb}^{(k-1)i} = \sum_{c\in C} x_{bc}^{ki} \qquad \forall b \in B, \forall i \in I, \forall k \in K \setminus \{k=1\} \quad (4.17)$$

$$\sum_{b\in B} x_{bc}^{ki} \geq \sum_{b\in C} y_{cb}^{ki} \qquad \forall c \in C, \forall i \in I, \forall k \in K \setminus \{k=K\} \quad (4.18)$$

$$fl_{at} \geq 0 \qquad \forall \lambda_{at} \in \bar{A} \quad (4.19)$$

$$fl_{ab}^{ki} \geq 0 \qquad \forall \beta_{ab}^{ki} \in \bar{B} \quad (4.20)$$

$$fl_{bc}^{ki} \geq 0 \qquad \forall \gamma_{bc}^{ki} \in \bar{\Gamma} \quad (4.21)$$

$$fl_{ct}^{ki} \geq 0 \qquad \forall \epsilon_{ct}^{ki} \in \bar{E} \quad (4.22)$$

$$s_i \geq 0 \qquad \forall i \in I \quad (4.23)$$

$$r \geq 0 \qquad (4.24)$$

$$w_{hb}^{1i} \in \{0,1\} \qquad \forall \zeta_{hb}^{1i} \in \bar{Z} \quad (4.25)$$

$$x_{bc}^{ki} \in \{0,1\} \qquad \forall \gamma_{bc}^{ki} \in \bar{\Gamma} \quad (4.26)$$

$$y_{cb}^{ki} \in \{0,1\} \qquad \forall \delta_{cb}^{ki} \in \bar{\Delta} \quad (4.27)$$

$$n_a \geq 0 \qquad \forall a \in A \quad (4.28)$$

The S-ICEP objective function (4.1) combines multiple objectives. It aims to minimize the expected evacuation time ($r(\xi)$), the number of people not evacuated ($P\left(\sum_{a\in A} n_a(\xi)\right)$), and the normalized total cost of the evacuation plan ($\sum_{i\in I} cf_i(z_i)/\sum_{i\in I}(cf_i + cv_i(T))$) and ($\sum_{i\in I} cv_i(s_i(\xi))/\ \sum_{i\in I}(cf_i + cv_i(T))$). The first stage decision variable (4.2) determines the set of resources that will be used for evacuation, which fixes the fixed-cost component of the evacuation plan cost. The uncertain second-stage determines the evacuation time for every provided scenario given the evacuation fleet from the first stage. The second stage is essentially a slightly modified version of the D-ICEP, with the objective consisting of the total evacuation time, as in the D-ICEP, plus the variable cost and a penalty that is applied for every person that could not be evacuated. This allows for not evacuating the entire population if a scenario is extreme and has a low probability. The ranking of objective components is ensured through normalizing the cost components, such that their maximum influence on the objective function is 1. This ensures that an improvement by at least one time unit in evacuation time will always dominate the cost objective so that evacuation speed is prioritized over cost. It is left to the modeler to decide the granularity of time units - minutes or even seconds - considered in the objective. Restricting the influence of the evacuation cost in this way is based on Sherali's [133] approaches for lexicographic multi-objective functions. This objective function further includes a penalty that is applied for every person that could not be evacuated, which is modeled through the added decision variable n_a, as indicated in constraint (4.28). In combination with replacing constraint (3.6) with constraint (4.10), this ensures that the problem will still provide an evacuation plan, even if parameter T is set so low that not everyone can be evacuated. Decision makers can adjust the size of P to control the desired risk level for not evacuating everyone in extreme scenarios. The remaining constraints of the second stage are almost the same as the constraints of the D-ICEP with a few modifications. As mentioned above, an upper time limit parameter was added (4.6). Constraint (4.9) was added to ensure that flows can only be allocated to a resource route if the resource was also selected in the first stage. Furthermore, for D-ICEP constraints (3.9), (3.10), and (3.11) the RHS was replaced by z_i as shown in constraints (4.13) through (4.15), to make sure that routes can only be connected if the resource was selected in the first stage. Otherwise the S-ICEP constraints are equivalent to the D-ICEP constraints presented in Chapter 3. In the following section, the S-ICEP is analyzed for its structural challenges, sensitivity to set sizes, objective functions, and parameter choices, and their effects on the feasibility of the model.

Scenarios

For the S-ICEP, using a set of reasonably varied and realistic scenarios is the main challenge, as it is crucial for obtaining meaningful results. The S-ICEP model provides the modeler with flexibility in determining which parameters they want to modify. A modeler could, for example, investigate the effects of seasonal population fluctuation on the evacuation time for one specific disaster case. Alternatively, for areas with stable populations, a modeler could investigate the effects on different affected populations. Furthermore, differences in weather patterns that influence travel times or pick-up and drop-off point access can be modeled.

As mentioned in Section 4.3.2, once the uncertainty that the S-ICEP considers during the planning process is resolved, emergency planners face a D-ICEP, which may be different from all the scenarios considered. The goal of the S-ICEP, therefore, is to provide a resource set that can perform well in case of an actual disaster. Therefore, the number and variety of scenarios should be chosen in a way that approximates the underlying uncertainties without overfitting the solution. If sufficient data is available for the region of interest, this is how scenarios should be designed. The challenge with planning for disasters is that sufficiently detailed data on where a disaster could occur and how it would evolve is often difficult to obtain. In some cases, specific scenarios can be obtained through collaboration with experts, such as experienced first responders or emergency planners, who can rely on experience to identify where disasters are likely to occur and can evaluate the relative probability of the scenarios. To make the results robust, the modeler should ensure that scenarios cover a variety of realistic cases that may include differences in the total number of evacuees, the number of evacuation areas affected, and their distribution in between the evacuation areas. Differences in weather patterns that may affect the accessibility of certain pick-up and drop-off points should also be considered, as well as differences in the number of evacuees that self-evacuate. Therefore, a mix of sophisticated data sets (e.g. census data for population estimates) and subject matter expert inputs can be used to design realistic scenarios. However, every additional scenario increases the complexity of the model, which is why the right balance between accurately representing the underlying uncertainties and keeping the number of scenarios limited is important.

Resource Sets

Section 3.3.3 already discussed the importance of setting parameter K for the D-ICEP. The S-ICEP has an additional degree of freedom through modifying the considered set of resources I. While determining the optimal set of resources is the objective of the S-ICEP, the size of the potential resource set I also inflates the problem size. Table 4.4 illustrates the effect on the number of variables. The bounds from equation (3.24) and (3.25) should be considered when determining the size of the potential resource set.

Evacuation Time Limits

T is provided to allow emergency planners to set a desired maximum evacuation time. Reviewing the S-ICEP formulation from Section 4.3.3, it is easy to verify that an unreasonably small T will cause the resulting evacuation plan to not evacuate the entire population in some or all scenarios. Instead of simply letting the model return infeasible in this case, this modeling choice provides the emergency planner with additional information by how much the target T was missed, since it is indicated through the number of non-evacuated people. An emergency modeler may then consider requesting more evacuation resources in the area. However, setting T too high also has downsides from a computational perspective. Through setting T, the solution space can be significantly restricted. However, finding a feasible lower bound to T is not trivial, because it can only be obtained by solving the S-ICEP problem and is essentially the goal of the problem.

$$\min\ T = \min\ r\ (s.t.\ \text{ICEP constraints}) \tag{4.29}$$

However, this property can be useful during the emergency planning process. Through experimenting with S-ICEP, modelers can find out how much time a route plan is expected to take. This is further investigated in Section 4.3.4 with regards to solution time. An upper bound to the time limit can be derived by maximizing r, although this is not of much use in solving the problem.

Penalty Parameters

The choice of the penalty parameter P applied to the S-ICEP strongly affects the provided policy. This penalty parameter is mostly an applied measure of calculated risk in the design of the evacuation plan instead of the true cost of not evacuating a person from the affected area. It is supposed to dominate the other terms in the objective function and if chosen too small, solutions may be favored that evacuate a smaller population than possible because it might be comparably cheaper to leave people in the affected area than conducting an additional round trip with a subset of resources. Similarly, an unreasonably large choice of P may result in an impractical rule that no person can be left behind in any scenario, no matter how unlikely and extreme that scenario might be (e.g. a scenario with relative probability 0.5%, since the effect on the objective function is still very high even though the penalty is discounted by the probability). A lower bound that ensures dominance over the time and cost components can be established as in (4.30).

$$P \geq T + \sum_{i \in I} (cf_i + cv_i(T)) \tag{4.30}$$

There are caveats to using the penalty parameter as introduced in Section 4.3.3. It is not possible to control how many people have to be evacuated at minimum. Compared to requiring everyone be evacuated, the penalty parameter also increases computational run time as the solution space increases. To find the right balance, the modeler could determine what percentage of the population should be guaranteed to be evacuated in any scenario and add constraint (4.31) to the second stage of the S-ICEP model formulation, where m equals the fraction of the population that is guaranteed to be evacuated in every scenario.

$$(1 - m) \sum_{a \in A} d_a \geq \sum_{a \in A} n_a \tag{4.31}$$

To further control for how many scenarios are allowed to not evacuate the entire population, a chance constraint could be added in the first stage of the S-ICEP. Depending on the desired probability of complete evacuation e, constraint (4.32) would model this. However, this could further complicate solving the problem as it would introduce a non-linearity.

$$Pr\left(\sum_{a \in A} n_a(\xi) = 0\right) \geq e, \qquad \forall \xi \in \Xi \tag{4.32}$$

4.3.4 Objective Functions for S-ICEP

Balanced Objective Functions

The primary objective function of the S-ICEP used in Section 4.3.3, further denoted as *Bal_1*, is a multi-objective formulation that prioritizes evacuation time over cost. For evacuation purposes, this is a reasonable balance. Instead of focusing on minimizing the most time consuming route, an alternative formulation aims to minimize the overall sum of route times to generate higher efficiency in individual route choices. This revised balanced objective function was denoted as *Bal_2* (4.33).

$$\frac{\sum_{i \in I} cf_i z_i}{\sum_{i \in I}(cf_i + cv_i(T))} + \mathbb{E}\left[\sum_{i \in I} s_i + \frac{\sum_{i \in I} cv_i s_i}{\sum_{i \in I}(cf_i + cv_i(T))} + P \sum_{a \in A} n_a\right] \tag{4.33}$$

Conservative Objective Functions

More conservative but simpler objective functions can be considered that solely aim to minimize the expected evacuation time, ignoring the fixed and variable cost imposed by the resource usage. Depending on whether to minimize for r or for $\sum_{i \in I} s_i$, these can optimize total evacuation time or the sum of all route times. Equation (4.34) denotes *Cons_1*. Alternatively, equation (4.35) provides *Cons_2*.

$$\min \ \mathbb{E}\left[r + P \sum_{a \in A} n_a\right] \tag{4.34}$$

$$\min \ \mathbb{E}\left[\sum_{i \in I} s_i + P \sum_{a \in A} n_a\right] \tag{4.35}$$

Economic Objective Functions

Economic objective functions can also be considered that minimize the expected evacuation cost. The expected variable cost is calculated as the sum of each variable cost rate multiplied by the time consumption of each selected route segment over all selected resources, plus the penalty cost for leaving a person behind. This objective therefore automatically ensures cost efficient route choices. This objective function was denoted *Econ_1* (4.36).

$$\min \sum_{i \in I} cf_i z_i + \mathbb{E}\left[\sum_{i \in I} cv_i s_i + P \sum_{a \in A} n_a\right] \tag{4.36}$$

If *Econ_1* is considered to be too budget focused and if a non-dominant incorporation of evacuation time is desired, then the total evacuation time can be discounted by its upper bound, as shown in the multi-objective objective function (4.37), which is denoted as *Econ_2*.

$$\min \sum_{i \in I} cf_i z_i + \mathbb{E}\left[\sum_{i \in I} cv_i s_i + \frac{r}{T} + P \sum_{a \in A} n_a\right] \tag{4.37}$$

Discretization of Objective Functions

All objective functions can further be discretized into a deterministic equivalent if the number of scenarios is finite. Equation (4.38) provides an example for the objective function *Bal*_1 with two scenarios with probabilities p_1 and p_2, where $\sum_{\xi \in \Xi} p_\xi = 1$.

$$\begin{aligned} \min \quad & \frac{\sum_{i \in I} cf_i(z_i)}{\sum_{i \in I}(cf_i + cv_i(T))} + p_1 \left(r(\xi_1) + \frac{\sum_{i \in I} cv_i(s_i(\xi_1))}{\sum_{i \in I}(cf_i + cv_i(T))} + P \sum_{a \in A} n_a(\xi_1) \right) + \\ & p_2 \left(r(\xi_2) + \frac{\sum_{i \in I} cv_i(s_i(\xi_2))}{\sum_{i \in I}(cf_i + cv_i(T))} + P \sum_{a \in A} n_a(\xi_2) \right) \end{aligned} \tag{4.38}$$

Effects of S-ICEP Objective Functions

To investigate the effect of the objective functions further, the three test data sets presented in Table 4.2 were used to investigate model sensitivity. All computational runs were made on a Mac with a 2.6-GHz Dual-Core Intel Core i5 CPU, using an implementation of S-ICEP in the Pyomo interface for Python on the Gurobi 9.0 commercial solver, with a run-time limit of 3600 sec. As recommended by the Gurobi environment, the deterministic equivalent of the S-ICEP was solved. The settings chosen for Gurobi 9.0 were to solve the problem using the root node model of the MIP as it delivered the best performance. Using the concurrent version of the solver did not provide improvements in run time for this model.

Table 4.2: Test Data Sets for Different Objective Functions for S-ICEP

	I1	I2	I3
Sets		*Set size*	
Scenarios	2	3	4
Potential Resources	6	6	8
Initial storage locations	1	2	3
Evacuation locations	3	4	5
Evacuation pick-up points	5	6	8
Safe drop-off points	2	3	3
Round trips	6	8	8
Parameters		*Setting*	
Penalty	5,000	5,000	5,000
Evacuation time limit (min)	120	240	500
Variable Type		*Quantity*	
Continuous Variables	832	2,718	6,640
Binary Variables	858	3,328	8,352

By applying the objective functions introduced in Section 4.3.4 to the data sets from Table 4.2, the results displayed in Table 4.3 were obtained. The table presents the key parameters of the solution for each data set and each objective function, and the expected evacuation time for each scenario.

Table 4.3 shows that for all data sets, conservative objective functions generally led to short evacuation times. The solutions provided by the balanced objective functions provided almost the same solutions with regards to total evacuation time, but with more efficient resource choices. This shows that adding the cost component to the objective function helps in reducing expected cost while maintaining quick evacuation plans, though the Bal_1 objective, that includes the minimization of the total evacuation time, was more reliable. The results for data set $I2$ show that Bal_2 does not lead to the same type of evacuation time as $Cons\_2$, although both include the sum of route times objective. It can furthermore be observed that objective functions that minimized the sum of route times ($Cons\_2$, Bal_2)

Table 4.3: Experiment Results for Different Objective Functions

Data set	Objective	Objective	Exp. Time (min)	Cost ($)	Run-time	Resources
I1	*Cons_1*	100.32	(72, 119)	5,671.67	2.05s	6/6
	Cons_2	327.04	(90, 120)	5,552.13	0.93s	6/6
	Bal_1	101.83	(72, 119)	5,671.67	5.15s	6/6
	Bal_2	327.98	(90, 120)	5,052.13	0.75s	5/6
	Econ_1	2,955.64	(102, 120)	2,955.64	1.09s	4/6
	Econ_2	2,956.58	(102, 120)	2,956.58	1.25s	4/6
I2	*Cons_1*	118.22	(132, 159, 82)	6,255.75	31.14s	6/6
	Cons_2	233.62	(232, 190, 82)	5,573.58	1.71s	6/6
	Bal_1	119.6	(132, 159, 82)	5,155.77	725.32s	5/6
	Bal_2	234.56	(232, 229, 82)	5,073.58	4.30s	5/6
	Econ_1	2,522.19	(228, 228, 226)	2,522.19	48.13s	3/6
	Econ_2	2,522.19	(219, 229, 169)	2,522.19	29.8s	3/6
I3	*Cons_1*	117.72	(132, 313, 88, 91)	6,989.66	7.80s	8/8
	Cons_2	290.92	(282, 495, 142, 182)	6,384.41	3.88s	8/8
	Bal_1	118.82	(132, 313, 88, 91)	6,821.52	3,600.00s*	8/8
	Bal_2	291.79	(282, 495, 142, 182)	5,384.41	4.36s	6/8
	Econ_1	2,614.04	(374, 495, 321, 317)	2,614.04	61.34s	4/8
	Econ_2	2,614.04	(374, 495, 270, 242)	2,614.04	6.52s	4/8

*Results were aborted after 3600s; the best available solution is displayed.

did not provide the same solution quality with regards to total evacuation time. In fact, minimizing the sum of route times produced results that were closer to solutions of economic objective functions, since the variable cost term was a function of time. Economic objective functions can find reasonably quick solutions, but only if decision makers define tight upper time limits. This is visible in the results for $I1$, where the upper time limit T was set to 120, which is close to the lowest feasible time of 119 of the second scenario. Modelers should therefore carefully consider their priorities when applying these functions to the problem and consider the settings of parameter T.

In addition, any objective function that involved minimizing the total evacuation time instead of the sum of route times showed a significantly larger computational run-time, particularly for $I3$. This indicates the commercial solver's solution discrimination was more difficult when minimizing the total evacuation time. The effect appears amplified by how far away T is set from the optimal solution of each scenario. This is illustrated by the differences between Bal_1 and Bal_2. For data set $I1$, the second scenario had a minimum total evacuation time of 119, but the upper time limit was set to 120, which corresponds to just 0.8% above the optimal solution. Here, Bal_1 showed a run time approximately 6.9 times as high as Bal_2. In $I2$, this factor is increased to approximately 168.7. The time limit was set to 240, which is 81 (50.9%) more than the longest minimum total evacuation time reached for this scenario. In $I3$, while the run for Bal_1 was aborted at $3600s$, the factor is already 825.7 times the run time of Bal_2. In this case, T was set to 500, which is 187 (59.7%) above the longest minimum evacuation time for this scenario.

Learnings from Experiments

This illustrates two main findings: the difficulties of the solver to perform effective solution discrimination for minimum evacuation time objective functions, and the sensitivity of the solver to the setting of parameter T in comparison to the minimum total evacuation time for these functions. This makes these objective functions particularly challenging to use for large problems, as the problem cannot easily be decomposed into a problem for each resource. This gives the modeler multiple options when aiming to reduce the computational run time of Bal_1 when it is unclear how to set T:

1. Start with low settings for T and perform algorithm runs, which will likely result in high penalties due to people left behind but short computational run times. Based on the results, gradually increase T and re-run the algorithm until a solution with no one left behind can be obtained.
2. Start with any setting for T and run Bal_2 instead of Bal_1 and gradually decrease T and perform additional runs until a plan is returned that leaves people behind. Choose the previous setting for T and run again with Bal_1. This should return a reasonably short run time for Bal_1 as the gap between the minimum total evacuation time and T should be small enough. This approach takes advantage of the fact that the minimum possible total evacuation time using Bal_2 is equivalent to the optimal solution of Bal_1. Thus if $T = \min r$, Bal_2 would deliver the same solution as Bal_1.

3. Consider alternative approximate solution methods, such as heuristics, metaheuristics and decomposition methods.

This has further implications on how to solve D-ICEP during emergency response. If planing with S-ICEP has been performed and a variety of realistic scenarios have been considered, a estimate on a reasonable upper time limit may have been achieved. The D-ICEP can then be executed during an emergency response situation with T added as an upper time limit, thus accelerating the solution time. Another strategy is to use the solution for the scenario obtained from S-ICEP that is closest to the situation D-ICEP faces, and provide it as a warm start to the solver. Considering that particularly the primary multi-objective function of S-ICEP (Bal_1) is challenging to solve with a commercial solver in a timely manner, details on a heuristic approach to solving the problem are provided in Section 4.4.

4.4 Heuristic Solution Approaches

4.4.1 Heuristic for the S-ICEP

The analysis in Section 4.3.4 showed that the primary objective function *Bal_1* is most difficult to solve for a commercial solver. Since it is also the primary objective function of the S-ICEP, this section focuses on solving the S-ICEP with this objective function efficiently. Using the heuristic developed for the D-ICEP and presented in Chapter 3, a framework that can find a solution to the S-ICEP is introduced. It consists of a greedy heuristic search framework that starts with an empty resource set and adds a resource to the fleet on every iteration, depending on whether adding it improves the total evacuation plan cost. The algorithm terminates if no additional resource improves the solution or if all available resources have been added to the resource fleet. Algorithm 6 describes this algorithm.

Algorithm 6 is structured similarly to the D-ICEP heuristic in that it greedily selects a resource to be part of the solution set if that resource improves the solution in expectation. However, to reduce algorithm run time, the algorithm always adds a resource into the set

Algorithm 6: S-ICEP Heuristic: Optimal resource fleet

```
Result: A cost- and time-efficient evacuation plan
initialize the best cost as the penalty cost inflicted by not evacuating any person;
initialize the current resource fleet as an empty set;
initialize n := 0;
while current cost < best cost AND not all resources are in the resource fleet do
    best cost = current cost;
    sort the list of candidate resources by maximum capacity, time to availability and maximum
      speed;
    Add the nth entry of the list of candidate resources to the set of resources;
    for t in scenarios do
        Run D-ICEP Heuristic Phase 1 with set of resources;
        Run D-ICEP Heuristic Phase 2 with set of resources;
    end
    proposed cost = total cost of the S-ICEP evacuation plan considering scenario probabilities
      and cost parameters;
    if proposed cost < current cost then
        current cost = proposed cost;
        delete the nth resource from the list of candidate resources;
    else
        delete the nth resource from the resource set again;
        n+ = 1;
        if n equals the length of the candidate resource set then
            break the loop;
        end
    end
end
```

if it provides an improvement and does not consider whether another resource would have provided a larger gain. Alternatively, a more involved approach could be chosen in which the impact of adding every possible resource is tested before any are selected. But this would greatly increase the run time, because there is no simple way to determine which resource will provide the biggest improvement. Taking into account the results of the experiments on the D-ICEP heuristic showing that the local search heuristic does not iterate much until it cannot find further improvements, a theoretical run time from the D-ICEP of $O(m^2nj)$ is obtained. If the algorithm were to test the addition of each potential resource every iteration, this would result in a theoretical run time of $O(n^3m^2tj)$ for the entire algorithm, where n is the number of resources, m is the number of evacuees, t is the number of scenarios and j is the number of pick-up nodes. Therefore, the solution described in Algorithm 6 was chosen, which returns a worst case theoretical run time of $O(n^2m^2tj)$, if both phases of the D-ICEP heuristic are run. If only the first phase is run, the worst case run time is $O(n^2m(j+k))$, where k is the number of drop-off nodes. While this approach reduces the share of the solution space that is explored, it allows us to find a solution more quickly.

The run time can also be reduced by providing the algorithm with an initial resource set instead of starting with an empty set. The risk of missing the global optimum through this approach is low if parameter Q is not too large, since a small resource set generally leads to longer evacuation times. The rule for determining the initial resource set is presented in Algorithm 7.

Algorithm 7: S-ICEP Heuristic: Initial resource set selector

```
Result: A set of resources usable as a warm start to the S-ICEP heuristic
input the set of potential resources and the set of evacuation pick-up points including the
  evacuation demand for each scenario;
provide a minimum percentage of evacuation demand that needs to be covered by resources if only
  one trip to each evacuation location by every resource is completed and initialize as Q;
initialize the initial resource set as an empty set;
initialize the set of total pick-up points as an empty set;
for t in scenarios do
    for j in evacuation pick-up points do
        if j has evacuation demand and is not yet in the set of total pick-up points then
            Add j to the set of total pick-up points
        end
    end
end
for i in total evacuation pick-up points do
    Order the list of potential resources compatible with i by maximum capacity, time to
      availability and maximum speed;
    n := 0 while total evacuation capacity at node i in scenario j ¡ Q(evacuation demand at i) do
        if nth resource not in set of initial resources yet then
            add the nth resource to the initial resource set;
        else
            n := n + 1
        end
    end
end
```

Algorithm 7 selects the initial resource set on the basis of (1) whether, for every scenario, every pick-up node that has evacuation demand can be served and (2) whether it is possible to cover at least a certain percentage of evacuation demand at each pick-up node if it is visited by only one trip of each resource. The worst case theoretical run time of this algorithm is $O(jn)$ or $O(tj)$, where j is the set of evacuation pick-up points, n is the set of potential resources, and t is the set of scenarios, depending on whether tj or jn are larger. A warm start can be considered, where the problem is provided with an initial resource set that is capable of evacuating all scenarios, instead of starting from an empty resource set. In the following section, the variants of the S-ICEP heuristic are discussed regarding their run time and solution quality, on the basis of four test instances, similar to the experimental results presented for the D-ICEP in the previous section.

4.4.2 Numerical Experiments on the heuristic for the S-ICEP

This section describes tests of the developed S-ICEP heuristic in comparison to those of the Gurobi 9.0 commercial solver. Four test data sets were used, which are presented in Table 4.4, to illustrate the performance of the S-ICEP heuristic in comparison to Gurobi 9.0.

Table 4.4: Test Data Sets for S-ICEP Heuristic Evaluation

	S1	S2	S3	S4
Sets		*Set size*		
Scenarios	2	3	4	6
Potential Resources	6	6	8	20
Initial storage locations	1	2	3	6
Evacuation locations	3	4	5	8
Evacuation pick-up points	5	6	8	15
Safe drop-off points	2	3	3	6
Round trips (only for commercial solver)	6	8	8	20
Parameters		*Setting*		
Penalty	5,000	5,000	5,000	5,000
Evacuation time limit (min)	120	240	500	600
Variable Type	*Quantity (for commercial solver)*			
Continuous Variables	832	2,718	6,640	109,668
Binary Variables	858	3,198	8,324	178,740

Because the S-ICEP heuristic makes use of the D-ICEP heuristic, the structural challenges that the D-ICEP faces also apply to this algorithm. However, testing the algorithm showed whether to use both phase 1 and 2 of the D-ICEP. It also showed the effect of a warm start. Table 4.5 provides the results of the computational tests with the data sets in Table 4.4 for Gurobi 9.0, the greedy S-ICEP heuristic discussed in Section 4.4.1 using only the first stage, or both the first and second stages of the D-ICEP heuristic, and the S-ICEP heuristic, starting with an initial route set defined by the warm start rule (indicated by "+ WS") introduced in Algorithm 7 with parameter Q set to 20 percent. Figure 4.1 illustrates the results in a chart.

Table 4.5: Result Summary Data S-ICEP Heuristic Experiments

Data	Implementation	Objective	Runtime	Opt. Gap	Runtime Gap
S1	Gurobi	102.21	10.93s	-	-
	S-ICEP (incl. D-ICEP Ph. 1)	148.77	7.56s	31.30%	-30.83%
	S-ICEP (incl. D-ICEP Ph. 1&2)	148.77	10.7s	31.30%	2.10%
	S-ICEP (incl. D-ICEP Ph. 1 + WS)	148.77	4.91s	31.30%	-55.08%
	S-ICEP (incl. D-ICEP Ph. 1&2 + WS)	148.77	8.61s	31.30%	-21.23%
S2	Gurobi	119.65	3600s	(119.6) 0.04%	-
	S-ICEP (incl. D-ICEP Ph. 1)	155.6	11.39s	23.13%	-99.68%
	S-ICEP (incl. D-ICEP Ph. 1&2)	142.04	30.3s	15.80%	-99.16%
	S-ICEP (incl. D-ICEP Ph. 1 + WS)	155.6	5.63s	23.14%	-99.78%
	S-ICEP (incl. D-ICEP Ph. 1&2 + WS)	142.04	27.91s	15.80%	-99.22%
S3	Gurobi	120.19	144.83s	-	-
	S-ICEP (incl. D-ICEP Ph. 1)	162.6	51.65s	26.08%	-64.34%
	S-ICEP (incl. D-ICEP Ph. 1&2)	162.32	151.39s	25.95%	4.53%
	S-ICEP (incl. D-ICEP Ph. 1 + WS)	162.6	13.35s	26.08%	-90.78%
	S-ICEP (incl. D-ICEP Ph. 1&2 + WS)	162.32	31.07s	25.95%	-78.55%
S4	Gurobi	143.30*	3600s*	(109.77) 23.4%	-
	S-ICEP (incl. D-ICEP Ph. 1)	169.02	1937.11s	35.06%**	-46.19%***
	S-ICEP (incl. D-ICEP Ph. 1&2)	172.48	2954.66s	36.36%**	-17.93%***
	S-ICEP (incl. D-ICEP Ph. 1 + WS)	169.64	576.87s	35.29%**	-83.97%***
	S-ICEP (incl. D-ICEP Ph. 1&2 + WS)	167.42	1011.9s	34.43%**	-71.89%***

*Results were aborted after 3600s; the best available solution, optimality gap and best bound are displayed.
**Optimality gap estimated based on lower bound provided by Gurobi 9.0.
***Run-time reduction compared to run time limit of 3600s.

Table 4.5 shows that no tested configuration allowed the S-ICEP heuristic to reach the global optimum of the *Bal_1* objective function of the S-ICEP. This is caused by the fact that

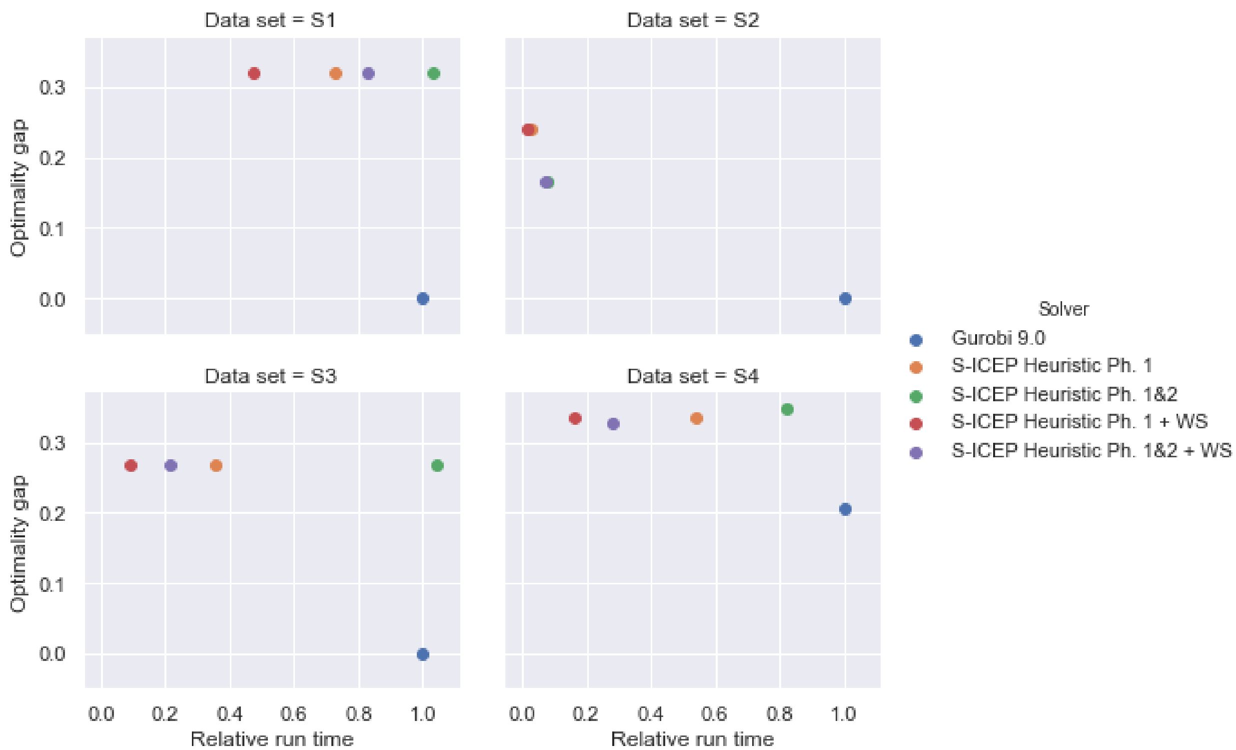

Figure 4.1: Test results for the S-ICEP: Run time for the S-ICEP variations relative to Gurobi 9.0 run time vs. optimality gap of solution

the underlying D-ICEP heuristic does not guarantee to find the global optimum, and the assumptions generated for the S-ICEP heuristic on resource selection also further simplify the problem. In some cases, using both phase 1 and phase 2 of the D-ICEP reduced the optimality gap. The run time of the algorithm, especially for larger problems, could also be significantly reduced through using the warm start for the initial resource set without sacrificing the solution quality of the S-ICEP heuristic. It is therefore recommended that the warm start feature be used if larger problems are investigated. In future research, additional numerical experiments can be conducted to investigate ideal parameter settings for parameter Q. Given the experiments presented in Table 4.5, it is evident that the S-ICEP heuristic is able to reduce the run time to find a reasonable solution for larger problems in comparison to an implementation of a commercial solver. However, the solution quality suffers significantly and to a much higher degree than for the D-ICEP heuristic. The reason is that the gaps in the second stage add up for each scenario and that the resource selection in the first stage of the heuristic is not reliable in finding the best resource set.

Despite the possibility of reducing the algorithm's run time through these tweaks, two main caveats of the logic-based heuristic for the S-ICEP remain. First, the algorithm run time of the S-ICEP heuristic still increases significantly with the problem size. While the increase does not happen at the same rate as that of the commercial solver, the solution quality is sacrificed significantly because the optimality of the solution cannot be guaranteed. Second, the complexity of the ICEP makes it difficult to efficiently explore the solution space if a structure-based approach is used. It is possible to add additional improvement checks to phase 2 of the D-ICEP heuristic, but additional features and layers increase the run-time complexity and thus also reduce the usability of the algorithm for larger problem sizes. The S-ICEP heuristic should therefore only be used if a solution needs to be obtained as quickly as possible. For planning purposes, the commercial solver is thus preferred, until an alternative solution method is available.

4.5 Conclusions

This chapter introduced the S-ICEP two-stage stochastic formulation with recourse. The S-ICEP allows scenario-based planning by optimizing the evacuation resource set over multiple disaster scenarios that differ in evacuee numbers, locations, and weather. This makes the model framework compatible with common evacuation planning practices. Alternative objective functions of varying risk levels were presented and explored by conducting numerical experiments. In addition, guidance on the use of the model and its parameter settings was provided. Moreover, heuristic solution approaches were presented to solve the problem quickly. Experiments showed that this heuristic also reduced the algorithm run time significantly in comparison to a commercial solver, but it did not reach the global optimum in any test case and showed large optimality gaps.

As mentioned in the Introduction section (Section 4.2), a real-world case study can be helpful to investigate the value of the model for practitioners and derive managerial insights in detail, and to learn more about the evacuation of isolated communities and explore how this model can best be applied. As mentioned in the discussion about scenario generation (Section 4.3.3), it can be challenging to obtain reliable data to solve the S-ICEP problem using existing data sets. Thus, subject matter experts should be included in the data design process, and close collaboration with first responders is necessary to make sure that the data assumptions provided to the model as inputs are realistic.

Future research could further focus on additional algorithmic solutions. One option is to expand the presented heuristic algorithm to search a larger share of the solution space, while balancing out the trade-off with computational complexity. Alternative solution methods on how to solve the ICEP models to a more reliable solution quality could consider metaheuristic frameworks [24] or decomposition methods [64].

4.6 Acknowledgements

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Chapter 5

THE ISOLATED COMMUNITY EVACUATION PROBLEM FOR RESPONSE PURPOSES

The work presented in this chapter represents a research manuscript that is planned to be submitted for publication to *Transportation Science* and is co-authored with Dr. Anne V. Goodchild and Dr. Linda Ng Boyle.

5.1 Abstract

During responses to evacuation notices, emergency managers and coordinators need to make decisions on resource allocation quickly. Frequently, information about the location and exact numbers of evacuees is incomplete or uncertain. This is especially relevant for evacuations that require the coordination of evacuation resources that are specifically for isolated areas. While the ICEP has provided a tool to plan the evacuation for isolated areas, it relies on accuracy of the demand numbers and distribution to provide a high quality solution. The research presented in this chapter provides a solution to this problem through two alternative approaches to handle uncertainty during emergency response. The proposed robust optimization (R-ICEP) and rolling-horizon optimization (RH-ICEP) variants of the ICEP, provide methods that optimize considering uncertainty sets and evolving information on demand numbers respectively. Computational results demonstrate that the rolling-horizon method consistently outperforms the deterministic baseline model, while the robust method outperforms only for certain problem structures, and to a lesser degree than the rolling-horizon method. Taking advantage of evolving information through the RH-ICEP is therefore the most reliable method for emergency response and can help emergency coordinators to respond more efficiently to isolated community evacuation.

5.2 Introduction

5.2.1 Motivation

This chapter aims to fulfill the third research question presented in Chapter 1. To make the ICEP useful for response purposes, some assumptions from D-ICEP and S-ICEP need to be relaxed. During an emergency, such as a wildfire, it is reasonable to assume that sufficient knowledge about the general disaster location and the affected area is known. This is in contrast to the problem question introduced for the S-ICEP from chapter 4, which is used for planning purposes and the goal is to prepare for a wide array of disaster scenarios that may not affect the same area. However, while the location may be known when an evacuation alert is released, it is likely that the number of evacuees at each potential evacuation pick-up location is highly uncertain and that evacuees arrive sequentially at the evacuation pick-up locations, such that new information is only revealed over time. This can lead to over and under estimations of evacuation demand at each location. Nevertheless, the emergency management authorities have to make decisions about resource allocation despite this lack of this information and start the evacuation procedure as soon as possible. With the goal to develop a solution procedure that enables authorities to solve this problem, the research presented in this chapter therefore solves the isolated community evacuation problem for response purposes. The presented solution comprises of two additional variants of the ICEP, using robust optimization (R-ICEP), and rolling-horizon optimization (RH-ICEP). The effectiveness of the proposed approaches and their advantages and disadvantages are investigated through numerical experiments and compared against the ideal case of no uncertainty and against using the D-ICEP as a baseline, which does not consider the uncertainty over the exact number of evacuees.

5.2.2 Contributions

For response actions, the main shortcoming of the deterministic version of the Isolated Community Evacuation Problem (D-ICEP) introduced in Chapter 4 is that it does not consider any uncertainty in information during the emergency. However, in many emergency situations the availability of reliable information is limited. In the case of isolated community evacuation, the main source of uncertainty is how many people have to be evacuated and where they have to be evacuated from. Weather can be another source of uncertainty and affect which evacuation pick-up points people will migrate to and how long it will take for recovery resources to get to the evacuation pick up points. A solution tailored to response solutions benefits from these considerations. At the same time, it is important to obtain solution results as quickly as possible. It is therefore important that a model formulation does not get too complex. The main contributions of this research are:

- The R-ICEP is the first formulation to solve the Isolated Community Evacuation Problem for response purposes using robust optimization for uncertainty on evacuation demand.
- The RH-ICEP is the first rolling-horizon optimization algorithm to solve the Isolated Community Evacuation Problem for response purposes for uncertainty on evacuation demand.
- The experiments conducted demonstrate that both algorithms result in better performance than using the D-ICEP when compared on the same data sets.

5.2.3 Background on Modeling Approaches

Regarding potential modeling techniques, two approaches were examined. A robust optimization formulation [19, 20, 78] of D-ICEP to handle uncertainty sets can be considered in a similar fashion to the robust counterpart to the BEP [72]. Robust optimization first appeared in the 1970s [136] and has shown to be effective at generating high quality solutions to problems with uncertainty. While pure robust optimization is criticized as overly conservative and thus considered as not having much practical use [23], Bertsimas and Sim [22] have developed a solution approach called cardinality-constrained robust optimization that allows so-called budgets of uncertainty to control the level of conservatism through a slightly larger problem. They tailored this problem type specifically to combinatorial problems with a network structure [23], which suits the ICEP for response purposes, as it is a mixed integer problem (MIP). For MIPs, if the uncertainty only concerns parameters used in the constraints, a sub-problem can be solved before the primary problem that fixes the parameters for the level of conservativeness that is desired. Afterwards, the primary problem can be solved just like a deterministic problem [23]. However, if the uncertainty sets directly affect the parameters used in the objective function, for a problem with n variables, $n+1$ non-robust versions of the original MIP have to be solved [23].

Another approach to incorporating uncertainty, a rolling-horizon optimization variant [130] of the D-ICEP formulation (RH-ICEP) is explored. The concept picks up the idea of dynamic programming [17] and updates the problem solution throughout a rolling horizon, whenever new information becomes available. This concept therefore takes some ideas from online optimization [84] where solutions are updated over time to reflect the latest model inputs, but does not aim to establish a competitive ratio compared to the offline problem. In terms of the D-ICEP, this concept can update the route plan during execution over time, while new information about the number of evacuees at each location becomes available, similar to applications of this concept to dynamic and real-time vehicle routing in urban environments, for example [8, 33, 41, 108, 146].

5.3 Methodology

5.3.1 The Robust Isolated Community Evacuation Problem (R-ICEP)

Assumptions

In comparison to the D-ICEP, most assumptions made in Chapter 4 remain the same. The only assumptions that change are:

1. The population of evacuees at the pick-up locations is uncertain.
2. Knowledge over uncertainty is only available in the form of an expected demand (mean) and a worst-case demand, represented through an uncertainty set.

The uncertainty over the population of evacuees at each location is represented as an interval between the expected demand $\bar{d}_a$ and the most extreme possible demand $\hat{d}_a$. In contrast to other robust optimization forms [20], only cases for higher than expected evacuation demand are considered here, as lower than expected demand makes isolated community evacuation less time consuming and thus considering lower demand does not contribute to make an evacuation route plan more robust to peaks in demand.

Formulation

Introducing a cardinality-constrained robust optimization version [23] of the ICEP, required a modification and expansion of the previously introduced deterministic version of ICEP (D-ICEP). The problem notation is introduced in Table 5.1, followed by the formulation.

Table 5.1: Notation Key for R-ICEP

Sets	**Set Description**	**Parameters**	**Parameter Description**
$i \in I$	recovery resources	q_i	passenger capacity of resource i
$k \in K$	potential round trips per resource	u_i	time to availability of resource i
s	source node	o_i	loading time of resource i
$a \in A$	evacuation areas	p_i	unloading time of resource i
$b \in B$	pick-up points in evacuation area	$\bar{d}_a$	expected value for evacuation demand at area a
$c \in C$	drop-off points in safe locations	$\hat{d}_a$	max. evacuation demand deviation at area a above $\bar{d}_a$
t	sink node	g_a	max. no. of self-evacuations from area a
$h \in H$	initial resource locations	t^i_{hb}	$\frac{distance(h \to b)}{\text{empty travel speed of resource } i}$: cost of arc ζ^{1i}_{hb}
$V \subseteq A$	evacuation areas allowed to deviate from expected demand	t^i_{bc}	$\frac{distance(b \to c)}{\text{loaded travel speed of resource } i}$: cost of arc γ^{ki}_{bc}
		t^i_{cb}	$\frac{distance(c \to b)}{\text{empty travel speed of resource } i}$: cost of arc δ^{ki}_{cb}, only $k = 1, ..., K-1$
		$\Gamma \in [0, \lvert A \rvert]$	Parameter to control at how many areas the demand is allowed to deviate from the expected demand
Arcs	**Arc Description**	**Variables**	**Variable Description**
$\alpha_{sa} \in \bar{A}$	source s to area a	fl_{at}	flow on arc λ_{at}
$\beta^{ki}_{ab} \in \bar{B}$	area a to pick-up b of trip k for resource i	fl^{ki}_{ab}	flow on arc β^{ki}_{ab}
$\gamma^{ki}_{bc} \in \bar{\Gamma}$	pick-up b to drop-off c of trip k for resource i	fl^{ki}_{bc}	flow on arc γ^{ki}_{bc}
$\delta^{ki}_{cb} \in \bar{\Delta}$	drop-off c to pick-up b of trip k to trip $k+1$	fl^{ki}_{ct}	flow on arc ϵ^{ki}_{ct}
	for resource i, for $k = 1, ..., K-1$	w^{1i}_{hb}	{**1**: if route on ζ^{1i}_{hb} selected, **0**: otherwise}
$\epsilon_{ct} \in \bar{E}$	drop-off c to sink node t	x^{ki}_{bc}	{**1**: if route on γ^{ki}_{bc} selected, **0**: otherwise}
$\zeta^{1i}_{hb} \in \bar{Z}$	initial resource location h to pick-up b	y^{ki}_{cb}	{**1**: if route on δ^{ki}_{cb} selected, **0**: otherwise}
	for resource i, on trip 1	r	total evacuation time
$\lambda_{at} \in \bar{\Lambda}$	area a to sink node t, for private evacuations	s_i	route completion time of resource i

$$\min \quad r \tag{5.1}$$

$$s.t. \quad r \geq s_i \qquad \forall i \in I \tag{5.2}$$

$$\begin{aligned} s_i = & \sum_{\zeta_{hb}^{1i} \in \bar{Z}} \left(t_{hb}^i w_{hb}^{1i}\right) + \sum_{\gamma_{bc}^{ki} \in \bar{\Gamma}} \left(t_{bc}^i x_{bc}^{ki}\right) + \sum_{\delta_{cb}^{ki} \in \bar{\Delta}} \left(t_{cb}^i y_{cb}^{ki}\right) + \\ & \sum_{\zeta_{hb}^{1i} \in \bar{Z}} \left(u_i w_{hb}^{1i}\right) + \sum_{\zeta_{hb}^{1i} \in \bar{Z}} \left(o_i w_{hb}^{1i}\right) + \\ & \sum_{\delta_{cb}^{ki} \in \bar{\Delta}} \left(o_i y_{cb}^{ki}\right) + \sum_{\gamma_{bc}^{ki} \in \bar{\Gamma}} \left(p_i x_{bc}^{ki}\right) \qquad \forall i \in I \end{aligned} \tag{5.3}$$

$$fl_{at} \leq g_a \qquad \forall \lambda_{at} \in \bar{\Lambda} \tag{5.4}$$

$$fl_{bc}^{ki} \leq q_i(x_{bc}^{ki}) \qquad \forall \gamma_{bc}^{ki} \in \bar{\Gamma} \tag{5.5}$$

$$\mathbf{l} = \underset{\{V \subseteq A, |V| = \Gamma\}}{\arg\max} \sum_{a \in V} \hat{d}_a l_a \tag{5.6}$$

$$\bar{d}_a + \hat{d}_a l_a = fl_{at} + \sum_{\beta_{jb}^{ki} \in \bar{B} : j = a} fl_{ab}^{ki} \qquad \forall a \in A \tag{5.7}$$

$$\sum_{\beta_{aj}^{ki} \in \bar{B} : j = b} fl_{ab}^{ki} = \sum_{\gamma_{jc}^{ki} \in \bar{\Gamma} : j = b} fl_{bc}^{ki} \qquad \forall b \in B, \forall k \in K, \forall i \in I \tag{5.8}$$

$$\sum_{\gamma_{bj}^{ki} \in \bar{\Gamma} : j = c} fl_{bc}^{ki} = fl_{ct}^{ki} \qquad \forall c \in C, \forall k \in K, \forall i \in I \tag{5.9}$$

$$\sum_{\zeta_{hb}^{1i} \in \bar{Z}} w_{hb}^{1i} \leq 1 \qquad \forall i \in I \tag{5.10}$$

$$\sum_{\gamma_{bc}^{ki} \in \bar{\Gamma}} x_{bc}^{ki} \leq 1 \qquad \forall i \in I, k \in K \tag{5.11}$$

$$\sum_{\delta_{cb}^{ki} \in \bar{\Delta}} y_{cb}^{ki} \leq 1 \qquad \forall i \in I, k \in K \setminus \{k = K\} \tag{5.12}$$

$$\sum_{h \in H} w_{hb}^{1i} = \sum_{c \in C} x_{bc}^{1i} \qquad \forall b \in B, \forall i \in I \tag{5.13}$$

$$\sum_{c \in C} y_{cb}^{(k-1)i} = \sum_{c \in C} x_{bc}^{ki} \qquad \forall b \in B, \forall i \in I, \forall k \in K \setminus \{k = 1\} \tag{5.14}$$

$$\sum_{b \in B} x_{bc}^{ki} \geq \sum_{b \in C} y_{cb}^{ki} \qquad \forall c \in C, \forall i \in I, \forall k \in K \setminus \{k = K\} \tag{5.15}$$

$$fl_{at} \geq 0 \qquad \forall \lambda_{at} \in \bar{A} \quad (5.16)$$

$$fl_{ab}^{ki} \geq 0 \qquad \forall \beta_{ab}^{ki} \in \bar{B} \quad (5.17)$$

$$fl_{bc}^{ki} \geq 0 \qquad \forall \gamma_{bc}^{ki} \in \bar{\Gamma} \quad (5.18)$$

$$fl_{ct}^{ki} \geq 0 \qquad \forall \epsilon_{ct}^{ki} \in \bar{E} \quad (5.19)$$

$$s_i \geq 0 \qquad \forall i \in I \quad (5.20)$$

$$r \geq 0 \qquad (5.21)$$

$$w_{hb}^{1i} \in \{0,1\} \qquad \forall \zeta_{hb}^{1i} \in \bar{Z} \quad (5.22)$$

$$x_{bc}^{ki} \in \{0,1\} \qquad \forall \gamma_{bc}^{ki} \in \bar{\Gamma} \quad (5.23)$$

$$y_{cb}^{ki} \in \{0,1\} \qquad \forall \delta_{cb}^{ki} \in \bar{\Delta} \quad (5.24)$$

$$l_a \in \{0,1\} \qquad \forall a \in A \quad (5.25)$$

When comparing the model with the D-ICEP introduced in Chapter 4, almost all constraints remain the same as in the deterministic problem formulation. A new binary variable l_a is introduced in constraint (5.25), which decides whether for a location a, the most extreme evacuation demand case $\hat{d}_a$ is considered or not. Constraint (5.6) defines the vector of $\mathbf{l}$ as the binary vector that maximizes the sub-problem of choosing a subset of all evacuation locations $V \subseteq A$ of size Γ, such that the sum of demand above expectation is maximized. The effect of this decision on the evacuation demand per location is incorporated into the R-ICEP problem in flow conservation constraint (5.7) and thus, the problem considers a higher demand than expected, making the resulting route plan robust to variations in the evacuation demand. Γ is a measure of robustness control provided by the modeler to determine how conservative the model results are desired to be, with $\Gamma = 0$ being least conservative (using solely the expected demand), and $\Gamma = |A|$ being most conservative (using solely the most extreme demand from the uncertainty set). An additional advantage of this formulation is that solving the sub-problem in advance, fixing the evacuation demand to robust levels, allows that the complexity remains limited to the complexity of D-ICEP described in chapter 4.

5.3.2 The Rolling Horizon Isolated Community Evacuation Problem (RH-ICEP)

Assumptions

The rolling horizon version of the ICEP (RH-ICEP) relies on the following additional assumptions compared to the D-ICEP:

1. The population of evacuees at the pick-up locations is uncertain at the time of decision making.
2. There is only an initial demand estimate for each evacuation area available.
3. Over time, demand information is updated whenever new information is obtained, until ultimately the true demand is known.

As can easily be verified in the previous section, the first assumption is the same as for the R-ICEP. The second assumption only requires an initial estimate on the demand, even if the estimate has a high error, that is used to start decision making. However, it is assumed that from different sources, additional information is obtained over time, generally making demand information more accurate until eventually the true evacuation demand is revealed.

RH-ICEP Algorithm

In contrast to the R-ICEP, no modifications to the formulation from the D-ICEP formulation are needed. Instead, the RH-ICEP only relies on changes in input data over time, sequentially updating the non-executed remainder of the problem solution, until no more updates are received and the true information is revealed. Algorithm 8 describes this process.

The Algorithm 8 takes advantage of the structure that the D-ICEP already offers. Upon receiving the first estimate for evacuation numbers, RH-ICEP solves D-ICEP to receive the initial route plan and starts executing the evacuation. Whenever the demand is updated through new information, the algorithm records the current position of each resource, and differentiates between three options:

1. A resource has been dispatched and is currently on the way to or from an evacuation location, evacuating people. In this case, the algorithm lets the resource finish this

Algorithm 8: RH-ICEP Algorithm

Result: A near optimal route plan

Initialize the initial estimates as the demand parameters d_a^0 for each evacuation area a;
Solve for an optimal route plan using D-ICEP with d_a^0 for each a;
$t := 0$;
Updated demand := False;
while *True* **do**
    $t+ = 1$;
    if *Updated demand == True* **then**
        Record current leg and positions of resources at time t;
        for *i in resources* **do**
            if *resource i dispatched and executing trip k of evacuation plan* **then**
                Let resource i finish trip k;
                Set earliest availability of resource i to time $t +$ time remaining to complete trip k;
                Set start location of resource i to end location of trip k;
                Subtract evacuees picked up at location a by resource i on trip k from *Updated demand* d_a^t at location a;
            else if *resource i not fully staffed yet* **then**
                Set earliest availability of resource i to earliest availability as per original data set;
            else
                Set earliest availability to time t;
            end
            Discard non-executed remainder of current route plan of resource i;
        end
        Solve for an optimal route plan using D-ICEP with d_a^t for each a;
        current route plan := executed share of current route plan + new route plan;
    else
        Continue executing evacuation according to current route plan;
        if *evacuation determined complete* **then**
            False;
        end
    end
end

operation until the evacuees evacuated on this leg have been brought to safety. It considers the corresponding resource to be available for an updated solution once this evacuation step is complete.

2. A resource is not fully staffed yet, and has not left its storage location. In this case, the earliest time the resource is available for an updated solution is after staffing.
3. A resource is available and not currently used. In this case, the resource can be used for an updated solution immediately.

Using the updated demand, the non-executed part of the previously existing route plan is updated by the route plan obtained from an additional iteration of the D-ICEP. The evacuation continues until either new information is revealed and another iteration starts, or until the evacuation is determined complete. Since the algorithm relies on the D-ICEP formulation for every update, the same considerations on complexity apply as discussed in chapter 4.

5.4 Numerical Experiments

5.4.1 Simulation Design

Numerical experiments were conducted to assess the performance of both the R-ICEP and the RH-ICEP and to investigate the circumstances where each would be beneficial. The objective was to identify how selected problem characteristics influence the effectiveness of the algorithms. Figure 5.1 illustrates the simulation process used for testing. First, a raw data set was modified with different data set parameter inputs through a randomized process, controlled by a random seed. This provided an experiment data set with data updates at times $t_0, t_1, t_2, ..., t_T$, where t_T is the time where the actual evacuation demand is revealed. This data set was then used for comparisons between the performance of different algorithms:

- As a benchmark, the D-ICEP was used to find the best route plan for the actual demand d_T. This represents a best-case scenario, in which no uncertainty exists, or where the initial estimate is the same as the actual evacuation demand. Whichever algorithm performs best in comparison to this benchmark can be determined most suitable for response purposes.

- As a baseline, representing the deterministic solution from chapter 6, the D-ICEP was run based on the initial estimate. If any evacuees remained after the plan had been executed and the information on the actual numbers was revealed, their evacuation was coordinated through solving another iteration of the D-ICEP for the remainder of evacuees and corresponding route plan was extended.
- The R-ICEP was tested through generating a route plan for the robust evacuation demand, which is controlled through parameter Γ, based on the uncertainty in the evacuee numbers. While, the chance for remaining evacuees is smaller if the plan is robust, this can still happen for smaller Γ values or if the actual evacuee numbers are higher than even the most extreme demand estimate in the uncertainty set. For that case, the remainder of the evacuation was optimized through solving an iteration of the D-ICEP, once the actual demand was known and appended to the existing route plan.
- The RH-ICEP was tested according to its algorithm structure, using the initial point estimate of evacuee numbers for the initial route plan. The non-executed part of the route plan was then updated, every time new information became available, until the last update was achieved using the actual evacuee numbers.

Using this set up allowed to assess the performance of all algorithms in a realistic way, that considers the cases, when after completion of a route plan, there are still evacuees remaining.

5.4.2 Data Sets

To obtain insights into how the algorithms perform under varying conditions, simulations needed to explore varying levels of key data set characteristics that likely expose the strengths and weaknesses of every approach. However, most traditional characteristics of routing data sets, such as the number of nodes, or the total demand do not sufficiently characterize an

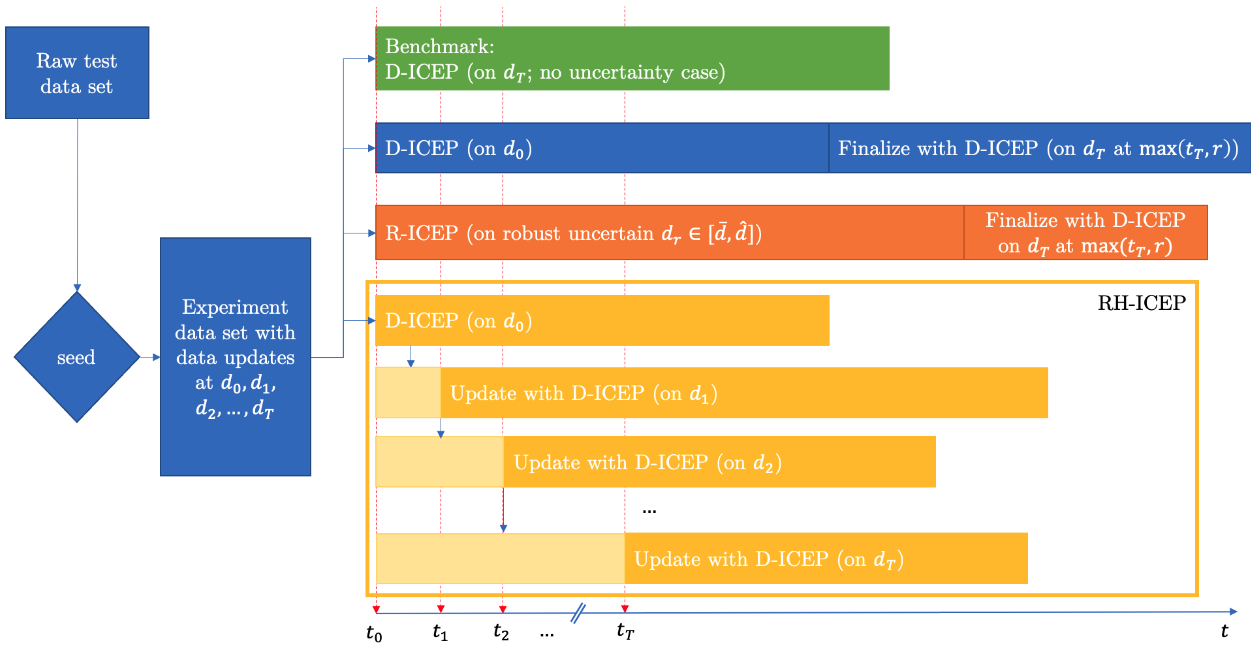


Figure 5.1: Simulation experiment set up

ICEP data set. Therefore, new measures were defined that can influence the ICEP structure through data. The first parameter of interest was the size of the problem in terms of the evacuation demand in relation to the size of the resource fleet. To express this in terms of an ICEP data set, a new metric, denoted the demand-capacity-ratio (DCR) was introduced, which describes the total evacuation demand, divided by the total capacity of the resource fleet, as higher demand generally leads to a higher number of required trips for a constant size resource set. For that reason, the time of the latest update is also scaled with the size of the data set, in proportion with the demand. Second, the R-ICEP and RH-ICEP react differently to the variance in the uncertainty set (for the R-ICEP) and the information updates over time (for the RH-ICEP). The variance in the demand estimates was described through a measure denoted the demand variance factor (DVF), which is defined as a multiplier for the total evacuation demand of a data set. The resulting variance is used to specify the sampling distribution that generates the random variates for the uncertainty set and the information updates in the simulated problem. Lastly, the information update interval, which is particularly important for the RH-ICEP, describes how often new information is received along the time horizon until the actual demand is revealed. Key characteristics of the test data sets are described in Table 5.2, and an overview of the parameters and the corresponding levels that were used to generate experiments is presented in Table 5.3. It should be highlighted here, that $D1$ consists of full compatibility of the resources with the pick-up and drop-off points, while $D2$ consists of limited compatibility between the resources and the nodes. Furthermore, the resource set heterogeneity, measured as the ratio between the capacity of the largest and the smallest resource in $D2$ is much higher than in $D1$. Both together results in a more heterogeneous fleet in $D2$.

Table 5.2: Test Data Sets for RH-ICEP and R-ICEP Performance Benchmark

	D1	D2
Sets	*Set size*	
Evacuation resources	5	6
Initial storage locations	1	2
Evacuation locations	3	4
Evacuation pick-up points	6	6
Safe drop-off points	2	3
Compatibility between resources and nodes	Full	Limited
Resource Heterogeneity	1.22	38.08

A full 3^k factorial experiment design [109] was created that included five randomly generated samples for each factor combination, controlled by a random seed. Experiments were executed on a Mac with a 2.6-GHz Dual-Core Intel Core i5 CPU, using implementations of the aforementioned algorithms using the Pyomo interface for Python using the Gurobi 9.5 commercial solver, with a run-time limit of 3,600 sec for each run. In total 2,025 experiments were executed.

Table 5.3: Parameter Levels Varied for Numerical Experiments

	Parameter Levels		
Setting	Low	Middle	High
Demand-capacity-ratio (DCR) $\left(\frac{\sum_{a\in A} d_a}{\sum_{i\in I} q_i}\right)$	2	3	4
Latest update	120 min	180 min	240 min
Demand variance factor	0.2	0.4	0.6
Information update interval	15 min	30 min	60 min

5.5 Results

A summary of the mean performance in terms of evacuation time of all tested algorithms across all simulation runs is presented in Table 5.4 including the standard deviation and the relative performance of each algorithm compared to the benchmark. The results for R-ICEP are displayed for each Γ value. At first, the results show that the performance gap compared to the benchmark is much lower for data set $D2$ than for $D1$. Furthermore, the baseline, represented by the regular D-ICEP, results in a mean evacuation time of approx. 318 and 464 minutes respectively for each data set. Compared to the benchmark, this results in a 23.9% and 8.8% performance gap for having uncertainty in the data set compared to the benchmark. The results further show that the best performing algorithm for both data sets is the RH-ICEP with a mean evacuation time of approximately 303 minutes and 440 minutes compared to 257 minutes and 426 minutes at the benchmark respectively. This results in a 18% and 3% performance gap caused by the uncertainty in the data. For the R-ICEP, the results are less similar between the data sets. For data set $D1$, the R-ICEP with the most conservative setting ($\Gamma = 3$) at about 309 minutes (20.3% performance gap), represents the second best result, and the R-ICEP with the least conservative setting ($\Gamma = 0$) at 311 minutes (20.9% performance gap) the third best result. For data set $D2$ however, while R-ICEP with the least conservative setting performs second best at 452 minutes (6% performance gap), the most conservative setting results in 484 minutes (13.5% performance gap). While the performance gap through the uncertainty is lower than for $D1$, the most conservative setting is not able to beat the baseline in D-ICEP on average. Furthermore, the table shows that the standard deviation of evacuation times achieved in $D2$ is significantly higher than in $D1$, despite modeling all experiments with the same parameters.

Table 5.4: Mean Performance of Algorithms

Model	Γ	D1			D2		
		Mean	*Std. Dev.*	*Rel. Perf.*	*Mean*	*Std. Dev.*	*Rel. Perf.*
Benchmark	-	256.96	46.30	-	426.12	133.43	-
D-ICEP	-	318.38	59.67	+23.90%	463.63	141.02	+8.80%
RH-ICEP	-	303.20	52.85	+18.00%	438.96	131.25	+3.01%
R-ICEP	0	310.58	45.51	+20.87%	451.66	133.76	+5.99%
R-ICEP	1	320.74	50.02	+24.82%	477.24	157.52	+11.99%
R-ICEP	2	325.33	57.29	+26.61%	486.09	161.69	+14.07%
R-ICEP	3	309.15	54.28	+20.31%	488.18	160.45	+14.56%
R-ICEP	4	-	-	-	483.51	157.25	+13.47%

Figures 5.2 and 5.3 show that the range of evacuation times produced by the D-ICEP is fairly large. For both data sets, the RH-ICEP achieves a range closer to the benchmark. For the R-ICEP, the range generally increases with increasing Γ values. The figures further show that using partially robust data sets does not lead to significant improvements in mean evacuation time over the most conservative or least conservative setting of the R-ICEP.

The results also indicate that the relative algorithm performance is fairly consistent across different variance factors and demand capacity ratios, as Figures 5.4, 5.5, 5.6, and 5.7 show. In particular, Figures 5.4 and 5.5 illustrate that the RH-ICEP shows the best trade-off between evacuation time and variance of evacuation time. It generally shows the most stable behavior to differences in the variance of demand estimates, due to its adaptive structure.

An additional component that was expected to influence the performance of the RH-ICEP is the update interval, but the results in Figures 5.8 and 5.9 indicate that the result does not seem to depend much on the update interval.

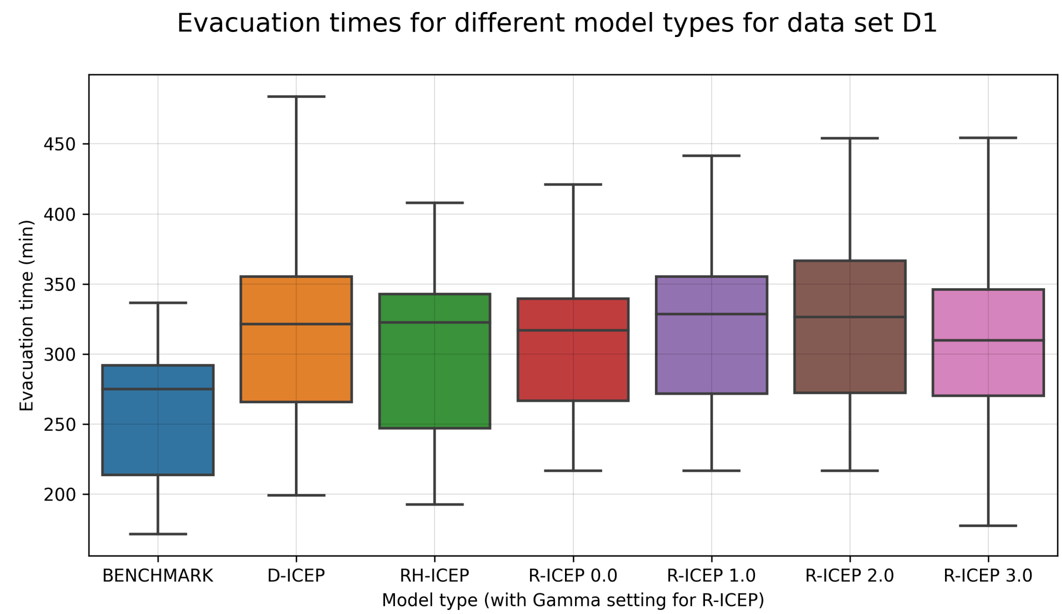


Figure 5.2: Evacuation time distribution per ICEP algorithms for data set $D1$

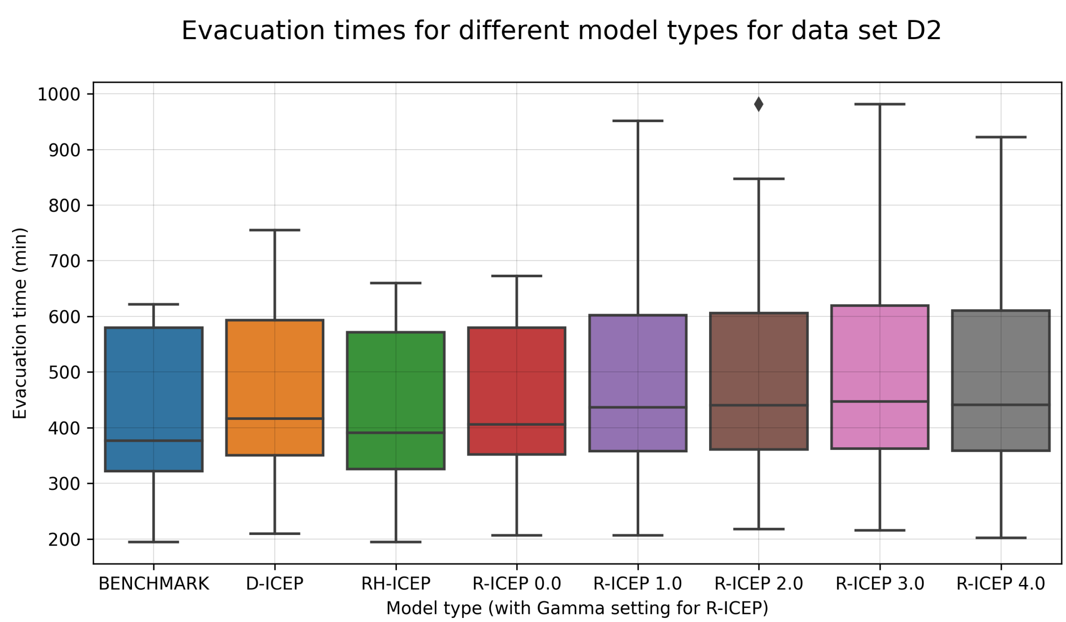


Figure 5.3: Evacuation time distribution per ICEP algorithms for data set $D2$

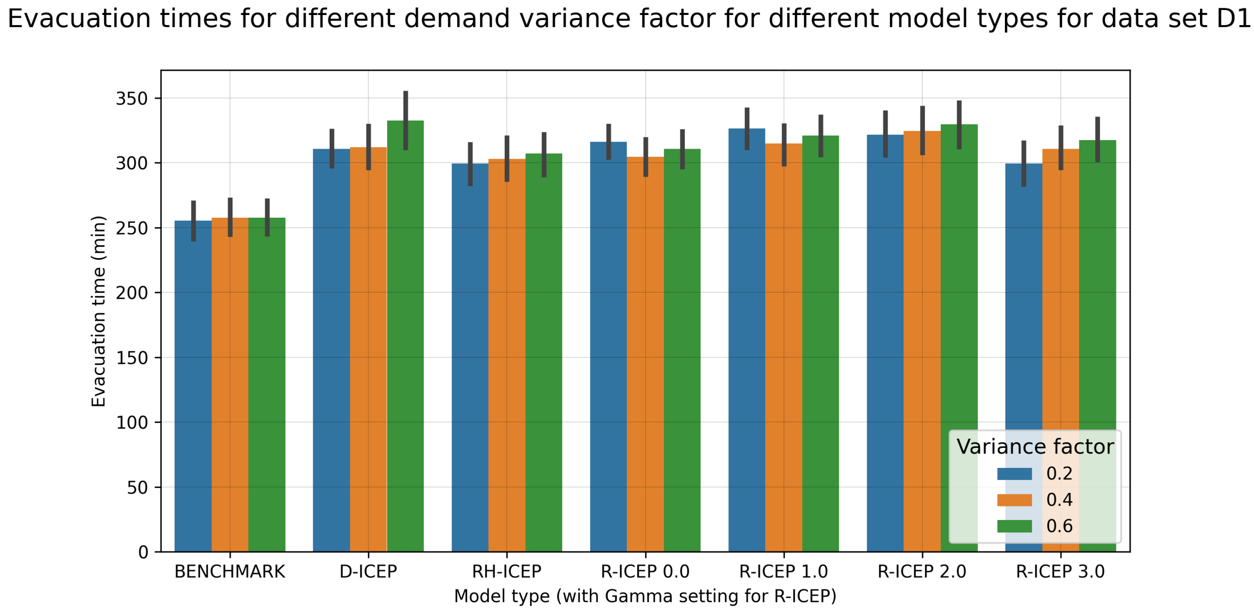


Figure 5.4: Evacuation time distribution per ICEP algorithms by Variance Factor for data set $D1$

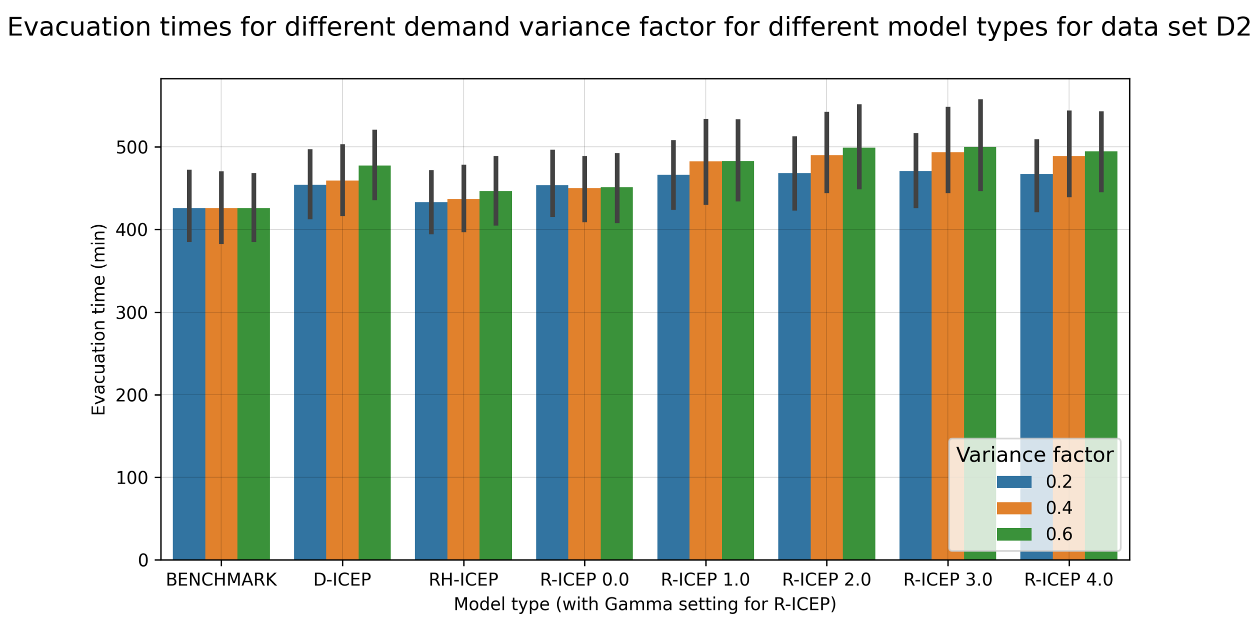


Figure 5.5: Evacuation time distribution per ICEP algorithms by Variance Factor for data set $D2$

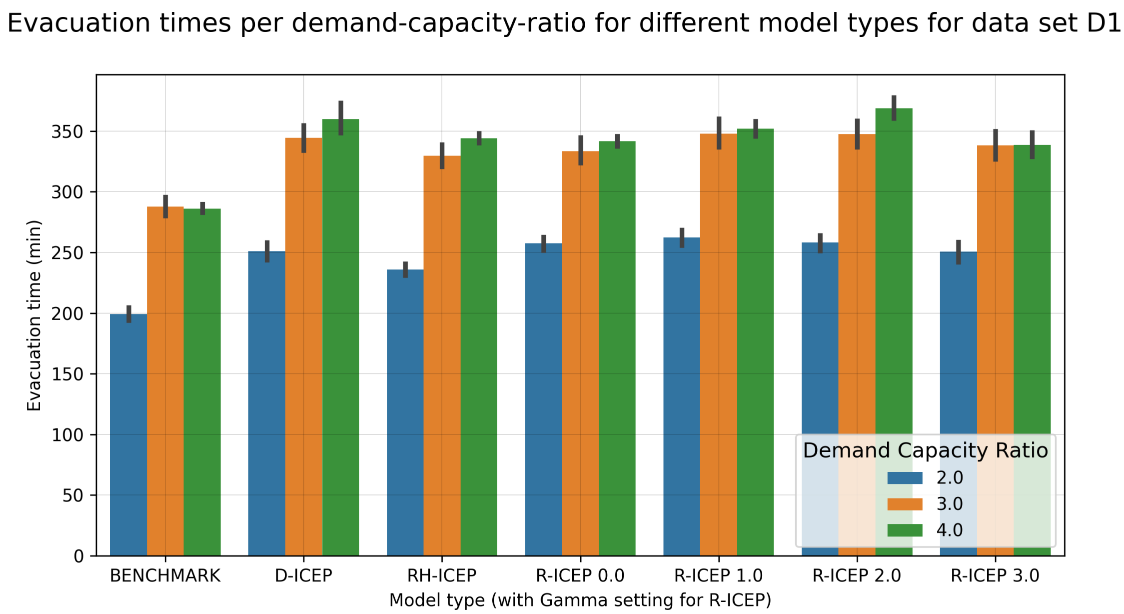


Figure 5.6: Evacuation time distribution per ICEP algorithma by Demand Capacity Ratio for data set $D1$

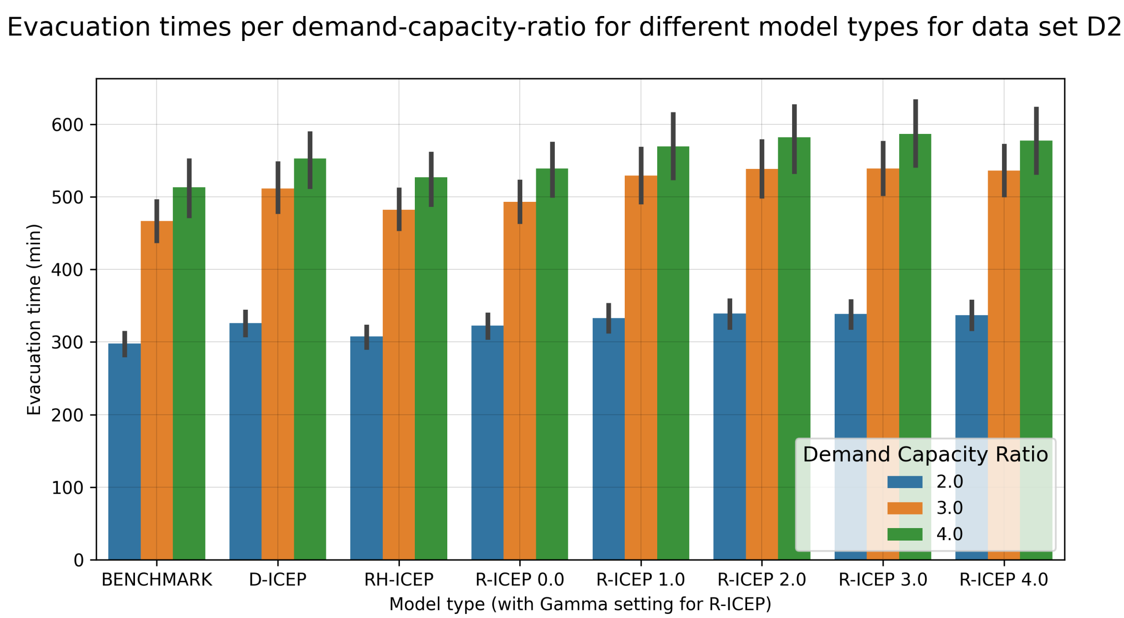


Figure 5.7: Evacuation time distribution per ICEP algorithms by Demand Capacity Ratio for data set $D2$

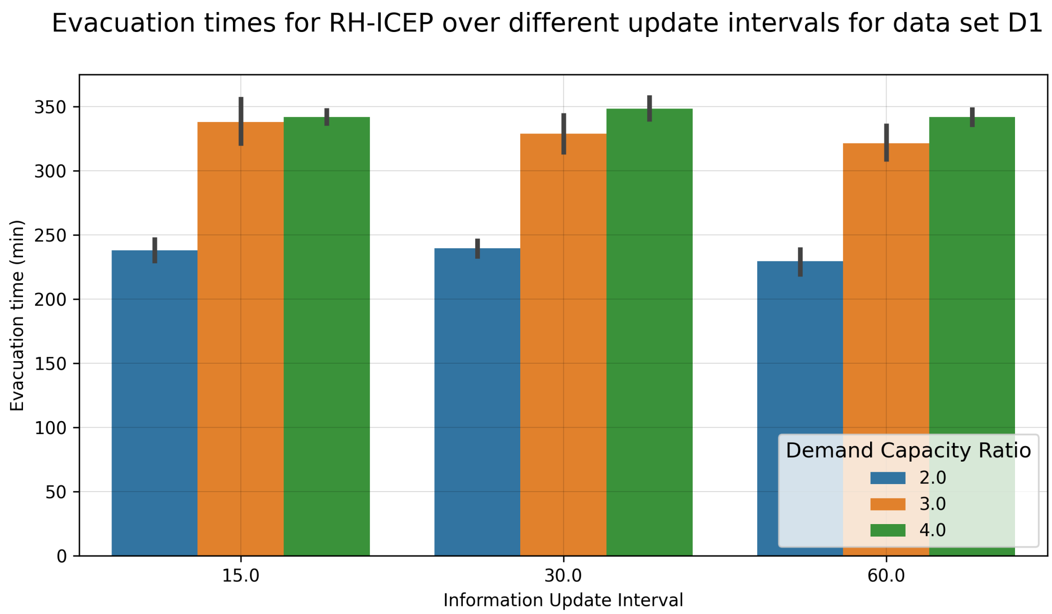


Figure 5.8: Evacuation time distribution per Update Interval for RH-ICEP for data set $D1$

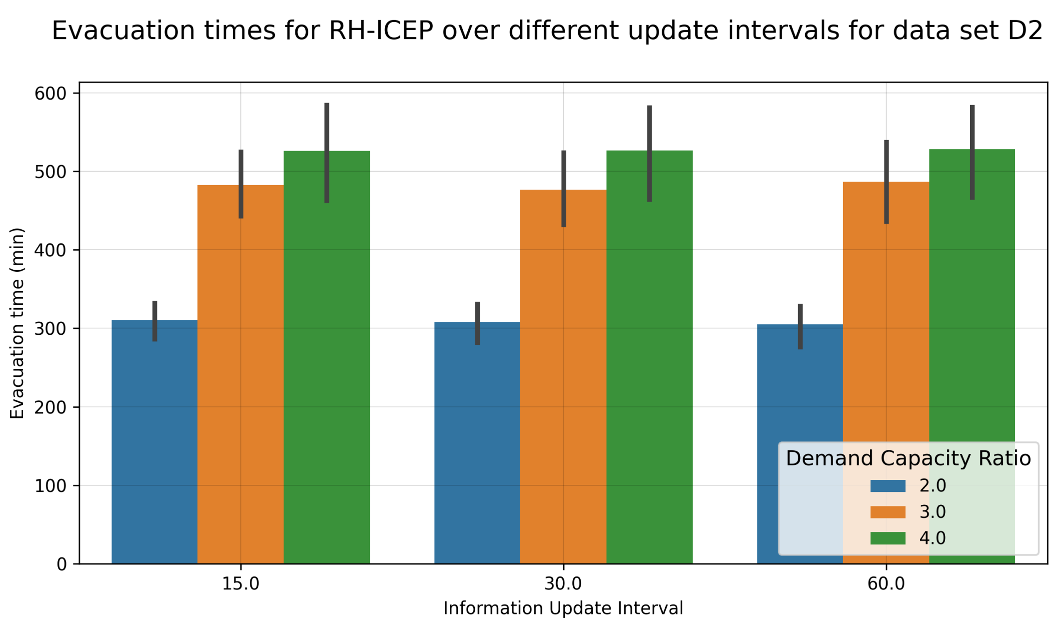


Figure 5.9: Evacuation time distribution per Update Interval for RH-ICEP for data set $D2$

To further investigate the significance of individual factors on the algorithm performance, an analysis of variance (ANOVA) was conducted with the relative performance of the algorithm of interest compared to the benchmark as the dependent variable. Note that only the final models with significant interaction effects are reported. Table 5.5 shows the final model fitted resulting from the ANOVA for the relative performance of the RH-ICEP, and Table 5.6 for the R-ICEP with $\Gamma = 0$, as this configuration showed the best results for R-ICEP on average. Visual inspection of diagnostics plots confirmed that the ANOVA is an appropriate method and that the residuals follow normality.

Table 5.5: ANOVA Results RH-ICEP vs. Benchmark

	Sum of Squares	df	F-value	p-value
Intercept	328.265	1.0	80,365.081	7.905e-323
DCR	0.044	2.0	5.344	5.321e-03
Update Interval	0.019	2.0	2.299	1.024e-01
Demand Variance Factor	0.048	2.0	5.877	3.193e-03
Compatibility	1.383	1.0	338.602	8.175e-49
DCR : Compatibility	0.031	2.0	3.797	2.370e-02
Residual	1.050	256.0		

Table 5.6: ANOVA Results R-ICEP ($\Gamma = 0$) vs. Benchmark

	Sum of Squares	df	F-value	p-value
Intercept	346.738	1.0	90,666	0.000
DCR	0.349	2.0	45.596	1.153e-17
Update Interval	0.007	2.0	0.916	4.016e-01
Demand Variance Factor	0.027	2.0	3.532	3.069e-03
Compatibility	1.473	1.0	384.572	6.624e-53
DCR : Compatibility	0.147	2.0	19.199	1.702e-08
Residual	0.981	256.0		

In both tables, it can be seen that the same main effects and interaction effects are significant, and the analysis confirms the findings from the plots in Section 5.5. In addition to the observations made through the charts, the compatibility between resources and nodes can be identified as having significant influence on the relative performance. Further, an interaction effect between the Demand Capacity Ratio and the compatibility between resources and nodes can be found. It is furthermore worth exploring what components influence the relative performance difference between the RH-ICEP and the R-ICEP ($\Gamma = 0$). Table 5.7 presents the ANOVA results for this comparison, with the ratio between the RH-ICEP evacuation time and the R-ICEP ($\Gamma = 0$) evacuation time as the dependent variable.

Table 5.7: ANOVA Results R-ICEP ($\Gamma = 0$) vs. RH-ICEP

	Sum of Squares	df	F-value	p-value
Intercept	254.623	1.0	75,310.90	3.216e-319
DCR	0.155	2.0	22.910	6.983e-10
Update Interval	0.028	2.0	4.067	1.824e-02
DVF	0.081	2.0	12.042	1.002e-05
Compatibility	0.000	1.0	0.035	8.507e-01
DCR : Compatibility	0.058	2.0	8.755	2.141e-04
DCR : Update Interval	0.011	4.0	0.850	4.950e-01
DCR : DVF	0.010	4.0	0.767	5.479e-01
Update Interval : DVF	0.002	4.0	0.135	9.695e-01
DCR : Update Interval : DVF	0.069	8.0	2.612	9.330e-03
Residual	0.787	239.0		

Table 5.7 shows that in contrast to ANOVA comparisons with the benchmark, the compatibility between resources and nodes does not significantly influence the difference in performance between the two algorithms, while the update interval shows significant influence. In addition, an additional significant three-way interaction term between the DCR, the update interval and the demand variance factor can be identified. This shows that there are multiple factors in the data set that cause the difference in performance between the two algorithms and that the differences cannot be accounted for through a single main effect. However, this does not affect the general outperformance of RH-ICEP over the R-ICEP.

5.6 Discussion

The results presented in Section 5.5 indicate that higher heterogeneity of the resource fleet and limited node-resource compatibility results in a lower performance gap caused by the uncertainty, as the algorithm runs show. A major reason for that is that despite uncertainty, a more heterogeneous resource fleet does not provide as much flexibility to route resources, as the feasible region is smaller. Thus, even if the demand is different, the solutions do not differ as much in their fundamental structure. In these cases, higher demand is usually compensated through additional trips of a resource that serves this area already, rather then completely different allocations between resources and destinations, as there are often not many alternative resources to be used on that route. Thus, the benchmark has a lower advantage through considering the actual evacuation demand.

Furthermore, the results demonstrated that the RH-ICEP performs best in comparison to the benchmark across all simulations. The capability of the RH-ICEP to update the plan with incoming information results in better solution performance. This represents a substantial improvement over the regular D-ICEP. In comparison, an improvement of 15 and 25 minutes respectively may not seem to be a large difference compared to the benchmark evacuation time of mean 258 and 427 minutes. However, a few minutes difference during an evacuation situation can determine whether fatalities occur or not and are thus of high value.

For the R-ICEP, the improvements over the D-ICEP are not as clear as for the RH-ICEP. While using the least conservative setting appears to generally result in good performance, taking full advantage of the robust capability of R-ICEP only shows this behavior for simulations based on $D1$, where it actually outperforms the R-ICEP with the least conservative setting. This is a counter intuitive finding, as the most conservative setting has a higher likelihood of evacuating the actual demand on the first attempt without requiring additional adjustments once the true demand is known and the plan has been executed. When the resources are more heterogeneous like in $D2$, the most robust solution may evacuate all evacuees, but it does so at a lower efficiency than the other models. The reason for this was identified when reviewing the generated route plans. It was found that a fully robust route plan can result in many unnecessary resource trips if the true demand is lower than the robust demand, which naturally increases evacuation time. As a lower share of resources are capable to evacuate a specific area in $D2$, this effect is amplified for such data sets. In addition, the robust route plan will require additional adjustments in the unlikely but possible case that the actual demand is higher than the range of the values considered for the robust data set. Using fully robust settings in the R-ICEP can therefore only be recommended for situations in which the fleet is fairly homogeneous and highly compatible with the nodes in the network, as only such a set up allows to take full advantage of the robust capability of the model. In more compatible data sets, using the least conservative setting is more promising as it results in a route plan that is completed earlier and is thus more flexible to adjustments once the true demand becomes known. Even better for all kinds of data sets is to use the RH-ICEP as it shows best adaptability across the entire bandwidth of data sets.

A reason for the low performance of partially robust algorithms across all simulations is that partial robustness of demand distributions creates an artificial tilt in the data set towards one or more evacuation locations, that results in an evacuation plan mostly allocating resources to these areas. If demand does not reflect a similar distribution as the robust demand, this requires additional adjustments after the robust route plan has been executed, especially if demand for other areas has been underestimated. Therefore, the performance of these settings is relatively low.

Remarkable is furthermore, that changes in variance factors, and demand capacity ratios do not significantly affect the performance rank of the algorithms, with the RH-ICEP still demonstrating the best performance on average. However, as the ANOVA tables show, the absolute performance differences between the algorithms can be attributed to a multitude of factors that are heavily dependent on the data set. It is therefore not possible to easily establish a theoretical competitive ratio, as is usually the goal for online optimization. Furthermore, the update interval does not change the quality of the solution a lot. The RH-ICEP's structure, that information is updated when new information becomes available leads to strong results irrespective of the frequency of updates.

5.7 Conclusions and Next Steps

This chapter has presented two modeling approaches to handle uncertainty over evacuation demand during emergency response when optimizing evacuation route planning with the ICEP. The first proposed modeling approach uses cardinality-constrained robust optimization to design routing plans based on uncertainty sets. The second proposed modeling approach consists of an algorithm based on the D-ICEP, that updates the non-executed part of the evacuation plan through a rolling-horizon optimization approach based on additional information as soon as it becomes available. These methods stand in contrast to each other on how to handle uncertainties in modeling. Numerical experiments were conducted that compared the performance of the two algorithms against a benchmark case without uncertainty, and a baseline case, where the D-ICEP was used based on the initial estimate for the evacuation demand. The experiments have shown that the RH-ICEP outperforms both the baseline and the D-ICEP in every instance by a significant margin. It furthermore outperforms all configurations of the R-ICEP on average, and in the majority of simulation instances. The R-ICEP only performs reasonably well across all data sets when using the least conservative setting, which corresponds to using the mean of the uncertainty sets. However, the experiments furthermore showed that for fully compatible ICEP data sets, the most conservative setting of the R-ICEP performs well. A key finding is that for problems with limited compatibility, robust optimization does not produce efficient solutions as many unnecessary trips are generated. In general it can be concluded that there is a lot of value in updating plans as new information becomes available through rolling-horizon optimization, and that using an initial point estimate as a starting point is sufficient to outperform initial considerations of entire uncertainty sets, such as in robust optimization, as it is more flexible. This is confirmed by the stability and lower variance of the results across varying parameter settings in the simulated data sets for the RH-ICEP. Therefore, the RH-ICEP can be recommended as the best available approach to solving the ICEP for response purposes.

In future work, varying settings of additional types of data set characteristics can be explored, that further describe data differences. In addition, it may be valuable to explore further how varying intervals in information retrieval influence the performance of the RH-ICEP. Moreover, additional testing on a real world data set, may lead to additional insights. It may be challenging to obtain such a data set from historic data as it requires a successful evacuation of an area and sophisticated record keeping of all launched evacuation efforts and resources. However, this can be solved through using the method during an actual emergency. Lastly, research on a combined robust and rolling-horizon method may lead to further improvements, combining the strengths of both approaches.

Chapter 6

PLANNING FOR MARINE-BASED EVACUATION: A CASE STUDY

The work presented in this chapter has been published under the title ”Evacuating Isolated Islands with Marine Resources: A Bowen Island Case Study” in in the *International Journal of Disaster Risk Reduction* and is co-authored with Jennifer McGowan and Dr. Anne V. Goodchild [93]. This chapter is not the copy of record and may not exactly replicate the authoritative document that was published.

6.1 Abstract

The introduction of the stochastic isolated community evacuation problem (S-ICEP) in Chapter 4 has provided emergency planners with a tool to prepare a community for a potential evacuation caused by a hazard and thus provided an important piece to the emergency response component of evacuation planning. However, the success of this model is dependent on the accuracy of input data, which is based on other evacuation planning components, such as hazard and shelter analysis, and inputs from emergency operations. Therefore, this chapter presents a collaborative approach that highlights the data-model interactions that form the basis of a successful evacuation study that involves mathematical programming. It applies the stochastic isolated community evacuation problem (S-ICEP) that optimizes the evacuation plan for Bowen Island in Canada through minimizing the expected evacuation time across disaster scenarios. These were designed with the participation of a broad range of stakeholders, from local residents and volunteer groups to agencies from all levels of government and companies, which integrates both academic and practical perspectives to maximize solution quality. Different options for fleet sizes, staging locations and scenarios

were considered. The results show that the optimized evacuation time for Bowen Island varies between 1 and 8 hours, as it strongly depends on the disaster scenario, the evacuation fleet, and can be accelerated by temporary staging areas. The suitability of the approach for evacuation studies can be confirmed through the identification of key improvements for increased community resilience and the inclusion of the results in the official Bowen Island evacuation plan.

6.2 Introduction

6.2.1 Motivation

Science has frequently connected the increased occurrence of natural hazards to climate change [114, 115, 144]. In largely forested areas, such as the west coast of North America, communities are vulnerable to natural hazards that affect forests, particularly fires. The increased severity of wildfire events since the year 2000 confirms the increase of wildfire events [149]. The increased frequency of such natural hazards, combined with past failure to reduce the risk for disasters sufficiently leads to an increased risk for disasters to vulnerable socio-ecological systems [116, 148]. Since wildfires are becoming an increasingly high threat [85] to societies, there is increased interest in providing solutions to make communities more resilient against wildfires [105]. Achieving community resilience is a complex task and many studies have investigated how to improve it, especially considering communities threatened by wildfires [40, 105, 116], such as preventative forest management and the design of community infrastructure and property layouts at the urban-wildland interface. Making communities more resilient and investing in disaster prevention is therefore the primary objective of disaster risk reduction and highly influences the effects on the community should a natural hazard occur. However, while the risk to the population can be reduced by appropriate resilience measures, a contingency plan is necessary as a last resort for the case that a disaster cannot be averted. Hence, an important aspect of a disaster contingency plan is to ensure the ability to evacuate the population quickly and efficiently [135]. Evacuations are particularly difficult in areas that have geographically challenging circumstances, such as a limited number of exit roads or no road access at all, as a recent geo-spatial data analysis by StreetLight Data showed for communities in the USA [138]. This particularly applies to marine communities, as recent disasters have shown: for example, during the 2020 Australia bushfires, a large part of the population of Mallacoota had to be evacuated using navy vessels after the fire front had cut off all exit routes [2], and during a wildfire in Greece in 2019, the population of beach villages had to be evacuated from the beach using boats [44]. The increased awareness of the risks of wildfires has motivated the Bowen Island Municipality (BIM) to review community preparedness plans and to prepare an evacuation plan for the heavily forested Bowen Island [36] as a last resort contingency. Bowen Island is located in Howe Sound, to the west of the Canadian west coast metropolis Vancouver in the Province of British Columbia (BC) and does not have a road connection to the mainland. Figure 6.1 shows a schematic map of the area around Bowen Island. The Bowen Island community, including many of the over 3600 residents [79], local government staff and elected officials, identified the need for evacuation planning during the summer of 2015, when smoke from wildfires on the nearby Sunshine Coast was visible from Bowen Island, and residents awoke to an orange sky. This nearby wildfire event prompted a review of the outdated 2007 Bowen Island Emergency Management Plan and the subsequent formation of an Emergency Program for the community. Geographically, Bowen Island's topography and road networks mean that limited routes are available for evacuation, with most of the island's sub-communities served by single terminating roads. Further, limited modes of transportation off-island are available, with the ferry providing one primary point of access and egress. While the ferry is the most utilized and affordable choice for getting to and from Bowen Island, vehicles and equipment can alternatively be transported by private barge, and private vessels can access the island at multiple points for passenger pick up and drop off.

In addition to the geographical challenges and the heightened awareness of the risk in recent years, multiple community plans and assessments had indicated that planning was imperative to ensure an effective evacuation of the island as far back as 2007. The Bowen Island Municipality Community Wildfire Protection Plan (CWPP) notes the potential for a large interface fire and that "under this scenario, rapid evacuation of residents and safe escape or refuge for firefighters would be essential. At present, action is required to bring evacuation and emergency response planning to a level where this type of emergency is taken into account." [27][p. 21]. The CWPP also recommended "developing a contingency plan in the event that smoke requires complete evacuation of the island" [27][p. 31] and that "an evacuation plan should be developed and appropriate evacuation routes should be mapped.

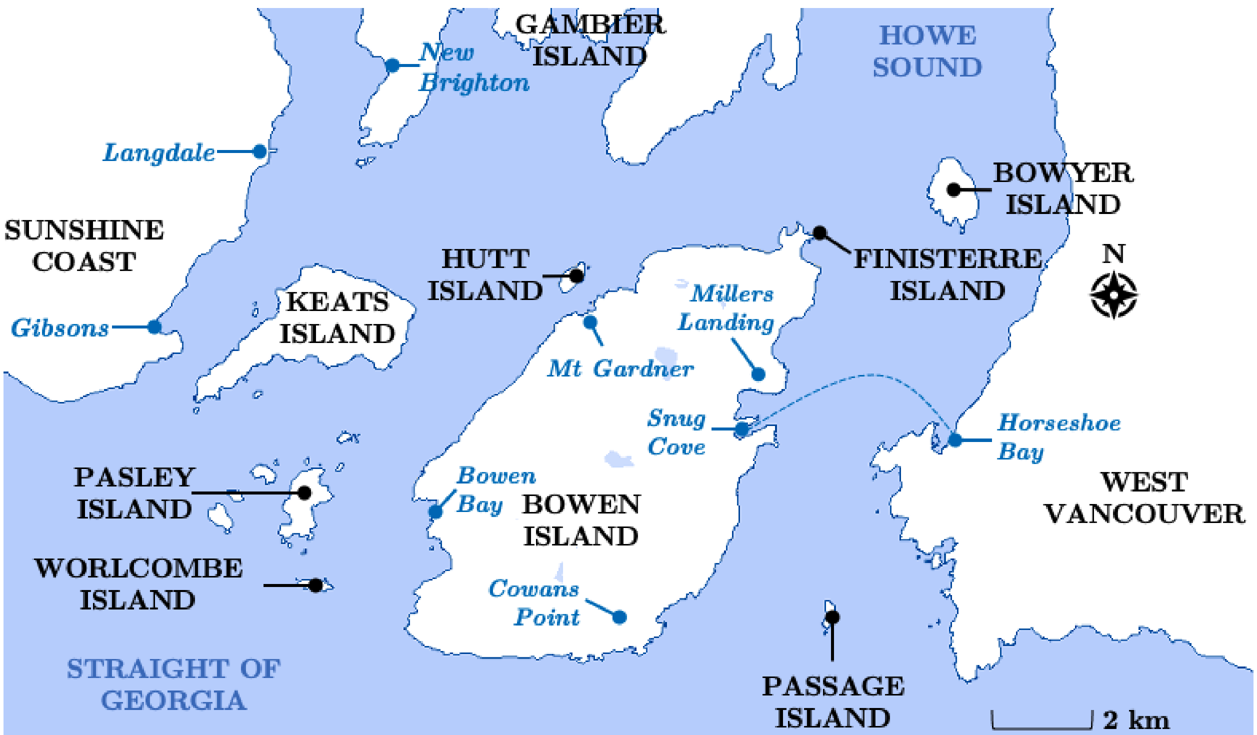


Figure 6.1: Map of Southern Howe Sound including major settlements and islands

A large fire may require the evacuation of the entire island and egress could be very restricted. A contingency plan for water evacuation should be developed in the event that the ferry is unavailable." [27][p. 33].

The 2018 BIM Hazard Risk and Vulnerability Assessment (HRVA) also stresses the importance of evacuation planning as critical to the Municipality's ability to conduct a successful evacuation [28]. The HRVA highlights the reality that the presence of multiple terminating roads makes the potential for evacuation by water a distinct possibility, and that "the multiple challenges posed by an island-wide evacuation make evacuation planning important to emergency preparedness on Bowen Island" [28][p. 26]. The HRVA recommends that the Municipality engage in formal evacuation planning, and that this work could also prove useful in re-supplying the island in the event of a BC Ferry Services Inc. infrastructure failure, as well as in re-supplying sub communities that are not accessible by road post-disaster. The heightened awareness of the local risk of wildfire and the anticipated challenges associated with evacuating the island, combined with the availability of funding for local government evacuation planning through the Province of BC and the Union of British Columbia Municipalities (UBCM), led the community to formally address the issue of evacuation planning beginning in 2019. While modelling of land based (vehicle) traffic had been incorporated into earlier planning, modelling of marine vessel traffic was identified as necessary in order to better understand potential opportunities, challenges and timelines under a variety of realistic evacuation scenarios. The community well understood the capacity of the ferry [30][p. 48], but did not have any knowledge of what the fleet of local vessels could contribute to reduce total evacuation time, nor what capacity existed should the ferry be unavailable and how to select appropriate route plans for these evacuation resources. To fill these knowledge gaps and take advantage of sophisticated modeling skills the local government did not have access to, the local government emergency manager of Bowen Island entered into a collaboration with the research team of the Supply Chain Transportation and Logistics Center (SCTL) at the University of Washington. This collaboration was a result of a chance meeting at a workshop on marine transportation resilience in the scope of 'Shipping Resilience: Strategic Planning for Coastal Community Resilience to Marine Transportation Risk' (SIREN), highlighting the importance of opportunities for researchers and practitioners to connect and collaborate in this type of forum. While collaboration did increase the time and resources expended, the integration of carefully collected ground level data with sophisticated evacuation modeling techniques, led to invaluable insights regarding expected evacuation times under different scenarios. The research questions defined for this collaborative study were:

- How to evacuate an island, where road-based evacuation is not possible, and marine resources have to be used to evacuate the population?
- How long does it take to evacuate the island under a variety of conditions?
- How to use this information to plan and prepare for a real-world evacuation and reduce the evacuation time?

Other island communities with similar characteristics around the world face similar challenges, see for example [138] for similar places in the United States. This shows the wider relevance of this problem, which is why answering these research questions systematically and rooted in methodology can be used as a template for similar studies in other regions.

Before investigating ways on how to evacuate an island, it is important to consider what makes this problems special compared to other evacuation problems. At first, the lack of a permanent road-based connection to the mainland makes it impossible for the majority of an island population to leave the area with a private vehicles or on foot. Instead, they have to move to the shoreline and evacuate by marine resources. Since the majority of people do not own boats that are readily accessible to evacuate themselves, they are dependent on others. Since there may be multiple potential vessel access points in a community that cannot easily be overseen, this is where it becomes necessary to evacuate the island through a coordinated effort that includes the management of vessel routes and passenger assignment. However, these plans are sensitive to changes in the nature of the hazard and the size of the population that is affected and one-size-fits-all approaches to evacuation plans become impractical. Thus directing the population to appropriate vessel access points and coordinating a potentially heterogeneous vessel fleet while considering a variety of disaster realizations are the main challenges in island evacuation that are not comparable to regular road-based evacuation. This chapter focuses on the latter of the two challenges.

6.2.2 Previous Work

There are different ways of how evacuation planning can be approached. From a practical perspective, the Province of BC provides some guidance to communities with regards to evacuation planning. Relevant to the Bowen Island case study, Emergency Management British Columbia has published a 47 page guide, "Evacuation Operational Guide for First Nations and Local Authorities in British Columbia: A guide to managing evacuations during emergency response", which provides "a simplified reference tool for Emergency Operation Centres (EOC) or designated community contacts to follow when issuing an Evacuation Alert, Order, or Rescind." [61][p. 3]. The document serves as a quick reference guide for community leadership during an evacuation: "Intended for use during the response phase of an emergency, this guide provides advice, information, considerations, and templates for all stages of an evacuation. The recommendations provided are not prescriptive." [61][p. 8]. The guide is not an evacuation plan template, but provides relevant details that should be included in evacuation plans such as quick reference information, protocols and procedures, relevant legislation, definitions, roles and responsibilities, and factors for consideration by decision makers. Internationally, similar evacuation planning frameworks exist elsewhere, and notable examples include the mass evacuation planning guidelines from New Zealand [112] and from the United States by the Federal Emergency Management Agency (FEMA) [63]. While many communities in British Columbia have evacuation plans or plans under development [143], marine model-based evacuation plans specific to islands have not been publicly shared. Locally, the cities of Whistler and Squamish completed a multi-modal evacuation plan for the Sea to Sky corridor, but their evacuation analysis is rather based on infrastructure access points than on modeling [124]. Provincially, Cortes and Quadra Islands have evacuation plans that focus on land based evacuation to marine points, but do not model marine traffic [137]. While information on the marine evacuation of Manhattan during 9/11 is available and may have some relevance in terms of the potential availability of spontaneous volunteers, learnings from the evacuation of over half a million people by water in urban New York are not necessarily applicable to a rural community of under 4000 residents [87].

Reviewing evacuation frameworks from a research perspective, Tüydeş [142] and Southworth [135] structure evacuation studies into five categories: (a) hazard analysis, (b) vulnerability analysis, (c) shelter analysis, (d) emergency response actions, and (e) behavior analysis. While all of these categories are relevant to the case study in this chapter, the core of this exercise focuses on the planning for and execution of emergency response actions, including the coordination of resources and evacuation flows. Modeling the emergency response for evacuations is a popular topic, particularly in emergency research and mathematical modeling. The large number of surveys on evacuation studies demonstrate the large body of existing research, see for example [5,12,56,57,83,100,123,153,154,154]. We therefore refrain from restating details on the extensive literature available and refer the interested reader to these reviews. In general the used methodologies range from systematic survey techniques over simulations to mathematical optimization. As the reviews show, a lot of research has been presented on how to plan for the emergency response action component of evacuations for areas that can rely on a solid road infrastructure. For that, emergency planners can mostly rely on the ability of the population to evacuate using private vehicles. Naturally, this assumption can not be made for the evacuation of islands without permanent road connections. While there are some studies that have investigated the resilience of island communities to hazards that can lead to evacuations [121, 147], these have not considered the systematic creation of a resource-based evacuation routing plan, but were rather based in hazard analysis [147], and spatial analysis [121]. In fact, the systematic and model-based evacuation of islands is a massively understudied problem, as not much previous work has been published on this topic.

While there are many evacuation models as the literature review in Chapter 2 shows, only the ICEP model has focused specifically on modeling the evacuation of isolated communities, such as islands. Chapter 3 presented an optimization model that calculates the optimal route plan to evacuate an isolated community through the use of a coordinated set of resources. Chapter 4 further provides a version of the model that allows for scenario-based evacuation planning. However, the aforementioned chapters used synthetic data to test the model and did not provide a case study. This chapter aims to answer the research questions presented in Section 6.2.1, and at the same time fill a knowledge gap for the ICEP formulations by providing a case study for this type of model.

6.2.3 Contributions

Previous work from both academic research and practice does not provide sufficient answers in terms of how to consider the special circumstances of island evacuation. The challenge, not frequently mentioned in academic modeling research, is that a successful evacuation planning study based on modeling techniques such as optimization requires substantial data collection efforts at the local and regional level and a close collaboration with other stakeholders, in order for the model to provide insights that are actually valuable for emergency management and first responders [9, 62]. If inaccurate assumptions on data are made by modelers, the results of the model can be drastically different and wrong conclusions can be drawn. This creates a need to conduct interdisciplinary research to validate data and modeling assumptions with communities itself and to investigate perceived risk levels and concerns within the communities.

While evacuation plans based on mathematical models can not predict what exactly what will happen during a disaster, especially considering hazard uncertainty and evacuation behavior, not taking advantage of modeling techniques can result in not fully leveraging the available data and therefore missing important learnings that can be derived from the collected information. Therefore, mathematical modeling in combination with thorough stakeholder management and data collection provides and important tool for disaster risk reduction. Given that the authors of this study had access to local and regional expertise as well as modeling expertise, this study takes advantage of these interactions to take an end-to-end collaborative approach to this problem. It should be mentioned here that previous research has identified Indigenous communities as highly knowledgeable about how to effectively evacuate their own communities based on experience [104], which poses a conflict between scientific and Indigenous approaches to evacuation that can cause misunderstandings in resilience planning and communication and ultimately result in disasters [9]. When evaluating the effects of this topic, the well researched topic of evacuation behavior [45, 141] plays a large role. However, attempting to resolve this problem entirely is beyond the scope of this chapter.

This research focuses on a substantial data collection and knowledge acquisition, which is then used to inform the aforementioned optimization model to produce an evacuation planning model that considers a wide variety of inputs from different stakeholders. With that, this case study fills an important research gap. At the same time, this work delivers a valuable contribution to the generation of an evacuation plan for Bowen Island itself. The contributions of the study presented in this chapter are therefore the following:

- This study represents the first reported attempt to systematically plan the evacuation of an island by marine resources beyond regular ferry operations based on an integrated approach of data collection, surveying, stakeholder management, and mathematical modeling. The strength of this data-backed approach is the end-to-end collaboration and integration of knowledge from the modeling expertise of academic researchers with the data and experience of emergency authorities and the process knowledge of municipal emergency managers to revise a model version that reflects the challenges on the ground and provides insight that can be used by emergency authorities.
- The model used in this case study further contributes to local evacuation planning on Bowen Island in multiple ways. Primarily, it helps emergency planners to better understand the amount of time potentially required to evacuate residents from the island. Modeling informed the community evacuation plan, specifically the alternate marine evacuation timetable: for Bowen Island, in evacuations involving population sizes of 1000 or more where ferry access is cut off, additional services from more distant

locations with higher capacity vessels are likely to be critical to reducing evacuation times. Finally, the concept of using locations less ideal for long term sheltering (e.g. smaller islands) as temporary staging areas had never been entertained prior to this work; but was found to drastically reduce evacuation times and is now incorporated into the Evacuation Plan [30].

- The process followed in the presented study can be used as a template for future evacuation studies and for planning for the evacuation of similarly geographically challenged communities. This tool thus delivers a significant contribution to interdisciplinary research around evacuation that helps to reduce the impact of disasters caused by natural hazards not only in theory but also in practice.

The remainder of this chapter is structured as follows. Section 6.3 presents the materials and methods that were used to complete the case study and reviews in detail the accessed and collected data sources that were used to gather the model inputs. Furthermore, Section 6.4 introduces considerations with regard to the scenario design, different options for shelter locations and evacuation fleet sizes. Section 6.5 concisely presents the results of the model and Section 6.6 discusses the implications of these results and finishes with a summary and a research outlook. The structure of the study is presented in Figure 6.2 and considers iterative approaches to both the Data Collection and the Modeling steps with stakeholders to maximize the insight delivered by the study.

6.3 Material and Methods

6.3.1 Data Sources and Data Collection

Data Requirements

To run the study using the S-ICEP model, a substantial data set validated by multiple stakeholders was required to maximize the value of the study for both research and practice. The following inputs were needed:

- The population size on the island and its fluctuation on different days and at different times;

- The distribution of residents around the different sub-communities of Bowen Island;
- The willingness and ability of the population to self-evacuate with private vessels;
- Potential docking points and shelter locations for recovery vessels;
- Realistic scenarios for wildfire emergencies on Bowen Island including weather information;
- Information on the existence, usual location, capabilities and limitations of potential recovery vessels, including cost parameters for vessel contracting and operating cost.

To gather all the information listed above, a multitude of sources was used, ranging from publicly available data to ground-level data collection through surveys and interviews with subject matter experts. The required data were collected collaboratively by both the research team and local government staff: dividing labor in this way overcame issues of staff capacity and ensured that relevant data was collected in a timely manner. In some cases, the local government was better positioned to collect or request relevant data (e.g. the resident survey), which resulted in more robust modeling results, acceptable by the local population. The following sub sections describe the information obtained from the corresponding sources, and further outline the challenges in obtaining this data. As illustrated in Figure 6.2, an approval loop with stakeholders after the completion of the data collection was worth the effort to ensure stakeholder acceptance of the modeling results.

Insurance Corporation of BC

In late 2019, data on the number of vehicles registered on Bowen Island (by postal code) were requested from the Insurance Corporation of British Columbia (ICBC) in order to estimate rates of vehicle ownership and potential capacity to self-evacuate (i.e. the ability for an occupant to exit an evacuation area without transportation assistance). The number of vehicles registered to Bowen Island addresses as of January 13, 2019, including temporary and storage policies, was provided to the Bowen Island Municipality by ICBC for a variety of vehicles categories including passenger, commercial, commercial trailer, utility trailer,

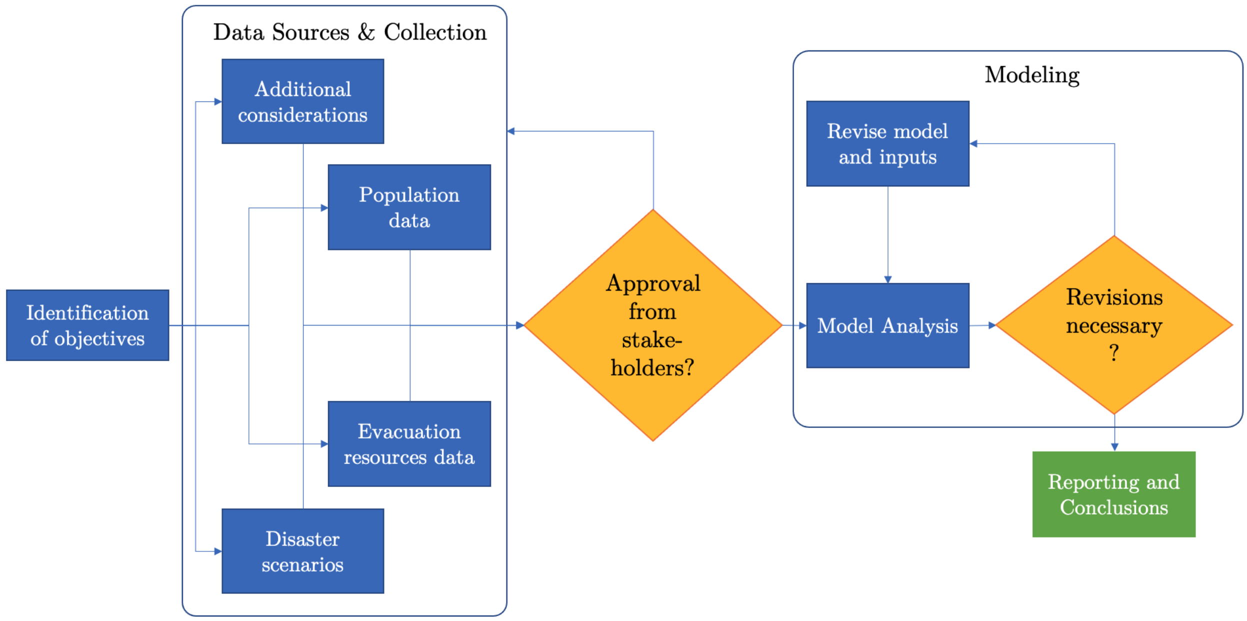


Figure 6.2: Case study process template

motorcycle/ moped and motor home. ICBC reported upon request that the total number of passenger and commercial vehicles and motorcycles/ mopeds (no trailers) registered to postal codes on Bowen Island was over 3030. Given population estimates obtained from census data, rates of household vehicle ownership are estimated at over 90% [30][p. 32].

Population Data

Government of Canada 2016 census data [79] was used to obtain population figures and thus inform estimates of how many people are on Bowen Island at any given time. According to the census, the total population of Bowen Island is 3680, of that, 640 are 0-14 years old [79]. According to census data, approximately 420 dwellings are utilized as seasonal or temporary homes, and anecdotally it is believed that the population increases by at least 1500 people in the summer months [31]. Additionally, day-trip and overnight tourists are anticipated to increase the population during the tourist season in particular. Further, the municipality of Bowen Island maintains estimates of household numbers at the sub-

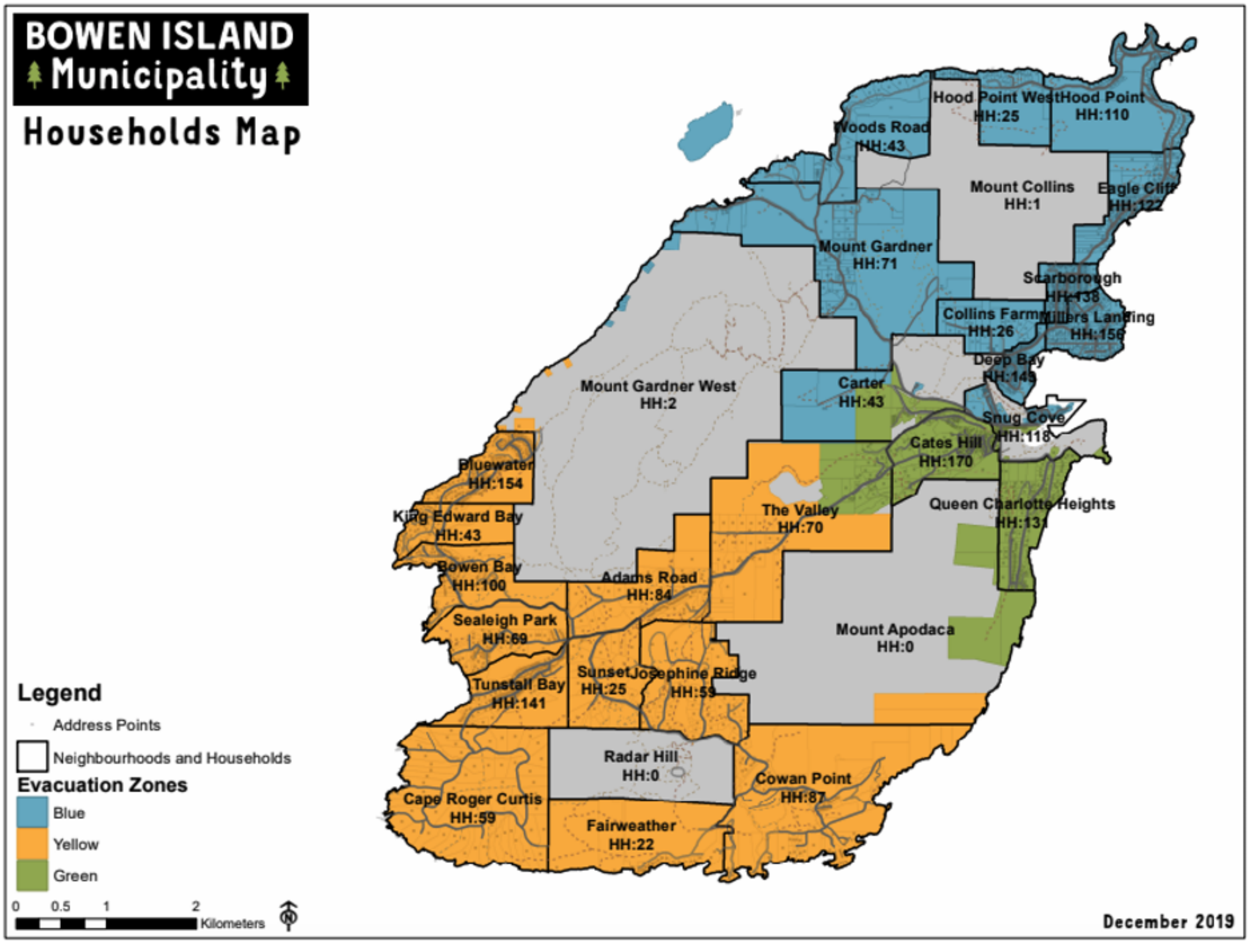


Figure 6.3: Household map of Bowen Island. Source: Bowen Island Municipality [30][p. 52]

community or neighbourhood level based on the number of dwellings in each area. This information is illustrated in Figure 6.3. The evacuation zones illustrated on the map are based on traffic control points and population size. Together with the assumption of 2.5 residents per household [79], this allowed to estimate the number of residents in, and thus potential evacuation demand from, each neighborhood.

Tourism and BC Ferry Services Inc. Ridership Data

BC Ferry Services Inc., which operates the only regularly scheduled ferry service between Bowen Island and the mainland, compiles ridership statistics that can be used to estimate the fluctuation in the number of residents and visitors across seasons, months, days and time of day, and that can be received upon request. Ridership data from 2015-2019 was requested from BC Ferry Services Inc. and subsequently reviewed and analyzed in order to estimate the number of people on the island at any given time. BC Ferry Services Inc. offers an “Experience Card”, which provides a discount to ferry riders and requires users to pre-load funds. Ridership by payment method was reviewed in an effort to determine tourist vs resident travel, based on the assumption that generally, those travelling without the use of an Experience Card were tourists. Analysis found that “the population of Bowen Island varies significantly based on the season, weather, and time of day due to visitors, commuters, and part time residents” [30][p. 53]. The Evacuation Plan lists factors for emergency operations centre staff to consider when estimating the population during an evacuation, and provides the reader with averages, to assist in adjusting the current number of people on the island according to the season, day of the week and time of day [30].

Island Survey 2019 Data

”The Island Survey 2019 was intended for Bowen Island residents and property owners and asked 51 questions in seven sections: Quality of Island Life, About your Household, Municipal Services, Transportation, Emergency Preparedness, Housing, and the Local Economy. It took about 15 minutes to complete online. The survey launched early September 2019 and was open for five weeks, until mid October. The survey was available online through the municipal website and in paper copy from Municipal Hall. It was advertised on the municipal website, in the local newspaper (the Bowen Island Undercurrent), in a mail drop to all Bowen Island mailboxes, in the weekly municipal e-newsletter and through the municipal social media channels (Facebook, Twitter, Instagram). [...] A total of 523 responses were collected, which represents 18% of the adult population of Bowen Island according to the 2016 Government of Canada Census [79]. The responses indicated an 88% completion rate." [29][p. 2] Two evacuation specific questions were asked as part of this survey, and the answers were used to inform marine evacuation modelling demand estimates. When asked, "In the event of an evacuation order, are you able to self-evacuate the island by private boat," approximately 19% of respondents answered yes, and just over 80% said no: 488 responses were received. Respondents were then asked, "If you are not able to self-evacuate the island by private boat, how are you most likely to access the ferry": response rates by answer choice appear in the Table 6.1.

Table 6.1: Summary of Answers to Island Survey 2019 Question: "If you are not able to self-evacuate the island by private boat, how are you most likely to access the ferry"

Answer Choices	**Responses**	
	Percentage	*Total Answers*
By foot	25.00%	117
By bicycle	1.92%	9
By scooter or motorcycle	1.50%	7
with a vehicle	66.03%	309
I can self-evacuate the island by private boat	5.56%	26
	Total Answered	468
	Skipped	55

Bowen Island Fire Rescue Expertise

Local stakeholders such as Bowen Island Fire Rescue were engaged to provide data in order to ensure the model is as accurate as possible. Realistic scenarios that could trigger an evacuation were developed in partnership with the Bowen Island Fire Rescue Chief and the Bowen Island Municipality Emergency Program Coordinator: the scenarios were chosen based on historical events as well as near misses, where a fire with the potential to get out of control had occurred previously, and in many cases could have easily escalated given slightly different circumstances. As well, wildfire risk factors identified in the 2018 Hazard, Risk and

Vulnerability Assessment [28], such as steep slopes or areas known for high levels of seasonal human recreational activity, were incorporated. Scenarios developed were also verified with the Fire Chief prior to running the model to ensure accuracy and legitimacy.

Marine Vessel Operators

Vessel fleet availability, capacity, and capability information was obtained from regional vessel operators with ownership of appropriate vessels to perform evacuations, including multiple local water taxi operators [47, 68, 90, 107, 139], the Canadian Coast Guard [80], Royal Canadian Marine Search and Rescue [126], BC Ferry Services Inc. [13], and others.

Regarding the use of cost parameters for recovery vessels, in British Columbia, costs associated with an evacuation are generally recoverable from the Provincial government and thus, costs are not likely to be a major factor in local government evacuation calculations [60, 61]. As per the BC Provincial Government's Evacuation Operational Guide for First Nations and Local Authorities in British Columbia, "Emergency Management BC can provide financial reimbursement to First Nations and Local Authorities for eligible expenses related to evacuations." [61][p. 8]. While cost was not a significant planning factor in this scenario, in other jurisdictions, including remote communities and those in which the costs of evacuation borne by local government may not be recoverable, this could be a decisive factor.

Weather Reporting Services

Season and weather are critical components of wildfire behaviour and can be the difference between a fire being contained or getting out of control. Weather information (in particular wind speed and direction) for scenarios was chosen based on realistic parameters on record [81] as well as scenarios that have been observed by local first responders in the past to cover a variety of possibilities. Analysis found that due to tourism, the island's population varies based on weather [30], and this was incorporated into modelling by increasing the anticipated number of evacuees on hot sunny days.

Workshop with First Responders and Local Authorities

A table-top exercise, based on a wildfire evacuation scenario, was held in early 2020 in order to test the preliminary evacuation plan for Bowen Island. Participants included BIM staff and representatives from BC Ferry Services Inc., North Shore Emergency Management, Metro Vancouver Regional District, Cormorant Marine, Metro Vancouver, First Bus Company, the University of Washington and others. The input data for the modeling approach was subsequently revised to incorporate feedback from participants and observers of this exercise.

Workshop with Government, Agencies, and Non-Governmental Organizations

Furthermore, on February 28, 2020, the preliminary modeling approach was presented at a SIREN workshop with representatives from the Royal Canadian Coast Guard, the Canadian Red Cross, the Bowen Island Emergency Program, Emergency Management BC, the BC Ministry of Transportation and Infrastructure (MOTI), and Qathet Regional District. Additional input on potential shelter locations, potential recovery vessel sources, recovery vessel availability times, and was gathered and incorporated into modeling considerations.

Marine Dock Inventory Development

To identify the location of all usable docks, and what challenge they posed in terms of access from land (i.e. are they suitable for evacuations? Are there any obstacles like stairs?), their size, and the depth of the surrounding water at different tides (i.e. what vessel size they could be used by), and inventory of marine docks was collected. This information was collected by a local community volunteer and confirmed with marine vessel operators and local stakeholders during the table-top exercise.

Nautical Charts

Nautical distances in between the docks on the island and the ports on the mainland are necessary to obtain since they determine the travel times in between these locations. Point-to-point distances are not realistic distance measures, because the direct distance might be obstructed by landmarks or flat water, and thus routes had to be generated that take the shortest nautical distance. This data was collected from a nautical chart tool [129].

Data Collection Challenges and Learnings

During the acquisition of the required data mentioned above, multiple challenges and difficulties were identified that should be considered in any comparable study.

- It can be challenging to approximate population number fluctuations and distributions over time, even with available census data. On islands without permanent road connections, ferry ridership data is helpful to estimate fluctuation, but high uncertainty remains over the distribution. It can be helpful to gather data on lodging and seasonal residents through surveys.
- When using surveys to collect data, it is critical to achieve a representative sample of the entire population both in demographics and spatial distribution to make sure that the data is usable. Especially for disaster preparation, this is crucial to ensure that the right conclusions are drawn.
- While mapping out inventories of possible access points for emergency resources, it is important to remain attentive to potential access points that do not immediately appear suitable but that require more disaster preparation, e.g. docks that are not in good shape, or decommissioned ferry access points.
- The creation of realistic scenarios needs to draw from multiple sources. The primary source should be an entity with fire rescue expertise, such as a fire department, secondary considerations can come from other participants, such as other first responders, evacuation resource providers, and weather services. Every entity will consider different elements of scenarios challenging and it is important to make sure the selected scenarios cover all of these concerns. The task of the research team is to compile all of these concerns into a set of scenarios that all parties can agree on before the model is run to ensure that the results are accepted and understood as relevant for the community.

An iterative approach of presenting proposed scenarios to stakeholders and collecting feedback through workshops is an approach to accomplish this.

It is important for a research team to consider the aforementioned challenges to ensure a smooth data collection process and analysis.

6.3.2 Modeling Methodology

Model functionality

The S-ICEP is a two-stage stochastic recourse programming formulation [131] that allows for the scenario-based planning of the evacuation of an isolated community, such as an island. The main difference between their model and other evacuation models (e.g. [11]) is the use of external resources. Almost all other models used in evacuation planning assume road-based evacuation routes and thus assume that a population primarily leaves the area by personal vehicle. This allows the models to evaluate individual vehicles as flow variables since every vehicle only leaves the affected area once. If like in an island case however, the evacuation needs to be executed by a coordinated set of vessels, these vessels may have to do multiple trips and go to different locations after another to evacuate the area, thus creating a multi-trip problem that results in a routing problem. While there are similar models for homogeneous vehicle type evacuation, such as the Bus Evacuation Problem (BEP) [25], the use of heterogeneous vessel fleets and the lack of an existing road infrastructure further complicates the problem as trips between resources are not interchangeable, which this model considers. The model therefore fits the objective of this case study well, and has been revised based on feedback from the emergency management team, the response team, and through resident surveys to make sure that model assumptions accurately reflect population concerns. To introduce the reader to the functionality of the revised model, the key elements of the model inputs and outputs are restated here and explained at the example of the case study presented in this chapter. For details over the mathematical model structure we refer the reader to Chapter 4. The model takes the following inputs:

- The set of shelter locations with respective docks that can be accessed by marine vessels;
- The set of evacuation areas, where the evacuee populations are located;
- The set of evacuation pick-up docks, that can be accessed by marine vessels and are allocated to exactly one evacuation area;
- A fleet of potential recovery vessels including the vessel capacity, the vessel travel speed in loaded and unloaded condition, impacts of weather on vessel travel speed, loading time, unloading time, the vessel storage location, the time to availability of the vessel, variable operating cost, and fixed cost for contracting;
- A compatibility matrix indicating which vessel is compatible with which evacuation pick-up dock;
- A distance matrix providing travel distances between shelter locations and potential docking locations on the island;
- A set of disaster scenarios that cover a realistic range of disaster possibilities. These include the relative probability of the scenario compared to the other scenario, the number of evacuees at each affected evacuation area, the percentage of the population that is able to self-evacuate, and weather information;
- A maximum allowed evacuation time. This ensures that evacuation plans remain timely;
- A penalty cost assigned to each evacuee that could not be evacuated. This ensures that the model attempts to generate a plan that evacuates as many evacuees as possible within the maximum allowed evacuation time.

After optimizing the evacuation plan considering all the inputs listed above, the model outputs are the following:

- A vessel fleet that is optimal across the investigated scenarios;
- Optimal route plans for each individual scenario using the vessel fleet from above.

The functionality of S-ICEP is illustrated in Figure 6.4, which takes the inputs explained above. The model consists of two decision stages, which are divided by a probabilistic event, a scenario-independent first stage and a scenario-dependent second stage. The first stage optimizes a fleet of vessels that causes a low expected evacuation time and cost across all scenarios. It obtains the information of how a vessel fleet performs in different scenarios from the second stage, which makes an optimal evacuation routing decision for each scenario. For each two-stage stochastic model with recourse, there exists a deterministic equivalent that sums up all scenario decisions multiplied by their respective probabilities into one large problem. The objective functions are structured in a way that the goal of minimizing the evacuation time dominates the goal of minimizing cost. Thus, if multiple evacuation time-minimal solutions are available, the solution that results in the lowest cost is chosen. Depending on how well the selected scenario set represents possible real world disasters, the resulting vessel fleet will be the best solution to tackle the real world disaster, once it occurs.

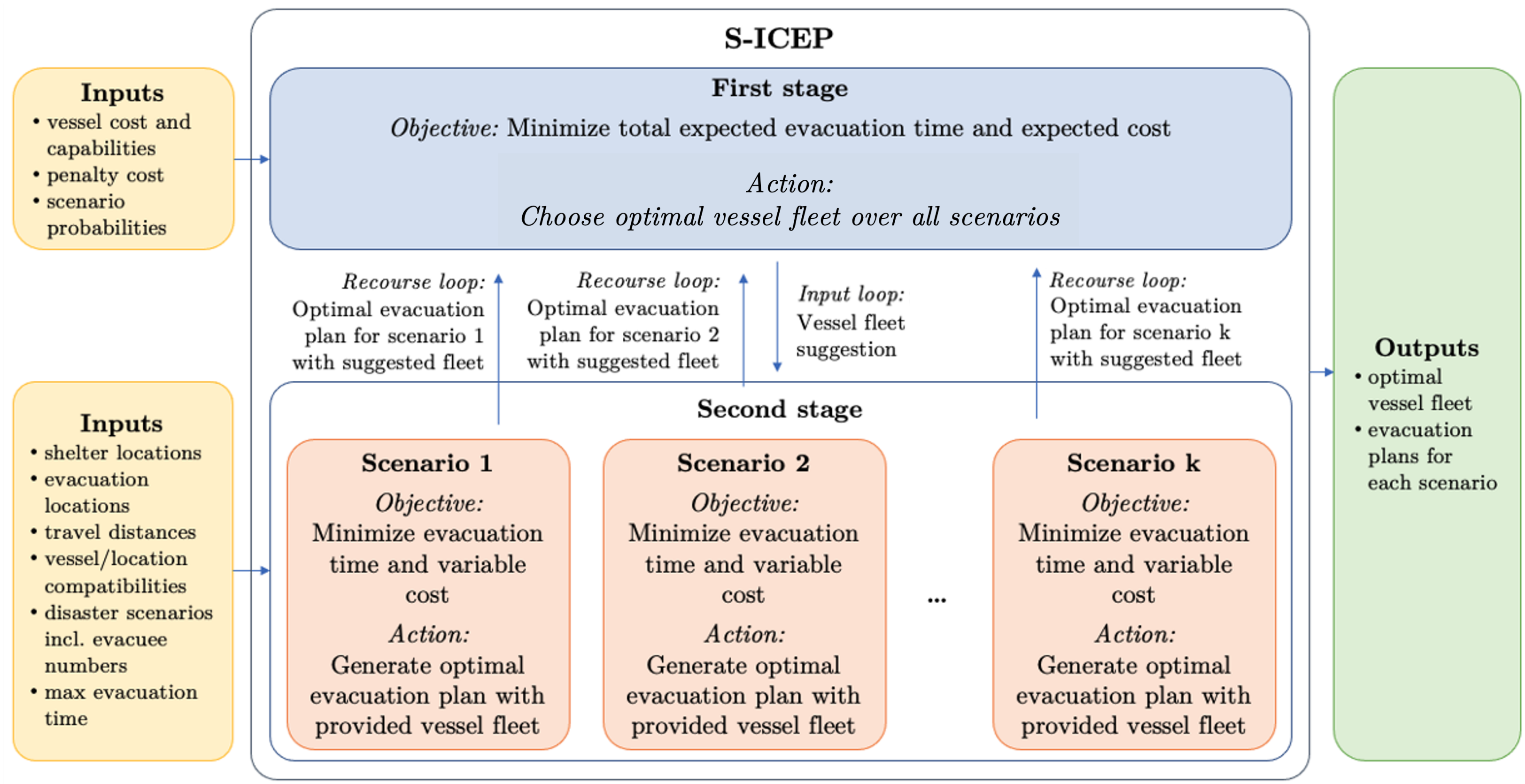


Figure 6.4: Illustration of the two-stage model structure of S-ICEP

This way, the emergency planner receives information on which vessels to rely on in case of an emergency, and agreements between emergency management and the vessel providers can be put in place. As an additional benefit, the optimal route plans for each scenario can reveal which areas of the island are particularly vulnerable to disasters that require evacuation. Through running multiple iterations with different configurations on shelter locations, planners can investigate the effect of considering additional shelter locations on evacuation time and assess the vulnerability of a location to a particular disaster scenario.

Objective Function Selection

Chapter 4 further provides alternative objective functions. As previously mentioned in Section 6.3, for this case study cost considerations were not necessary. Therefore, it was decided to use the simpler conservative objective function that solely focuses on minimizing the expected evacuation time over all scenarios. For the readers convenience, this conservative objective is presented in equation 6.1 in terms of the case study of this chapter.

$$\min \qquad comp(\zeta) + P \sum_{a \in A} fl_{an}(\zeta) \tag{6.1}$$

$comp(\zeta)$ represents the expected total evacuation time of the route plan across all disaster scenarios. P represents a penalty value that is assigned to every evacuee that is expected not to be evacuated (fl_{an}) with the route plan. This way, the model automatically penalizes not evacuating the entire population and forces the solution algorithm to try to avoid leaving anyone behind, unless there is no other option. Since this case study receives a collection of deterministic disaster scenarios with relative occurrence probabilities, the stochastic objective function can be discretized into a deterministic equivalent, as equation 6.2 shows for k scenarios, where the sum of all relative probabilities equals 1, as equation 6.3 shows.

$$\min p_1 \left(comp_1 + P \sum_{a \in A} fl_{an1} \right) + p_2 \left(comp_2 + P \sum_{a \in A} fl_{an2} \right) + ... + p_k \left(comp_k + P \sum_{a \in A} fl_{ank} \right) \tag{6.2}$$

$$\sum_{i=1}^{k} p_i = 1 \tag{6.3}$$

As mentioned previously, it is imperative during the modeling process to take the special properties and considerations of the data set on hand into account and to consider the interactions between the data and the model this causes. For the Bowen Island case, it can be valuable to consider alternative shelter locations, and make these decisions part of the model itself. It is possible to alter the model framework to include variables that account for the optimal selection of shelter locations and include a corresponding cost term in the objective function. However, Chapter 4 provides some guidance that the computational effort to run the model to an exact solution is already pretty high, and with exponentially increasing complexity, it is reasonable to run the model multiple times for different shelter location configurations, since the number of options in for the presented case study is relatively small.

6.4 Data Model Interactions

6.4.1 Shelter Locations

It is important to consider whether using additional shelter locations that are not default choices would significantly reduce evacuation time and costs. In the area around Bowen Island default shelter locations would be areas that have a larger accessible port or marina and that have a good connection to additional infrastructure for first response and evacuee support. For this case study, Horseshoe Bay, Fisherman's Cove and Gibsons were selected as the default shelter locations. Figure 6.5 shows the map of the case study area with markers for the evacuation docks, shelter locations and vessel evacuation routes. Figure 6.5 marks the

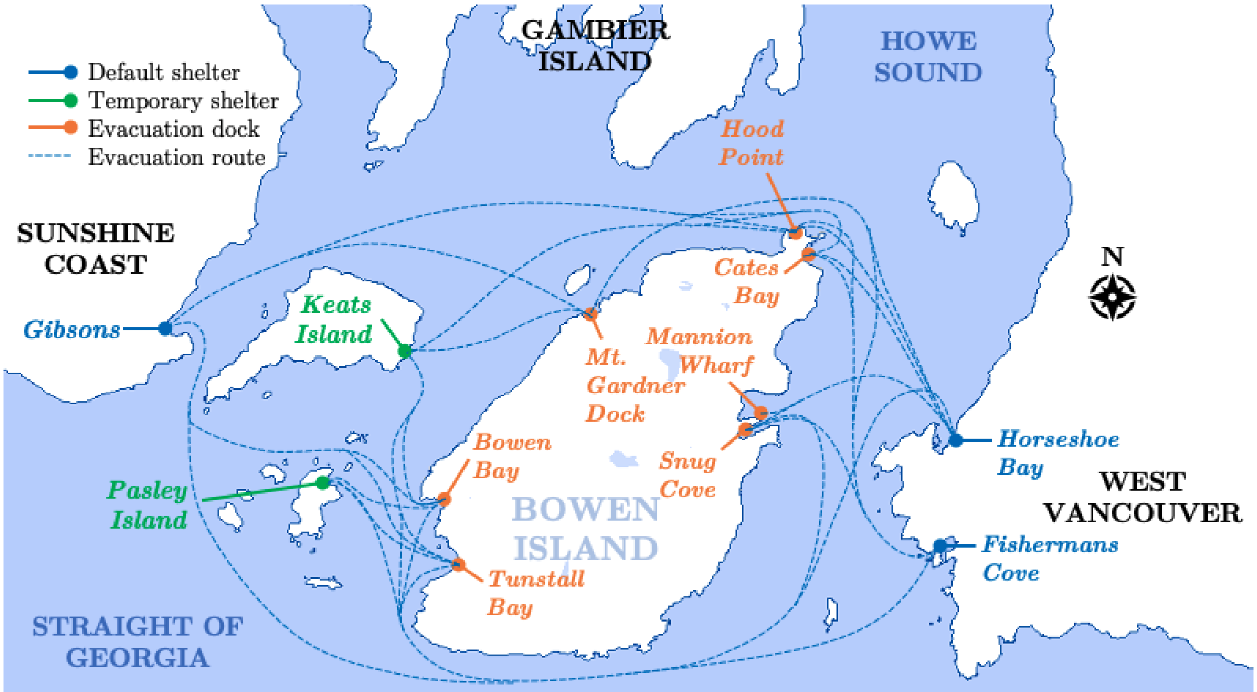


Figure 6.5: Map of Southern Howe Sound with evacuation docks, shelter locations, and routes

default shelter locations on the map in blue. In addition, other temporary shelter locations should be considered. Even though the lack of access to further infrastructure and supplies may only make these suitable as a temporary staging location before evacuees get transported further, the resulting reduction in evacuation time may significantly contribute to the safety of the evacuees. When running the S-ICEP model for different staging considerations, the sensitivity of the model results to these changes can provide decision guidance on temporary shelter locations. For this case study, the temporary shelter locations are Keats Island and Pasley Island, and are marked in green in Figure 6.5.

6.4.2 Scenario Design

The scenarios were generated in collaboration with the Bowen Island Fire Rescue Fire Chief on the basis of local expertise with regards to high-risk or vulnerable areas and experience with previous wildfire incidents on Bowen Island. Thus, the four scenarios presented in this study focus on particularly challenging fire scenarios that are both likely and that would be difficult to contain by first responders. Table 6.2 describes the scenarios in detail. The maps in Figure 6.6 visualize the affected areas for every scenario in red.

As Table 6.2 shows, the scenarios considered for the case study vary in their size and how likely they are to occur in comparison to each other. It is important to note that the variety of these real-world scenarios ensures that also extreme scenarios, both on the upper and lower probability end are included in the analysis.

6.4.3 Evacuation Fleet

In addition to considering different shelter locations and testing for the sensitivity of the model results based on these, it is important to consider from how far away an evacuation fleet should be sourced. For a coordinated evacuation effort, both vessels that are regularly located in the Howe Sound area and vessels that are located further away can be useful for evacuation. Using the S-ICEP model framework with two different fleets allows to test the marginal effect of considering only local resources or also considering resources that are located further away. Table 6.3 presents the resources considered for the evacuation study. These resources were considered after evacuation workshops and evacuation simulations that were completed together with first responders and local vessel operators. These discussions included exchanges on the compatibility and availability of the vessels.

6.5 Modeling Results

To generate optimal results for the case study, an instance of the S-ICEP was implemented using Python as a general purpose language and was executed on a Mac with a 2.6-GHz Dual-Core Intel Core i5 CPU. The model was implemented using the deterministic equivalent of the conservative objective function 6.1 presented in Section 6.3. The model was run considering each scenarios listed in Section 6.4.2, for both the primary and the entire fleet from Section 6.4.3 and for different configurations on shelter locations listed in Section 6.4.1. An overview

Table 6.2: Wildfire Scenario Descriptions

Scenario	**Description**	**Affected population**	**Approx. private evacuations**	**Usable docks**
1: Mount Collins Relative probability: 40%	On a hot summer weekend with southwesterly winds, a wildfire starts on the southern flank of Mt. Collins and cuts off traffic at the Legion branch on Scarborough Road and cuts off the northern part of the island. An evacuation notice for Snug Cove, Millers Landing and all communities north of the Legion is issued.	3,308	204	Hood Point Cates Bay Snug Cove Mannion Wharf
2: Mid Island Relative probability: 10%	A wildfire starts south of Grafton Lake and makes Grafton Rd impassable, which cuts off the western part of the island. It's a hot summer weekend and strong wind causes a western expansion of the fire; an evacuation notice is issued for all communities west of Grafton Lake.	4,289	344	Tunstall Bay Bowen Bay
3: Killarney Lake Relative probability: 15%	A campfire south of Killarney Lake gets out of control midweek and Mt Gardner Road becomes impassable. An expansion of the fire to the north due to southeasterly winds forces the municipality to issue an evacuation for Mount Gardner.	300	29	Mt. Gardner
4: Eagle Cliff Relative probability: 35%	A wildfire emerges at Eagle Cliff and cuts off the northern part of the island. Easterly winds drive the fire northwest along the shore and forces the EOC to evacuate all communities north of the fire location. Evacuation needs to be executed, as the fire threatens residences.	708	148	Hood Point Cates Bay

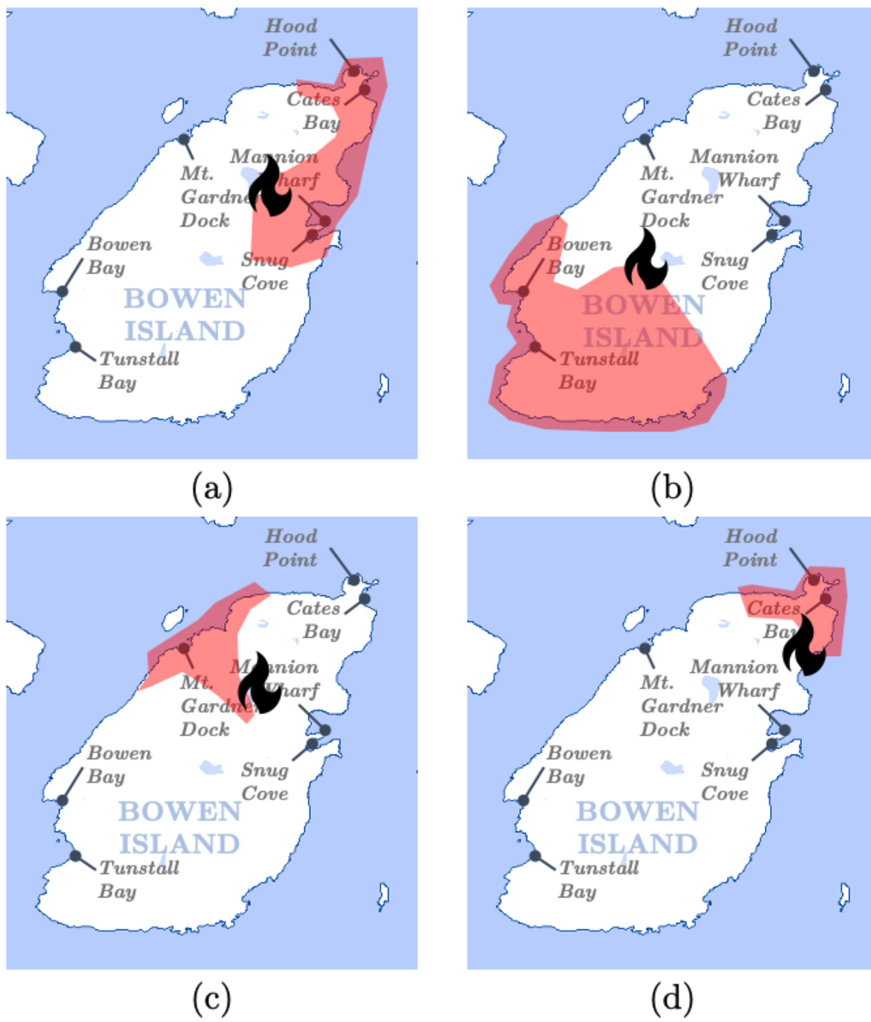


Figure 6.6: Visual illustration of affected areas for wildfire scenario 1 (a), 2 (b), 3 (c), and 4 (d). Map sourced from Google [77]

Table 6.3: Candidates for the Evacuation Fleet

Vessel Provider	Vessel Type	Number of Vessels	Location (Port)	Fleet Category
BC Ferries [13]	Vehicle and passenger ferry	1	Horseshoe Bay	Local
Cormorant Marine [47]	Water taxi	4	Snug Cove	Primary
Mercury Water Taxi [107]	Water taxi	3	Horseshoe Bay	Primary
Sunshine Coast Water Taxi [139]	Water taxi	1	Gibsons	Primary
Harbor Ferry Bertram [68]	Water taxi	1	Gibsons	Primary
Kona Wind Charters [90]	Water taxi	2	Gibsons	Primary
Royal Canadian Marine Search and Rescue (SAR) [126]	SAR boat (up to 12 passengers)	3	Horseshoe Bay / Gibsons	Primary
Royal Canadian Marine Search and Rescue (SAR) [126]	SAR boat (up to 12 passengers)	1	North Vancouver	Regional
Royal Canadian Coast Guard [80]	SAR vessel (above 12 passengers)	3	Kitsilano	Regional
Royal Canadian Coast Guard [80]	SAR hovercraft	2	Richmond	Regional

of the results condensed in one figure is illustrated in Figure 6.7. Figures 6.8 to 6.11 illustrate the evacuation progress over time for each affected location.

For the Mt. Collins Scenario, the result shows that the evacuation time with the primary fleet takes around 165 mins. Extending the fleet can reduce the total evacuation time to 150 mins. The reason for the low improvement is that the secondary vessels are located farther away and thus, require more time to reach the affected area. Due to the geographical location of the Mt. Collins scenario, using Keats and/or Pasley Island as shelter locations does not provide any benefits. Figure 6.8 further confirms this, as the evacuation time savings generated by using the entire fleet, irrespective of the staging choice only reduce the expected evacuation time for both affected locations marginally. Furthermore, it can be seen that the objective function of the model that minimizes total evacuation time shows to be very efficient, as the achieved evacuation times for both locations are very close to each other. This shows how efficient the model is at allocating vessels strategically to the right locations. Hence this also confirms that there is no room to shortening the evacuation

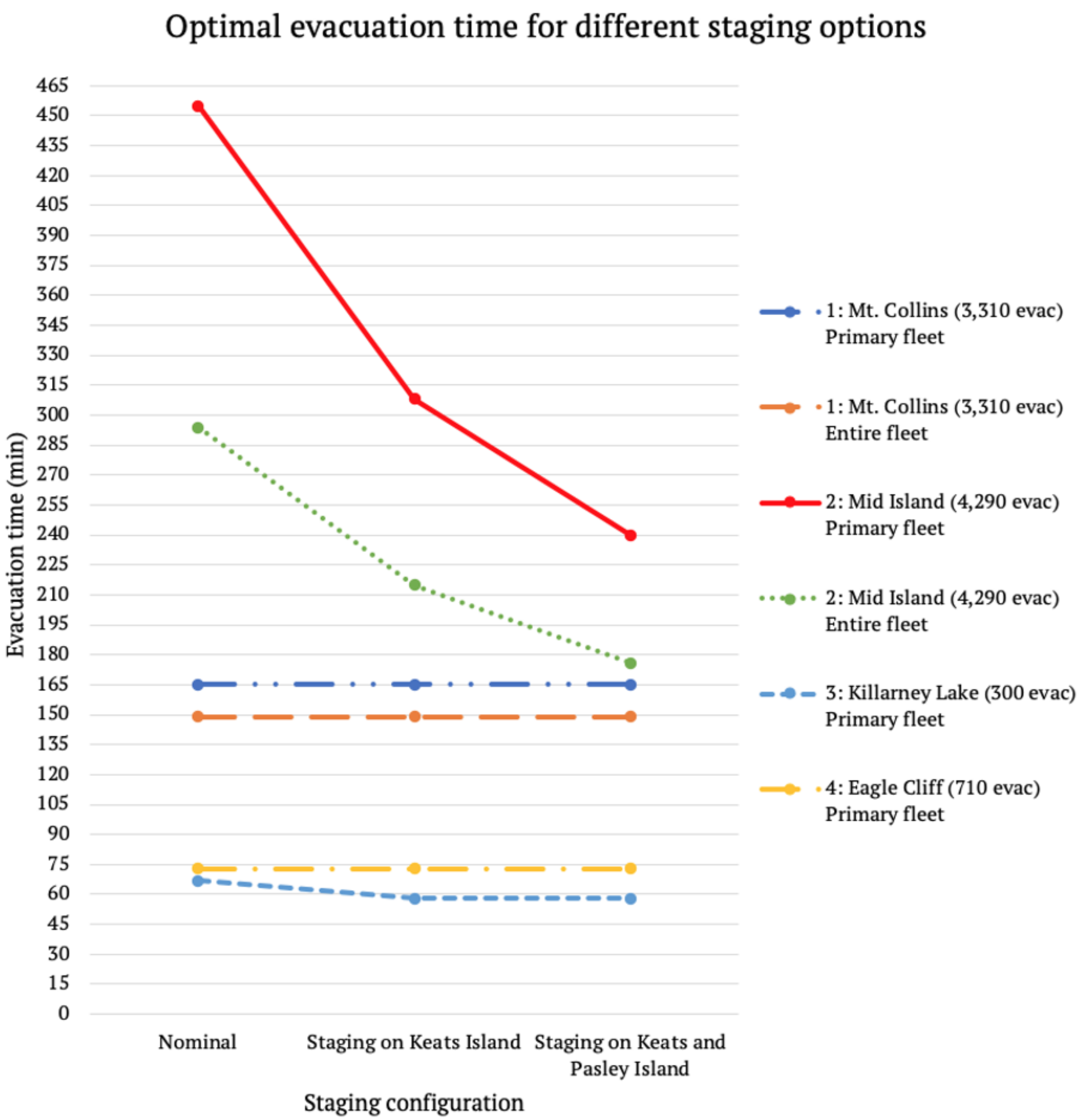
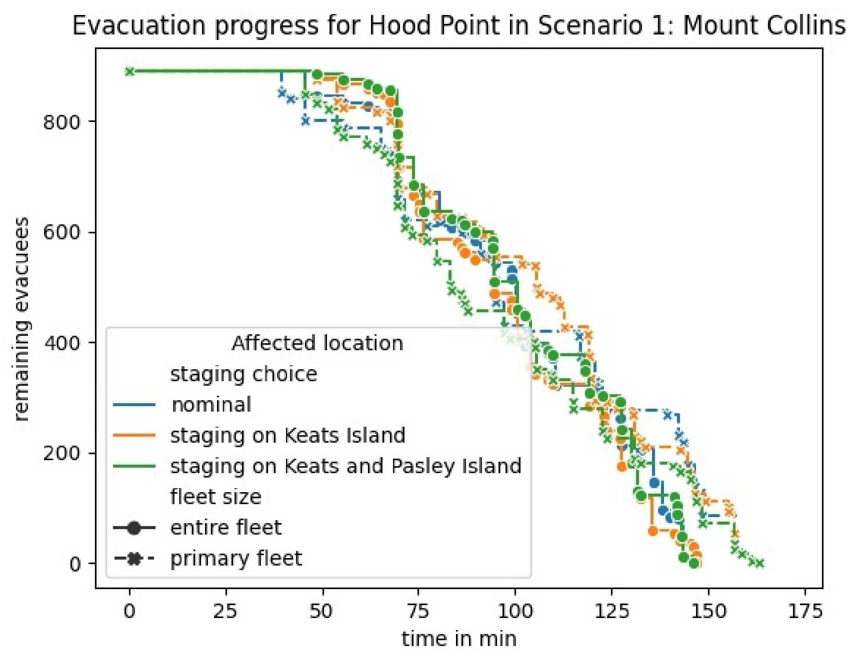


Figure 6.7: Results from marine evacuation modeling for Bowen Island

time through shifting resources in between locations. For the Snug Cove evacuation plan we can further see how large the contribution of the ferry is, indicated by the large drops in evacuation numbers every time the ferry made an evacuation, significantly reducing the slope of the evacuation curve.

For the Mid Island Scenario, the model returned large differences in evacuation times in between different model configurations. Using only the primary fleet and not considering shelter locations on Keats and/or Pasley Island, a marine evacuation would take more than 450 mins, if vessels are routed optimally. This is caused by the limited number of access points on the western shore of Bowen Island, which only allow the usage of relatively small vessels. However, the evacuation time can be significantly reduced by considering shelters on Keats Island (308 mins) or both Keats and Pasley Island (240 mins) as temporary staging locations. Despite the small size of compatible vessels, the reduction in distance the vessels have to cover to evacuate the population strongly improves the evacuation time. This positive effect can be even increased by also using the secondary fleet, which leads to evacuation times of approx. 295 mins (nominal), 215 mins (shelters on Keats Island), and 175 mins (shelters on Keats and Pasley Island). Hence, the benefit of temporary shelter considerations is large. The evacuation progress illustrated for both affected locations in Figure 6.9 shows that the effect of different configurations in staging choice and fleet size has similar effects on both affected locations, with similar outcomes for evacuation time for both locations.

For the Killarney Lake scenario, the proximity of the Mt. Gardner Wharf to Keats Island, a temporary shelter on the island enables a reduction of evacuation time from approximately 70 mins to 57 mins. However, due to the larger distance, considering additional shelters on Pasley Island does not provide any benefits. Further, the small size of the scenario allows a relatively quick evacuation of the area with the vessels from the primary evacuation fleet. Due to the time it takes for the secondary fleet to reach the area, activating these vessels does not offer any benefit. Since the Killarney Lake scenario only affects a single region, Figure 6.10 shows the effect of strategic staging. What is remarkable about this result is how large the time share is to get the resources to the affected area. This is due to the



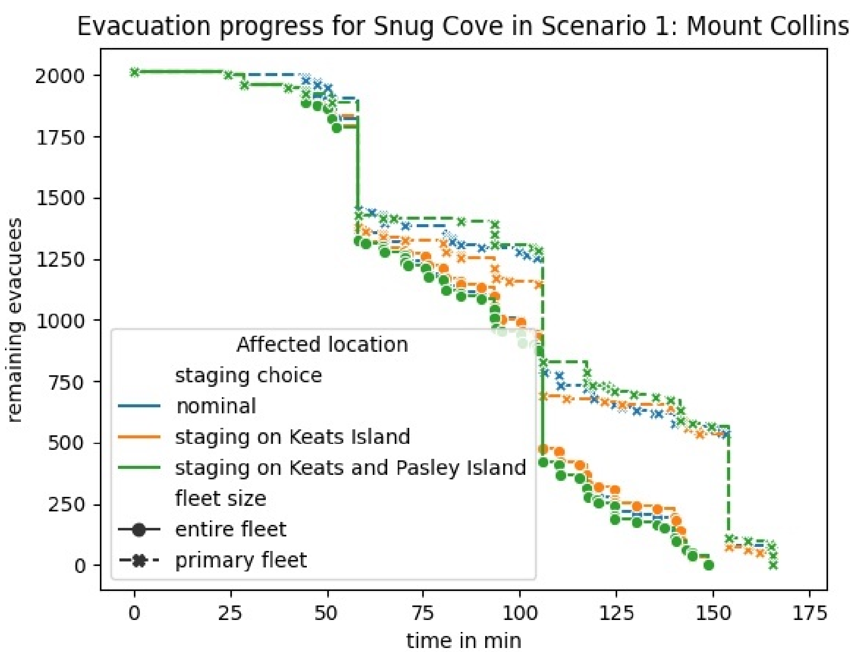
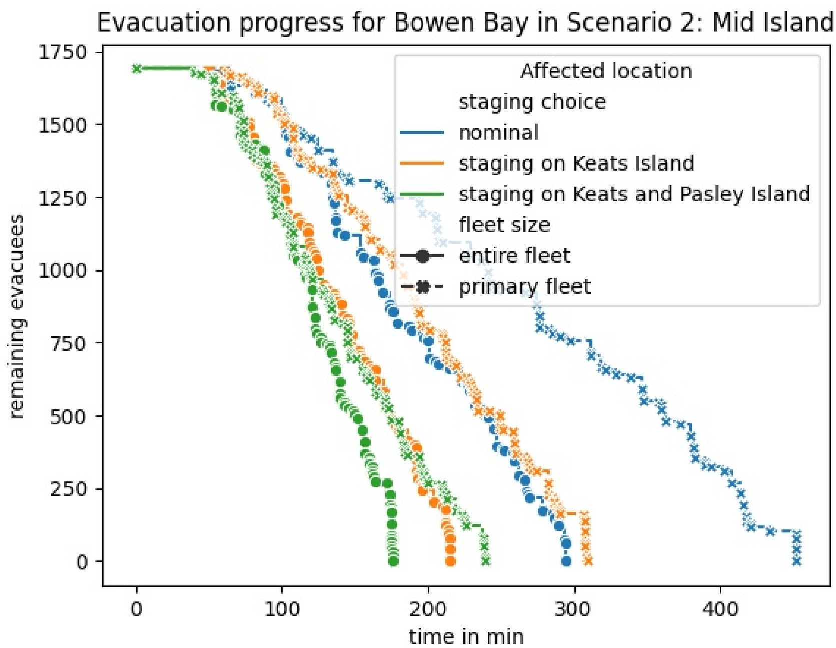


Figure 6.8: Scenario 1: Mount Collins - Evolution of remaining evacuees over time for different configurations



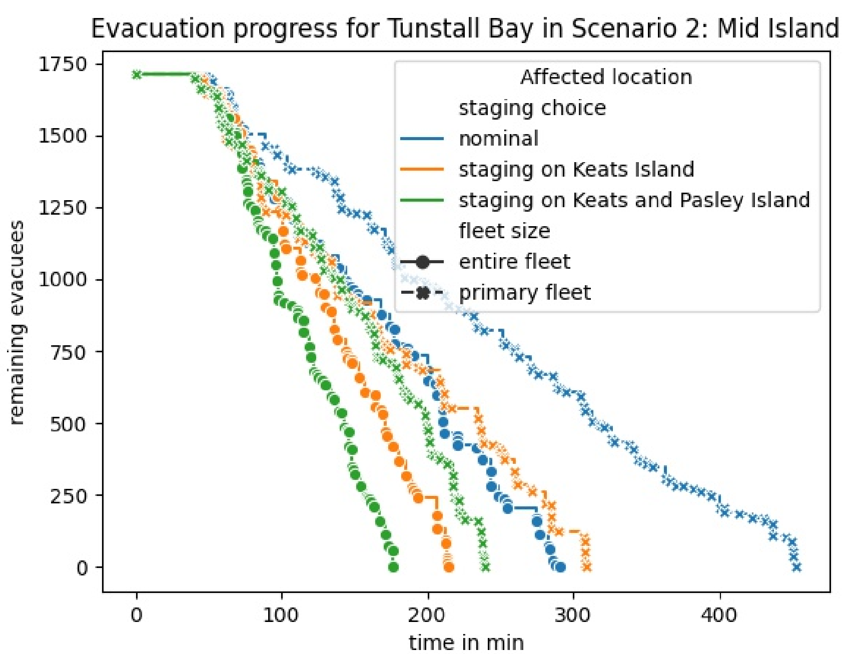


Figure 6.9: Scenario 2: Mid Island - Evolution of remaining evacuees over time for different configurations

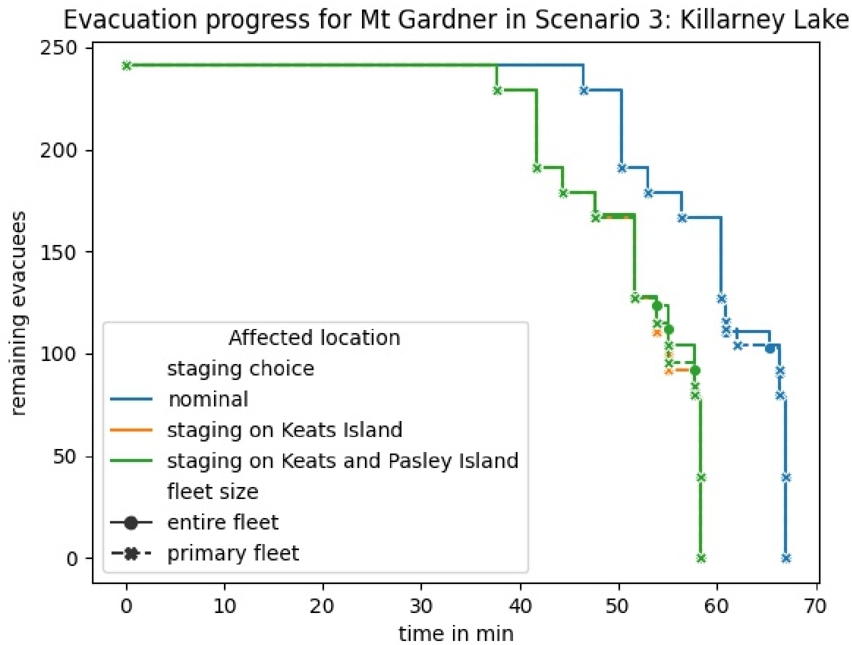


Figure 6.10: Scenario 3: Killarney Lake - Evolution of remaining evacuees over time for different configurations

relatively remote location of the Mt Gardner wharf in relation to the regular locations of the response vessels. Stationing vessels closer to the region could improve the evacuation time.

Similarly, for the Eagle Cliff scenario, the evacuation time is approx. 74 minutes under all configurations. The geographical location of the affected area results in no benefit by shelter locations on the islands west of Bowen Island. Due to the small size of the scenario, using the secondary evacuation fleet is not beneficial to reducing evacuation time. Figure 6.11 confirms that the evacuation time could only be further reduced if the size of the primary fleet would be increased.

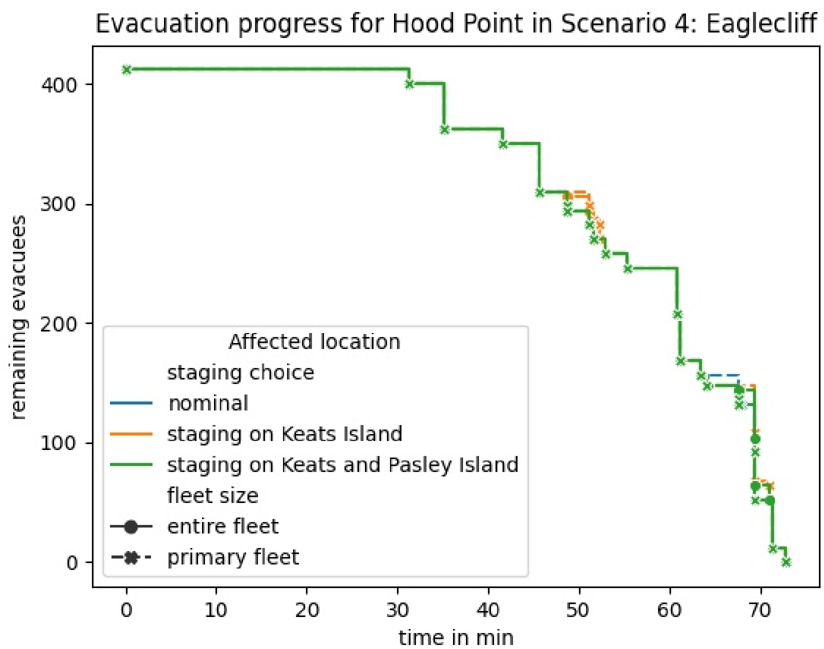


Figure 6.11: Scenario 4: Eaglecliff - Evolution of remaining evacuees over time for different configurations

6.6 Discussion

6.6.1 Implications of Modeling Results

The collaborative analysis has shown that the fleet of local (primary) vessels alone is able to manage scenarios of smaller size (approx. up to 1,000 evacuees). A further reduction in evacuation time could be achieved through permanently increasing the number of emergency response vessels in the immediate surroundings of Bowen Island (e.g. SAR landing vessels). However, during a smaller evacuation scenario, requesting additional vessels from more distant locations (e.g. Kitsilano, Richmond, Sechelt, Nanaimo, Squamish), does not enable a reduction of the evacuation time because it takes too much time to reach Bowen Island. For larger scenarios (approx. above 1,000 evacuees) however, requesting additional vessels from distant harbors will significantly reduce the time to evacuate the affected area. Even though it appears to be a natural conclusion that more resources will reduce the evacuation time that does not require extensive analysis, the study results present significant findings. Before the analysis presented above, no information was available as to what extent the ferry and the primary vessel fleet that is permanently in the area will be sufficient to evacuate the area and under what scenarios this could lead to serious problems. The only knowledge that existed previous to this study was that it would take the ferry approximately 11 hours to evacuate 4,000 people and approximately 27 hours to evacuate 10,000 people [30][p. 48]. These previous estimates did not include considerations on the use of multiple access points, additional vessels, or scenarios that affect parts of the island that are not accessible by the ferry. Using the S-ICEP provided a lot more insights.

The need for an extended vessel fleet is particularly high for areas that cannot evacuate through the Snug Cove Ferry Terminal, since the primary fleet is too small to move a large number of evacuees quickly. Hence, activating CCG, additional SAR vessels, and other options will decrease the time evacuees will be exposed to the hazard. For very large scenarios, it is further recommended to recruit any additional available vessel in the area. This could be harbor cruises, fishing boats and recreational vessels. While adding these vessels to the fleet will make coordination more difficult, the potential to further reduce evacuation time is high. For the Western parts of Bowen Island, the limited number of public and private docks makes it challenging to evacuate a large number of evacuees. Particularly in this area, the CCG hovercrafts and landing vessels are useful due to their ability to land directly at beaches. Furthermore, because the distance to the closest mainland harbor in Gibsons is relatively high, the model strongly recommends considering temporary shelters on Keats Island and Pasley Island to shorten the distance the evacuation fleet has to cover and thus allow the transportation of more evacuees in a shorter amount of time. An additional, though more unreliable approach, could be to create a temporary dock at a beach upon evacuation that allows serving the area with larger vessels. Examples could be to beach a barge or a floating dock to provide a usable path for evacuees to deeper water, where larger vessels can be used. We furthermore identified that across scenarios, the evacuation times for each affected locations obtained by the model are similar and evacuation vessels are allocated accordingly to obtain this. This is caused by the objective function that aims to minimize the total time of the entire evacuation plan. In case a prioritization between different locations is necessary (e.g. if in Scenario 2, the evacuation of Bowen Bay is more urgent than the evacuation of Tunstall Bay), a staged objective function or individual time limits for each evacuation time would need to be introduced.

With regards to general applicability of the results, the results show that up to a certain population size of island communities, the evacuation by vessels regularly stationed in the area may be sufficient to achieve reasonably short evacuation times. This is particularly the case when a large port with passenger ferry access is available. The results however also show that if such a port is not available, evacuations times grow significantly. In fact, the case study shows that a fast moving hazard may necessitate staging in neighboring locations that are less than ideal for long term evacuee support: while support (food, clothing, shelter) for evacuees on these smaller islands is unavailable or limited, the evacuation times could be significantly reduced when staging evacuees temporarily at these areas. Further preparation regarding establishing use of nearby staging areas in an emergency is warranted for evacuations of similarly challenged locations to facilitate staging in the affected areas. Alternatively, these results can also inform local land use planning and other community amenity discussion; ensuring that an island community has a well distributed network of access points, such as public boat docks can significantly accelerate evacuation procedures in case of an emergency. The obtained insights do not only support the evacuation plan itself, but are further instrumental for reducing the risk for a disaster through preventative investments into infrastructure and recovery access points. These results could only be identified through using the integrated end-to-end collaborative approach that was taken combined with optimization-based modeling to revise the data collection and modeling process based on its interactions.

As already mentioned in section 6.2.3, despite the insights and their respective values described above, making decisions solely based on mathematical modeling is not perfect. The main difficulty lies in the problem of evacuation behavior. Thompson et al. [140] have reviewed over eighty-three eligible studies concerning evacuation behavior and the perception of risks associated with natural hazards in a vulnerable population, which is why we refrain from restating all these studies at this point and instead refer the reader to this review. The main conclusion from these studies is that it is very challenging to predict the behavior of humans while exposed to a hazard, as humans do not always act rational when in fear and the reaction is highly dependent on previous evacuation experience, cultural backgrounds, demographics, warnings, government orders, and local circumstances [38]. This can cause a serious disruption to an optimization model-based evacuation plan, if, for example, parts of the population refuse to leave their residences, self-evacuate, attempt to pick-up other family or household members from other locations, or move to a different evacuation point than expected [141]. On the other hand, the commander of an evacuation vessel may decide at their own discretion to take on a higher number of evacuees than the official maximum number of passengers the vessel is rated for. Furthermore, no matter how many scenarios a modeler uses, there are infinitely many ways on how a disaster can unfold, and thus a certain uncertainty level remains. This leads to the problem that it is almost impossible to know what exactly will happen if a hazard becomes a disaster and how long an evacuation will actually take. However, Thompson et al. [140] also mention that the existence of an evacuation plan itself influences evacuation behavior [97]. Hence, a marine evacuation plan generated with the proposed methodology gives valuable insights as mentioned above, as it gives clear indications on how to organize the marine evacuation, where the bottlenecks lie, and what properties of a potential disaster scenario influence what actions actually reduce the evacuation time and increase population safety. Therefore, instead of expecting that the outputs of the model can be interpreted literally at their exact values as recommendations that guarantee reduced risk, substantial safety margins should be applied. During disaster response, the gained insights can then be used to make decisions quickly and take advantage of the preventative measures taken based on the real-world hazard.

6.6.2 Conclusions and Future Outlook

The research presented in this chapter conducted a case study on finding an optimal evacuation plan for Bowen Island in Canada through the use of marine resources. This study was based on a collaborative approach between the research community and emergency managers with a high participation and involvement of a broad range of stakeholders, from local residents and volunteer groups to agencies from all levels of government and the private sector. The key findings of this study are that the total time of the marine transportation portion of the evacuation of Bowen Island can be kept below three hours if either the ferry can be used, or if the number of evacuees remains below 1,000 people. This drastically changes when the Western part of the island is impacted, where a large number of residents live, but where no larger port is available. This allows emergency planners to take action immediately to activate a larger set of resources if the western part of the island is effected, which is a consideration that was not made before. The study further identified that for similar islands, the use of temporary staging areas, even in locations with little to no infrastructure, can offer a quick relief and reduce evacuation time significantly. Alternatively, a permanent improvement of infrastructure can eliminate the problem of high evacuation times and thus reduce the risk for a disaster in the first place. This idea has not been entertained at the community level before and is another key finding of the study. In addition, the model results provide example route plans for each scenario that can be used as a baseline by emergency managers, if a comparable disaster occurs, but the time line is insufficient to allow for another modeling run. In particular, comparing the results of this study to the previously existing information about pure ferry evacuation [30], the additional capability of providing scenarios that cannot be evacuated through using the ferry alone and allowing for multiple access points and vessels show the value of using the presented approach. This further confirms that the model proposed in Chapter 4 is an appropriate tool to conduct real-world evacuation studies that provide meaningful answers to emergency planning and management. This is particularly the case when it is paired with an integrated approach that includes a substantial data collection effort that involves different stakeholders. The success of this approach is further confirmed by the inclusion of the results of this model in the official evacuation plan of Bowen Island [30]. The high involvement of subject matter expertise makes the findings of this study highly applicable to similarly structured communities with comparable environmental challenges, for which this study can be used as a template. The fact that the study has identified key bottlenecks for evacuation, validates it as a useful approach to reduce disaster risks and ultimately to help preventing a disaster through the preventative improvement of key infrastructure and staging areas. Both researchers and practitioners should however keep in mind the limited predictability of natural hazards and human evacuation behavior when using this approach and how much the model output depends on carefully selected data that is gained through interdisciplinary work with the targeted community and thus apply appropriate safety margins over the model results.

Regarding the lessons learned from applying the aforementioned ICEP model to a real world case study, the study process has shown that despite a sophisticated modeling technique, already moderate changes in the input data can lead to significantly different results. The involvement of a knowledgeable group of stakeholders and accurate input data is therefore crucial, and the lack thereof is a shortcoming of many other academic studies on evacuation. In hindsight, a larger set of scenarios would have enabled the study to cover a larger array of possibilities and produce more robust results. However, larger scenario sets are more difficult to obtain in detail from first responders and further significantly increase the size of the problem and thus increase the time it takes to run the model.

Additional future research could focus on integrating the model with the on-land transportation portion of the evacuation of islands, such as how to transport the population from their residences to the evacuation pick-up points, how to deal with traffic bottlenecks, how to accommodate for mobility impaired populations, and how to account for evacuation behavior. For larger communities where multiple ferries are used, the modeling approach should consider the capacity at the ferry terminal, to avoid being overly optimistic in the solutions, through serving more vessels than possible at the same time at a certain port. In addition, as already mentioned in the discussion section, it could be necessary to plan for evacuations with different priorities for different locations. For that case, model extensions are possible that either limit the maximum route time for a specific resource, or transform the objective function into a staged, prioritization function.

6.7 Acknowledgements

The work presented in this chapter has been performed in context of the project 'Shipping Resilience: Strategic Planning for Coastal Community Resilience to Marine Transportation Risk (SIREN)'. This project is financially supported by the Marine Observation, Prediction and Response (MEOPAR) Network of Centres of Excellence (NCE) under the Award Number 2-02-03-041, and by the Province of British Columbia. This funding source did not provide any support in study design; in the collection, analysis and interpretation of data; in the writing of the report; and in the decision to submit the article for publication. Evacuation planning on Bowen Island was supported by the Bowen Island Municipality and by the Province of BC through the Community Emergency Preparedness Fund, which is administered by the Union of BC Municipalities. This financial support is gratefully acknowledged.

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'Shipping Resilience: Strategic Planning for Coastal Community Resilience to Marine Transportation Risk (SIREN)'. This project is financially supported by the Marine Observation, Prediction and Response (MEOPAR) Network of Centres of Excellence (NCE) under the Award Number 2-02-03-041, and by the Province of British Columbia. This financial support is gratefully acknowledged.

Chapter 7

META-HEURISTIC SOLUTION APPROACHES FOR THE ISOLATED COMMUNITY EVACUATION PROBLEM

The work presented in this chapter has been submitted for presentation and publication under the title ”A Meta-Heuristic Solution Approach to Isolated Evacuation Problems” to the *Winter Simulation Conference 2022* and is co-authored with Dr. Anne V. Goodchild and Dr. Linda Ng Boyle [92]. This chapter is not the copy of record and may not exactly replicate the authoritative document that will be published.

7.1 Abstract

The ICEP is a routing model formulation that is used to optimize the planning and response to evacuation events of isolated communities, such as islands and mountain valleys that are not accessible by road and have to be evacuated by a set of recovery resources. Due to its routing structure, the ICEP is NP-complete and therefore the computational time does not scale well for larger problems. In this chapter, the ICEP is extended with an approximate solution method that can be solved in a more timely manner to meet the urgent needs of evacuation coordination decisions during an emergency. The chapter proposes using a Biased Random-Key Genetic Algorithm from the meta-heuristic domain to solve this problem. The chapter presents a new decoder method specific to the ICEP, that allows to translate in between an instance of the S-ICEP and the BRKGA. This method allows us to approximate the global optimum and is suitable for parallel processing. The method is validated through computational results that show the validity of the approach.

7.2 Introduction

This chapter presents an approximate solution approach to the Isolated Community Evacuation Problem (ICEP), a routing problem that models the evacuation of an isolated area using a fleet of coordinated resources when road-based evacuation is not possible. The problem generates an optimal route plan for the resource fleet that minimizes the total evacuation time of the area. It is therefore a combination of a network flow problem and a routing problem. Since the ICEP contains a routing component it requires some binary variables and is formulated as a mixed-integer program (MIP). Commercial solvers that solve the problem for an exact optimal solution therefore need to use solution methods appropriate for integer programming, such as Lagrangian relaxations, plane cutting and branch-and-bound/branch-and-cut methods to find the optimal solution. For large problem instances, it can take a significant amount of time to find the optimal solution since the trees generated by the branching methods grow exponentially in size. An additional challenge is posed by using an objective function that minimizes the total evacuation time instead of the sum of route times, which is commonly used in vehicle routing problems (VRP), since the total evacuation time is defined as the duration of the longest route generated among the resources. Experiments in chapter 4 have shown that solution discrimination is significantly more challenging for a commercial solver with such an objective function compared to minimizing the sum of route times. Since the problem aims to find a solution to respond to an emergency, it can be crucial to find a high quality solution quickly, and a near-optimal solution will suffice. A constructive heuristic that combines a greedy route plan generation with a local search has already been presented in Chapter 4, which produces results quickly. However, this heuristic does not reliably produce solutions close to the optimal solution, since it can get stuck at local minima. This is particularly the case for the stochastic version of the ICEP, denoted S-ICEP, which takes uncertainty over evacuee numbers and disaster location into account. While some in-depth analysis on the application challenges, data requirements and managerial insights for this modeling framework have already been obtained through a detailed real-world case study, solving the problem quickly is still a challenge. The proposed approximation method for the S-ICEP leverages a meta-heuristic framework that uses a Multi-Parent Biased Random-Key Genetic Algorithm (MP-BRKGA) [7]. The chapter introduces a S-ICEP specific decoder method that can be used to translate outputs from the MP-BRKGA into a unique solution to the S-ICEP. The method is validated by computational experiments. This chapter provides the following contributions:

- A decoder algorithm that translates standardized MP-BRKGA outputs into a solution to the S-ICEP, enabling the approximation of the optimal solution to the S-ICEP.
- Experimental results that demonstrate better performance of the proposed method compared to commercial problem solvers.

7.3 Methodology

7.3.1 Meta-Heuristic Solution Method Selection

A meta-heuristic method selection is developed to simplify the classification of the second-stage of the S-ICEP. However, a similar structure to the second stage of S-ICEP has not been observed in past studies. The closest related problem is the Bus Evacuation Problem (BEP) [25] and its variations [58], which solves a similar problem for on-land transportation using a homogeneous fleet of buses using a constructive heuristic. The approach provides a less complex solution since routes are interchangeable between resources without impact. A similar idea for a constructive heuristic has been applied to solve the ICEP in Chapter 3. However, the solution quality of this approach varies significantly depending on which input data set is provided. It thus does not produce solutions with a predictable quality. The BEP has further been approximated through considering more restrictive branching methods that establish bounds in a quicker way than a commercial solver and solve to these [73]. However, these problems neither show a performance guarantee and their performance is also highly dependent on the data set. The BEP in a simplified robust form has been successfully solved using a linear search and a tabu search approach with restarts [72]. Tabu searches are good algorithms to avoid getting trapped at local minima [69]. However, the presented linear and tabu search approaches, like the constructive heuristic presented by Bish [25] take advantage of the strong symmetry of the problem in between the different resources by adding or deleting resources and/or trips from the route plans and/or re-allocating them to other resources and are based on the interchangeability of route components in between resources. Using a similar logic with a heterogeneous resource set leads to either many infeasible solutions due to compatibility issues or not exploring the entire feasible region since some solutions will never be generated through this approach and generating space efficient tabu lists that avoid revisiting recently visited solutions is difficult. Experiments with an example case of the S-ICEP have confirmed this.

The search for approximate solutions is therefore generalized to routing and combinatorial problems. Specifically for stochastic combinatorial problems, which the S-ICEP belongs to. Bianchi et al. [24] have identified meta-heuristics that have shown to be successful in addition to tabu searches. These were ant colony optimization [59], simulated annealing [89], and evolutionary/genetic algorithms [75]. While there have been some successful applications for these algorithms to stochastic combinatorial problems, especially when paired with warm start procedures and local searches, the size of the feasible space in combinatorial problems often requires a simplification of the solution representation to fit into memory for larger problem sizes and the performance of these meta-heuristics cannot be reliably predicted for arbitrary problems and requires analysis specific to the problem at hand [24].

For that reason, a specific genetic algorithm type is selected as a way to escape the dimensionality problem of solution representation through a soft representation, the Random-Key Genetic Algorithm (RKGA) [14]. Traditional genetic algorithms, which use a variable representation in the chromosome however, are not per default suitable to solve combinatorial problems, since the use of binary and integer variables gives little flexibility to alternate solutions in a local search without making them infeasible. RKGAs on the opposite represent the solution in a soft way, where, instead of every chromosome element representing a variable, the elements, which contain random keys between 0 and 1 represent parts of the physical problem behind that can be translated into a feasible solution to the problem on every iteration and stored in a simple list of continuous values [14]. For example, for a Traveling Salesman Problem (TSP), the nodes can be represented in a list, and the list indexes can represent the customers in the network. Using the random key values generated by the algorithm for every customer, the list of customers can be sorted in ascending order, which represents a feasible tour in the TSP if visited in that order [14]. Like in a regular genetic algorithm, during every evolution chromosomes from the population are combined and crossed with each other to generate off-spring. After ranking the fitness of the available solutions in the population, the best solutions (e.g. top 10%) are determined the elite set. To enhance diversity and improve the solution over time, the worst solutions (e.g. worst 10%) are dropped from the population and replaced by random new chromosomes in every iteration. The RKGA will eventually find the optimal solution in expectation based on survival-of-the-fittest. Extensions of this methodology that improve the performance further for many problem types have been to bias towards the set of elite solutions in every evolution step (every off spring is generated from at least one elite-set solution) through Biased Random-Key Genetic Algorithms (BRKGA) [76]. The BRKGA has been further improved through using multiple parents to generate offspring instead of just two (MP-BRKGA) [7], which has proven to improve the performance of the regular BRKGA. This algorithm was chosen as its soft representation structure appears suitable to store the complexity of the S-ICEP problem, and the introduced randomness allows for exploring multiple areas across the feasible region and thus, escape local optima. An additional benefit of RKGA type algorithms that informed its selection as the method of choice is its suitability for parallel processing. Since in every evolution, all chromosomes have to be evaluated independently of each other, parallel processing can be a powerful tool that supports accelerating the algorithm. Since the only problem dependent part of the MP-BRKGA is the decoder function that translates the chromosome into a feasible solution to the S-ICEP, the main objective of this chapter is therefore the development of a decoder logic that suits the S-ICEP and its validation in computational experiments using the MP-BRKGA framework provided by

Andrade et al. [7].

7.3.2 Decoder Design

To design a decoder for the S-ICEP to be used in the MP-BRKGA, it is necessary to represent a solution through a single list of values between 0 and 1. The structure presented in Algorithm 1 was most successful in generating good route plans for the S-ICEP. First, generate a list of all pick-up and drop-off points, add an empty row (representing no node visit) and map them to a sequence of equally spaced threshold points between 0 and 1 (e.g. if there are 3 points in the list plus the empty one, the mapping would be $[0, 0.25, 0.5, 0.75, 1]$. For Ξ scenarios, I resources, and K maximum trips per resource, the chromosome will have the length: $\Xi * I * K$. Every iteration of the MP-BRKGA then generates a chromosome of values between 0 and 1. The procedure presented in Algorithm 9 then translates this chromosome into a feasible solution to the S-ICEP.

Figure 7.1 illustrates this decoder mechanism for an example. The design of this decoder allows that the continuous values generated by the MP-BRKGA can be decoded and used to generate feasible solutions to the S-ICEP in an efficient manner. This problem structure ensures that the entire feasible region is explored. Since the goal of this chapter is to identify and develop a method that can beat the time performance of a commercial solver while providing more reliable solution performance than the constructive heuristic presented in Chapters 3 and 4, comparative experiments are presented in the following section.

7.4 Experiment Results

Experiments were conducted to investigate whether the MP-BRGKA with the decoder developed above can beat the performance of an exact commercial solver. As a benchmark, the S-ICEP was implemented in a formal mathematical structure using the Pyomo modeling environment in Python 3.9, using the commercial Gurobi 9.0 solver. The MP-BRKGA was implemented using the Python MP-BRKGA package designed by Andrade et al. [7]. Consequently, the decoder was also implemented using Python, in an object-oriented struc-

Algorithm 9: MP-BRKGA Decoder for S-ICEP

Result: A feasible, near-optimal evacuation route plan

Initialize all resources $i \in I$, evacuees $e \in E$ as the evacuees, pick-up nodes $b \in B$, drop-off nodes $c \in C$, scenarios $\xi \in \Xi$;

Split the chromosome into Ξ parts of equal length $I * K$ (each representing the solution for one scenario ξ);

for *every chromosome segment* $\xi \in \Xi$ **do**

  Split each sub-chromosome into I parts of length K (each representing the route of a specific resource i in scenario ξ). **for** *every sub-chromosome segment* $i(\xi) \in \xi$ **do**

    Map the values between $[0, 1]$ at each index to the appropriate pick-up or drop-off point, based on threshold-based mapping;

  end

  Aggregate all route segments of all resources $i(\xi) \in \xi$ into a sortable list;

  Order the list of route segments by their respective arrival time;

  Allocate the evacuees at each pick-up point b to the resources i based on the order of resource arrivals, considering the respective capacity of every resource;

  Remove all route segments at each pick-up point after the last route segment that had passengers allocated. These trips do not need to be executed, as they do not carry passengers;

  Calculate route length s_i for each resource i, and denote the longest one as r;

  Calculate the operational cost for each resource i, and denote the longest one as r;

  Calculate the number of evacuees left behind n_a at each location a, if any remain;

end

For every scenario ξ, aggregate the values for $r(\xi)$, $\sum_{i \in I} cv_i * s_i(\xi)$, and the persons left behind $n_a(\xi)$;

Calculate the fitness of the solution through the S-ICEP objective, considering the relative probabilities for each scenario.

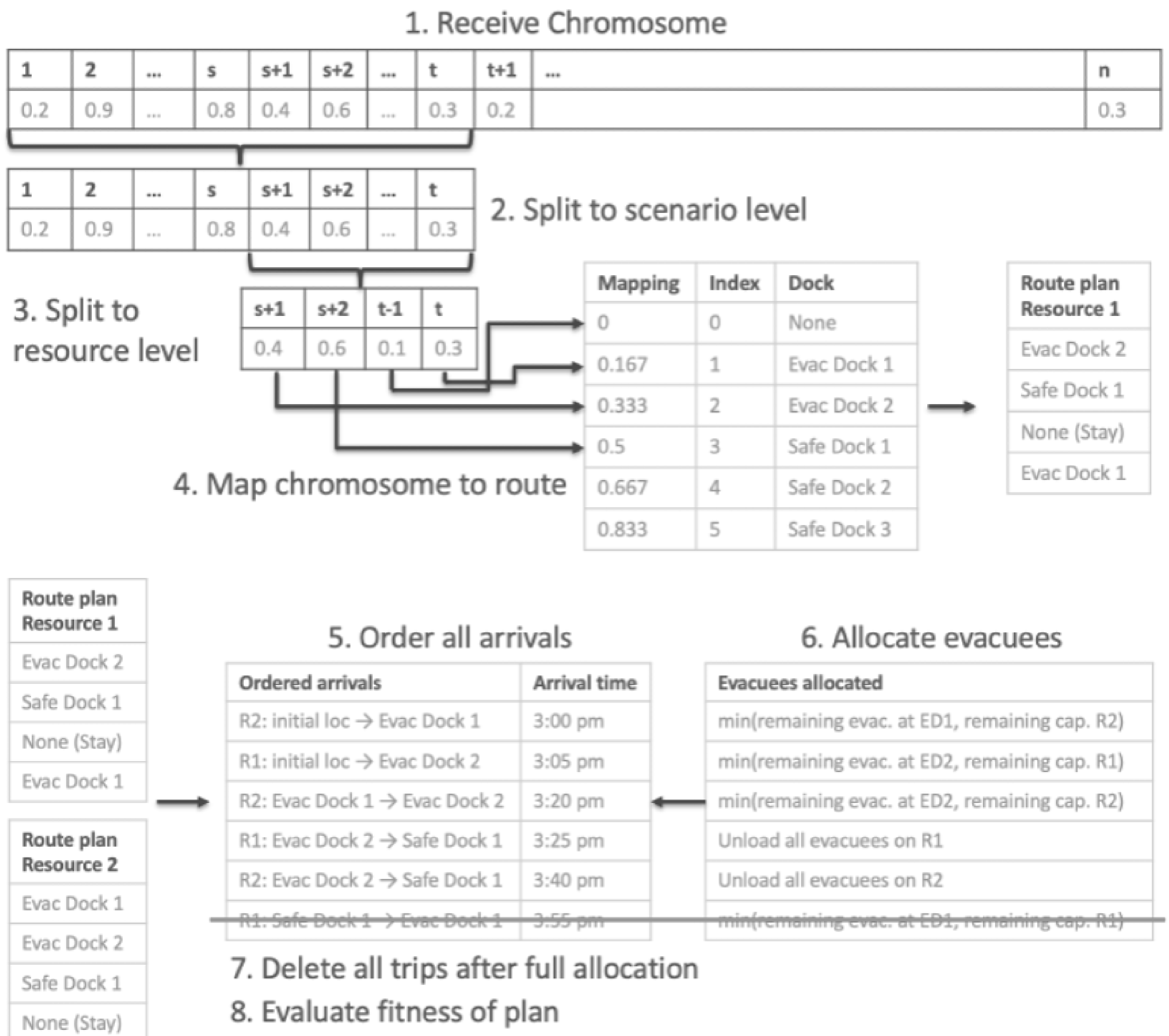

Figure 7.1: Example visualization of decoder translation from chromosome to feasible solution of S-ICEP

ture. The experiments on the MP-BRKGA were conducted in a concurrent and parallelized version. In addition, a random data generator was used for the S-ICEP with inputs on the number of scenarios, number of candidate resources, and the number of nodes. Using these parameters, the problem is then randomly generated using a set of uniform and gamma distributions, depending on the parameter at hand to keep the problems realistic (e.g. avoiding unrealistic examples where a resource has a capacity of 100,000 passengers). The MP-BRKGA maintains a solution population size proportional to the problem size itself and is determined through the following formula to keep enough chromosomes in the population to maintain a large enough level of variety: Population size $= \Xi * I * K$. Key metrics on the test data sets are presented in Table 7.1. For the study presented in this paper, a total of 5 randomly generated experiments have been conducted. The experiments were conducted on a cloud computing instance with 36 CPUs and 72 GB of RAM, and were aborted after a maximum run time of 1,800s, and a maximum evolution of 1,000 generations in the MP-BRKGA. The results are presented in Table 7.2. For Gurobi 9.0, only solutions from the concurrent run mode are displayed, as the parallelized run mode performed significantly worse due to increased computational overhead.

Table 7.1: Test Data Sets for MP-BRKGA Evaluation

	Test 1	Test 2	Test 3	Test 4	Test 5
Sets			*Set size*		
Scenarios	2	2	2	3	4
Potential Resources	6	4	2	5	20
Docks	7	5	5	8	6
Round trips	2	2	2	3	4
Parameters			*Setting*		
Penalty	5,000	5,000	5,000	5,000	5,000
Variable Type			*Quantity*		
Continuous Variables	416	550	650	8308	17,290
Binary Variables	413	595	758	12,875	24,820

Table 7.2: Experiment Results Gurobi 9.0 vs. MP-BRKGA Decoder

Data	Gurobi 9.0 (Concurrent)		MP-BRKGA (Concurrent)		MP-BRKGA (Parallelized)	
	Solution time	Objective	Solution time*	Objective	Solution time*	Objective
Test 1	5.51s	101.03	109.77s	172.00	142.41s	124.00
Test 2	2.36s	56.67	188.13s	56.67	17.65s	56.67
Test 3	116.15s	229.00	375.28s	324.00	928.2s	232.64
Test 4	1,800.00s	**313.04	805.57s	291.39	671.39s	259.73
Test 5	1,800.00s	**178.04	1,217.39s	218.25	908.63s	108.03

*Last improvement
**Runs aborted after 1,800s; best available solution displayed.

Reviewing the results presented in Table 7.2, MP-BRKGA was not able to beat Gurobi 9.0 in solution performance in all test instances. Only in Test 2 it was able to reach the objective value Gurobi was able to find, but in a much longer time frame than Gurobi, both for the concurrent and parallelized version of the MP-BRKGA. However, for the larger instances, the performance of the MP-BRKGA in comparison to Gurobi 9.0 is better, particularly for the parallelized version. While the methods that Gurobi is using guarantee convergence to a global optimum, the solution time becomes so long that the optimal solution cannot be reached within a reasonable time frame for emergency management. For these cases, the parallelized MP-BRKGA can be useful to obtain solutions in a more reasonable time frame. The underlying reasons and implications of these experiment results are discussed in the following section.

7.5 Discussion

The results from the experiments have shown that the implemented version of the MP-BRKGA has outperformed the Gurobi implementation for larger problem instances. This makes the method useful for large instances in emergency use, since obtaining solutions quickly is instrumental during situations where human lives are in danger. While the solutions generated by the parallelized decoder are fine solutions to the problem at hand, the algorithm speed could still be improved for smaller instances. Investigating reasons for this lack of performance, the first disadvantage that can be noted is that, the MP-BRKGA only approximates optimal solutions due to its iterative and randomized nature. The main problem in the decoder structure is that the feasible region of the S-ICEP is so large that the solution space that is searched by the decoder causes a lot of sub-optimal solutions to be generated. Even though this ensures a diversified set of chromosomes, it does not support the progression to a better solution. While it is difficult to develop meta-heuristic methods with performance guarantees, further efforts could be placed on letting the decoder bias towards solutions that have a high likelihood to improve the set of solution candidates, while reducing the risk that the global optimum is accidentally excluded.

Furthermore, the algorithm needs to evolve through many generations to receive solutions with good fitness values. This means that the speed of the decoder function is crucial in determining a short solution time. Unfortunately, the use of an object-oriented representation of the problem requires the use of for loops in Python. Since Python is a scripting language and therefore slow processing of for loops (lack of memory allocation, no full multi-threading), it is difficult to beat commercial solvers that run on faster programming languages.

7.6 Conclusions and Next Steps

In this chapter, a new decoder logic was presented to solve the S-ICEP problem through a MP-BRKGA. The decoder function is well suited to generate quality solutions to large instances of the S-ICEP problem in a reasonable time frame and thus provides an important contribution in identifying a faster way to solve the S-ICEP. This allows emergency personnel and planners and coordinators to make routing decisions that resolve a dangerous situation quickly.

The speed of the current implementation of the algorithm allows for improvements. One part of these improvements could be dedicated towards giving the decoder more bias to high quality solutions and thus decrease the number of generations that need to be evolved to get close to the global optimum. It could be considered to reduce the feasible region of the decoder to only generate solutions from regions that are promising to contain good route plans. For example, if a certain number of resources are being used, it is likely that a good solution will try to keep all available resources busy at all times to shorten the evacuation time, thus solutions that do not keep all resources busy could be discarded. Another direction with similar effect could be to make the decoder two-staged and implement a high level quick approximation of the objective value in the first step and only evaluate the objective function exactly if a certain threshold is reached to reduce the computational effort. This way, not much time is wasted on finding the actual objective value of solutions that are not promising anyways. A combination of both approaches can also be considered.

Another part of these considerations is implementation based and can be achieved through choosing a different way to implement this algorithm. In that sense, the next steps become more of an implementation challenge than a modeling or design challenge. A vectorized problem representation in the decoder has the potential to significantly accelerate the algorithm and should be considered to improve the solution quality.

Another approach would be to choose an entirely different solution approach to the S-ICEP, such as either other meta-heuristics [24], or a decomposition of the problem using column-generation methods that separates the problem into a route generation problem and an evacuee allocation problem analog to what has been done on VRPs [64,103]. Alternatively, there is potential for research to approximate solutions directly from input data using deep-learning on training instances [122].

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Chapter 8
CONCLUSIONS

8.1 Summary

The research presented in this dissertation has provided insights on the systematic evacuation of isolated communities using techniques from mathematical programming. To date, no studies have consider best approaches for the the evacuation of the population of isolated communities with limited road-based connections; this dissertation represents the first research contribution to approach this problem. The special characteristics that make this problem unique are the required reliance on a coordinated set of resources to evacuate the area, as the options for self-evacuations are severely limited, unlike for land-based evacuations. Furthermore descriptive of this problem are the separation between pick-up and drop-off node classes. Moreover, essential components are a limited compatibility between a potentially highly heterogeneous evacuation resource set and the nodes, such as an aircraft with a helipad or a passenger ferry with a private boat dock. Lastly, the requirement for an unknown number of trips per resource characterizes this problem.

The Deterministic Isolated Community Evacuation Problem (D-ICEP) introduced in Chapter 3 is the first model that considers the unique circumstances of isolated communities through a combination of a flow and a routing problem. This model's special structural characteristics are the limited compatibility between the evacuation resources, resource heterogeneity, and the trip expansion of the model network. Furthermore, the focus of the objective on minimizing the total evacuation time instead of individual resource route times distinguishes this model from other routing problems, which leads to challenges in solving the problem efficiently. For that reason, a two-phase structure-based heuristic was introduced that outperforms commercial solvers in solution time by 43 to 97%, though it does not reliably reach the same solution quality.

Considering the D-ICEP as a baseline tool, derivatives for evacuation planning and response management were developed due to different priorities for each of these tasks. For evacuation planning, a two-stage stochastic expansion was developed in Chapter 4 (S-ICEP) that allows scenario-based planning for diverse sets of disaster scenarios. Furthermore, this model allows a scenario-independent decision on an appropriate resource fleet to ensure that evacuation planning is done cost-efficiently. For this model, different objective functions that balance out the trade-offs between cost and evacuation time as priorities were presented, and analog to the D-ICEP, a structure-based heuristic was introduced, which did not perform as well as the D-ICEP heuristic. The S-ICEP thus represents a valuable tool for emergency planners and researchers to optimize the planning for evacuations of isolated communities.

For response management, Chapter 5 introduced two variants of the ICEP that handle uncertainty over the number of evacuees during an emergency, the R-ICEP based on robust optimization and the RH-ICEP based on rolling-horizon optimization. These models take different approaches on how to incorporate uncertainty into the evacuation plan, the R-ICEP is based on uncertainty sets in the beginning, the RH-ICEP adapts the plan successively during execution as soon as new data is available. Extensive computational experiments have demonstrated that the RH-ICEP is superior in handling the uncertainty of isolated community evacuation, particularly for problems with limited compatibility between nodes and resources. The obtained evacuation time compared to using the D-ICEP could be reduced by approximately 5% using the RH-ICEP methodology. The outperformance of the RH-ICEP was also shown to be robust across different data set configurations. The R-ICEP with the most conservative settings was identified to be only suitable for problems with high compatibility between resources and nodes. These results show that the RH-ICEP is a valuable tool for isolated community evacuation during emergency response, as it takes in new information over time and therefore is adaptive to changes during the evacuation execution.

The models presented in this dissertation should be feasible in practice. For that reason, an extensive real-world case study was presented in Chapter 6 that uses the S-ICEP for evacuation planning. This case study was conducted through a collaborative effort with the Bowen Island Municipality in Canada and presents a planning template for the evacuation of an isolated island, considering all efforts regarding data sources, data collection, mathematical modeling, and interpretation of the model results, resulting in recommended actions. The study stretches the importance of iterative data collection and modeling and represents a template for future evacuation studies in the field. It thus represents a significant contribution for both practitioners and researchers as it gives guidance on how to connect ground level emergency planning with mathematical modeling practically.

Due to the high complexity of the ICEP formulation and the unreliable performance of the presented structure-based heuristics, Chapter 7 introduces a meta-heuristic solution approach to solve the problem more efficiently. The solution presented is based on the MP-BRKGA framework and contains a customized decoder function that translates between the solutions space of the (S)-ICEP and the MP-BRKGA. Experiments using powerful cloud computing resources have demonstrated that with parallel computing, the MP-BRKGA can outperform the commercial solver for large instances, particularly when commercial solvers do not converge anymore due to memory problems. This chapter thus provides an essential contribution towards solving large instances of the ICEP that cannot be accomplished with a commercial solver.

In summary, the individual efforts spent on definition, modeling, planning, and testing for isolated community evacuation have delivered significant contributions to both the evacuation research field as well as the operations research and vehicle routing fields.

8.2 Limitations

The focus of this dissertation centers on solving the isolated community evacuation problem using mathematical modeling. This included model development, data collection, interpretation of results, and maximizing the model's utility depending on the use case. In the evacuation study structure presented in Chapter 2 these contributions mostly fall in the area of emergency response actions and touch on Hazard and Vulnerability Analysis. However, the dissertation did not address the behavior analysis of evacuees for isolated community evacuations. Studying evacuee behavior in isolated communities is vital to understand how and where people will arrive for evacuation and also where people are practical to pick up from during an emergency. Furthermore, it was assumed that shelters are predetermined and do not require additional analysis. The dissertation made no conclusions regarding the impact of evacuation behavior and micro-level circumstances around shelters on the effectiveness of the presented Isolated Community Evacuation Problem.

Furthermore, the research presented limited the modeling optimization component to the routing model that organizes the resource set and thus minimizes the evacuation time. The complementary problem of effectively transporting evacuees to pick-up points, and to final destinations from drop-off points was not addressed. There are interactions between the two problems in that the arrival rate at the pick-up points influences the effectiveness of a generated plan, particularly for the ICEP for response purposes from Chapter 5.

From a modeling perspective, the research focused on optimization techniques and did not investigate the potential of alternative modeling approaches, such as simulation models, to solve the ICEP. Within optimization modeling, the dissertation focused on approximately solving the routing problem through structure-based heuristics (Chapter 3 and 4) and a meta-heuristic (Chapter 7) for instances that were too large to be solved by a commercial solver effectively. Many other solution approaches exist to approximate the optimal solution to similar routing problems. This dissertation does not conclude on whether the proposed methods outperform any alternative approximation method.

Concerning the performance of models tailored to response purposes (Chapter 5), the list of parameters investigated to influence the performance of the proposed RH-ICEP and R-ICEP algorithms is not exhaustive and instead a subset of potential parameters of interest. Parameters directly related to real-world differences between data sets, such as geographic distributions of pick-up and drop-off points, varying intervals of information retrieval, or other characteristics of the evacuation resource set have not been investigated in this dissertation.

8.3 Outlook on Future Work

The findings presented in the literature review (Chapter 2) showed that the evacuation of isolated communities is an understudied but important problem. While this dissertation made progress in defining, describing, and solving the problem through mathematical modeling, many open questions remain that will inspire future studies in this area. One key question that remains is how the transportation of evacuees from residences and other places to evacuation pick-up points can be organized in a way that works with limited resources within the community itself while avoiding traffic back-ups that can delay the evacuation process and considering the needs of mobility-impaired populations. Another remaining question is where the pick-up and drop-off points for isolated community evacuations should be located and how to consider this in community and infrastructure design. Since evacuation resources used in the ICEP, such as vessels or aircraft, usually require specific infrastructure to be useful for evacuation, access points are usually predetermined by available infrastructure. Spending research effort on how to account for the risk of evacuation needs in infrastructure design will be valuable in the future, as the findings in the case study on Bowen Island in Chapter 6 have demonstrated. This furthermore also affects the determination of potential shelter or safe locations, as shorter distances will reduce evacuation time.

Moreover, the effects of evacuation behavior in isolated communities and their impacts on the model qualities are questions that will require answers in the future. It could be helpful to develop an entire isolated community evacuation framework that allows simulating the entire environment, including the ICEP routing component and the extensions mentioned above. Researchers could gain additional insights from such a simulation environment, particularly if recent insights on evacuation behavior are incorporated [150], as it is difficult to gather detailed data from real-world evacuations through observation.

Another aspect that needs to be addressed in future work is how the different ICEP modeling types can be incorporated into regular evacuation planning (S-ICEP) and response components (RH-ICEP and R-ICEP). The tools are only practical for emergency planners and responders if they can be used quickly and efficiently by non-technical personnel. For that reason, efforts on user design for the tools will be part of future work. Succeeding in such an integration further increases the likelihood of actual usage in emergencies. The resulting experiences from using the models will help revise the models and tools further.

The relaxation of multiple assumptions in the network model itself can be investigated from a modeling perspective. First, the assumption that evacuation resources do not require downtime is only realistic for smaller evacuation scenarios that take only a few hours and do not require refueling or crew replacements. Furthermore, it should be explored how capacity constraints at evacuation pick-up and drop-off points will affect the solutions; as for larger problem sizes, it can become more relevant to consider that every access point can only serve a certain number of evacuation resources at any given time. Moreover, allowing resources to visit multiple evacuation pick-up points directly after another without having to return to a drop-off point before can be investigated to see whether additional gains in solution performance can be achieved. Lastly, a prioritization feature could be considered that allows for prioritizing specific locations over others in the evacuation process, based on how urgent the evacuation from that specific area is. This would be useful if a threat affects one area more than another. However, all of the extensions above will make the model more complex, and the trade-offs between model accuracy and model complexity have to be considered when adding these. These trade-offs also need to be considered when revising the RH-ICEP and R-ICEP to further consider uncertainty in the travel times of a resource. For the effectiveness of the RH-ICEP and R-ICEP, future work could also investigate additional data set characteristics or modeling circumstances that the analysis in this dissertation did not address. This will provide further guidance on when to use which model.

Regarding efficient ways how to solve the ICEP problems, challenges remain for large problem instances, where commercial solvers struggle with the size and complexity of the problem. While the MP-BRKGA-based solution method presented in Chapter 7 provided a method to solve larger instances, future work can investigate other solution approaches that build upon these findings. Examples are other meta-heuristics [24]. Alternatively, model decomposition frameworks, such as column generation that separate the route generation component from the optimal resource allocation component and thus reduce the complexity [103] could be investigated. Another alternative would be to investigate further recent research approaches that aim to predict the model outputs through machine learning [21] or deep learning techniques [122]. Training a deep learning model based on a large sample of ICEP test cases that were solved to optimality could allow for predicting the outputs for an instance solely based on the model inputs without having to perform the optimization procedure. This way, a large portion of the computation time required to solve the model could be reduced.

The research directions highlighted above demonstrate the variety of future work that can help to shed more light on the problem of isolated community evacuation and deliver more tools that improve the safety of people around the world, which further highlights the importance of the research presented in this dissertation.

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Appendix A
RESEARCH CODE REPOSITORIES

The programming code developed and implemented for the research presented in this dissertation is available on Github and is subject to future revisions and updates as research needs require.

- Latest version of code repository for exact implementations of D-ICEP (Chapter 3), S-ICEP (Chapter 4), and RH-ICEP & R-ICEP (Chapter 5):
  `https://github.com/singfie/ICEP-exact-implementation`
- Latest version of code repository for structure-based heuristics for D-ICEP (Chapter 3), and S-ICEP (Chapter 4):
  `https://github.com/singfie/ICEP-structured-greedy-heuristics`
- Latest version of code repository for MP-BRKGA package for S-ICEP (Chapter 7):
  `https://github.com/singfie/ICEP-MP-BRKGA-solver`