Optimization Modeling Approaches to Evacuations of Isolated Communities

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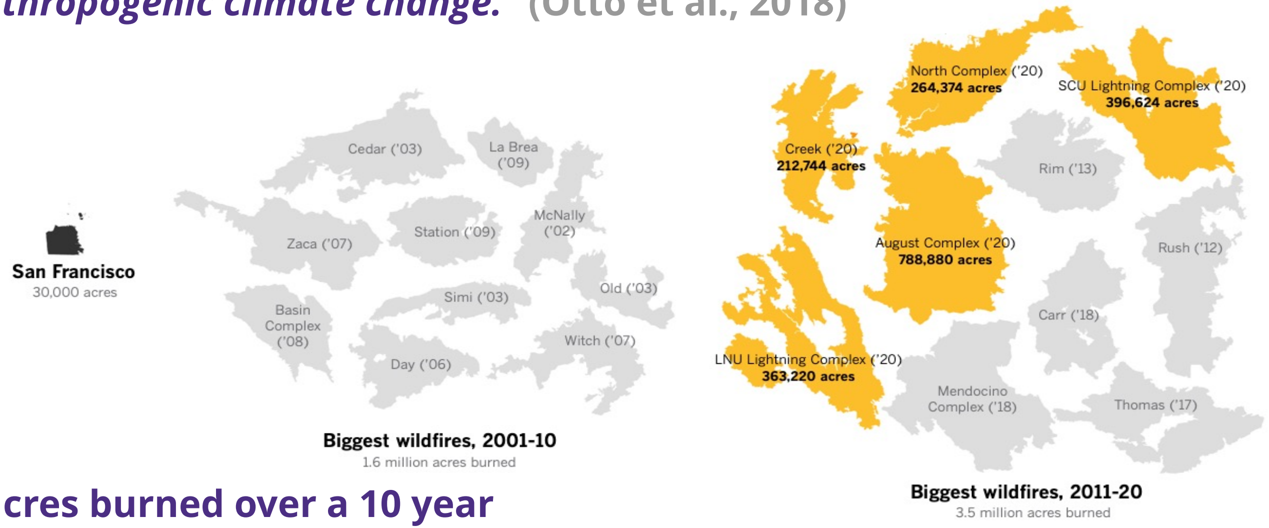
Motivation

Increasing disaster frequency and severity

> *"Increasing likelihood of extreme weather events is the most noticeable and damaging manifestation of anthropogenic climate change."* (Otto et al., 2018)



The total number of acres burned over a 10 year span in California wildfires increased by 50% over the last 10 years (LA Times, 2020)

Source: https://www.latimes.com/projects/california-fires-damage-climate-change-analysis/

Disaster Management

- *"Disaster risk reduction and more robust development planning are crucial in adapting to the increasing risks associated with climate change."* (van Aalst, 2006)
- One component of risk management: Evacuation planning and response

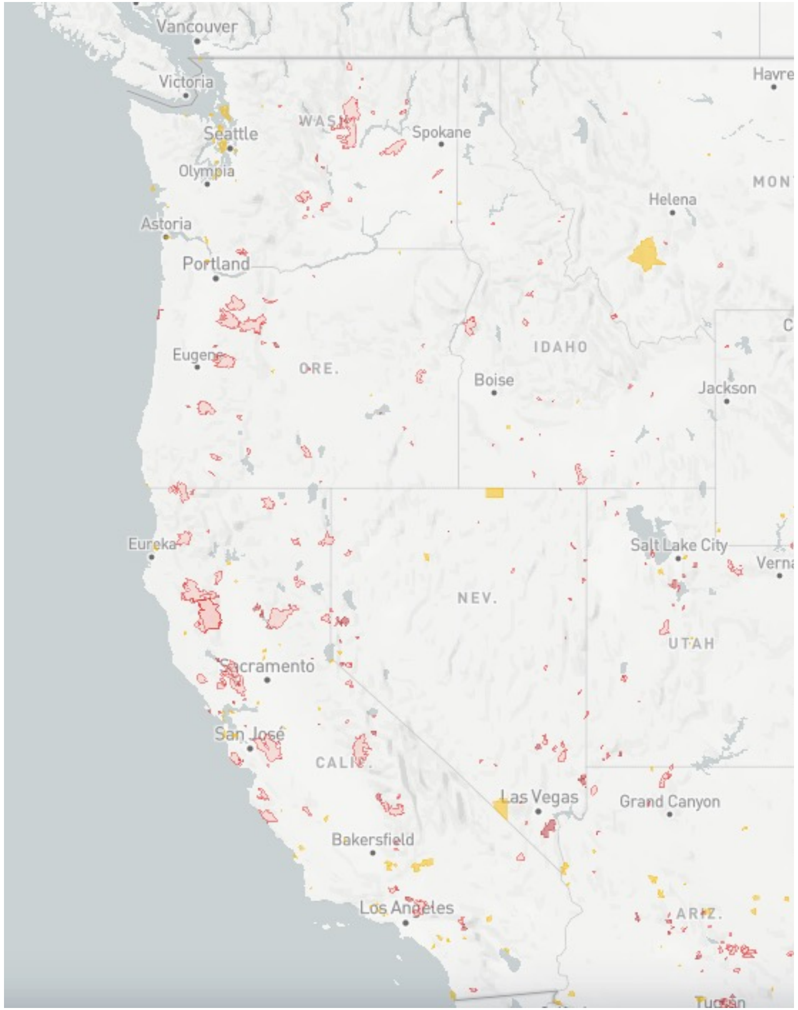
Source: https://www.canyon-news.com/hurricanes-tornadoes-earthquakes-emergency-survival-plan/79632

Source: https://www.courthousenews.com/wp-content/uploads/2019/10/Evacuation.jpg

Vulnerable Communities

"(…) coastal settlements, including in small islands and megadeltas, and mountain settlements are exposed and vulnerable to climate extremes (…)."* *(IPCC, 2012)

- **Many islands, coastal, and mountain settlements with potentially disrupted or non-existent evacuation routes**
- **Around 800 such communities in the U.S. alone (StreetLight Data, 2019)**
- **Self-evacuation may be impossible**



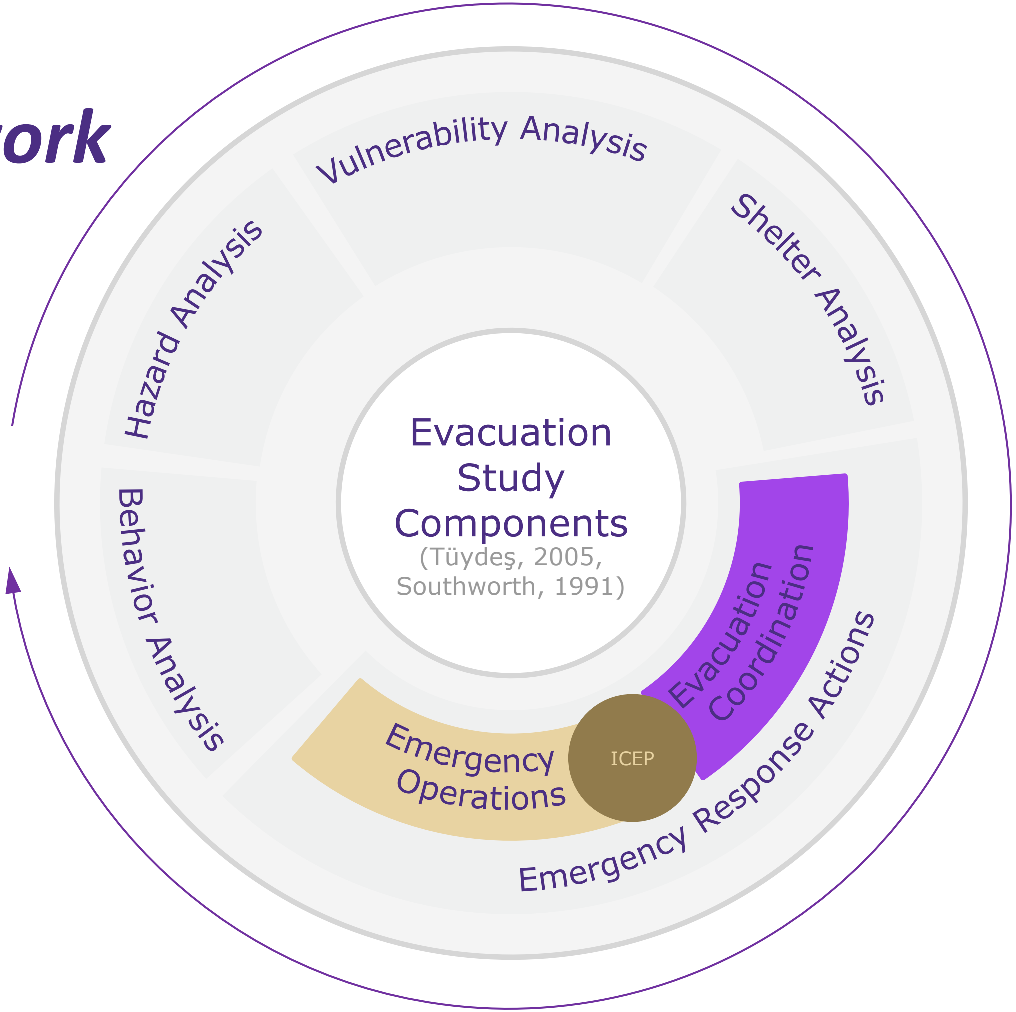
Source: https://www.streetlightdata.com/limited-evacuation-routes-map/

Motivating Question

Isolated Community Evacuation Problem (ICEP):

How to evacuate an isolated community without land-based evacuation routes as quickly as possible?

Evacuation Framework



Research Objectives

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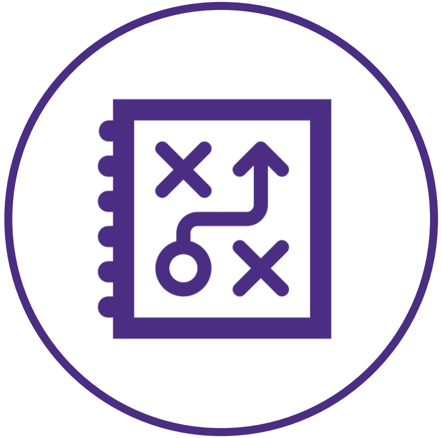
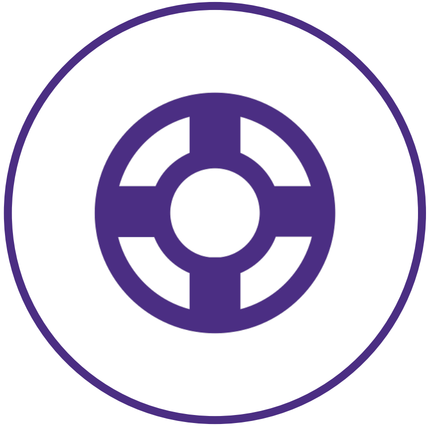
Design a new formulation to optimize ICEP evacuation routes

ICEP for evacuation planning



ICEP for evacuation response

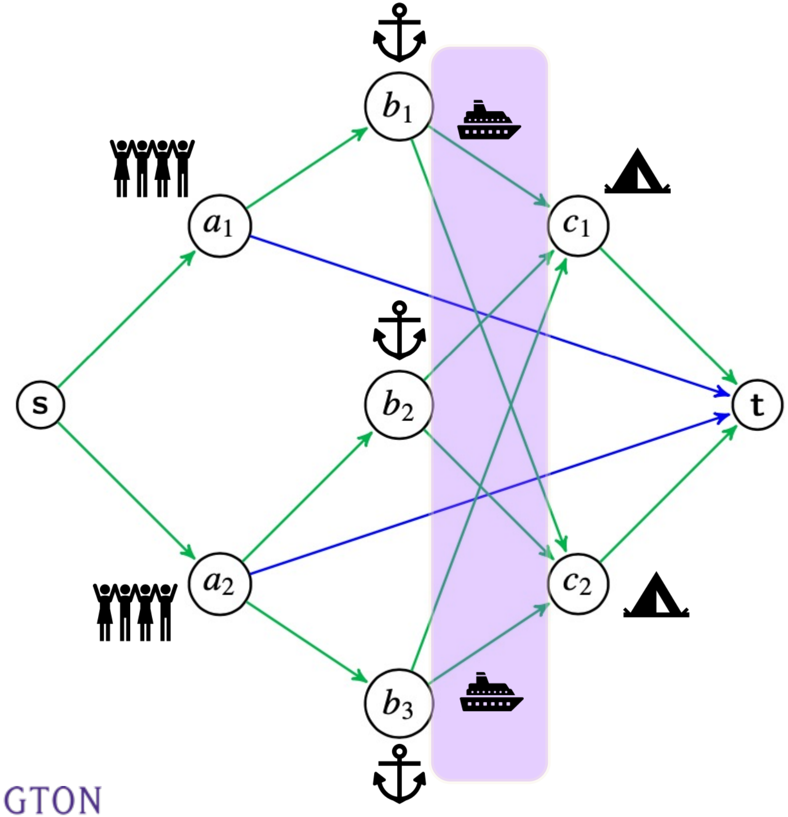


Contributions of this Dissertation Research

- **New formulation (ICEP)** that models optimal evacuation of isolated communities without road-access through a coordinated resource fleet
- **Heuristic and meta-heuristic solution approaches** to the model makes it possible to get quality solutions quickly
- ICEP-based **planning tool** for emergency planners and researchers to prepare for a potential disaster
- ICEP-based **response tool** to make good decisions in times of uncertain numbers of evacuees during a disaster

Formulations for D-ICEP and S-ICEP

Network flow problem



Evacuation area

Pick-up location (dock)

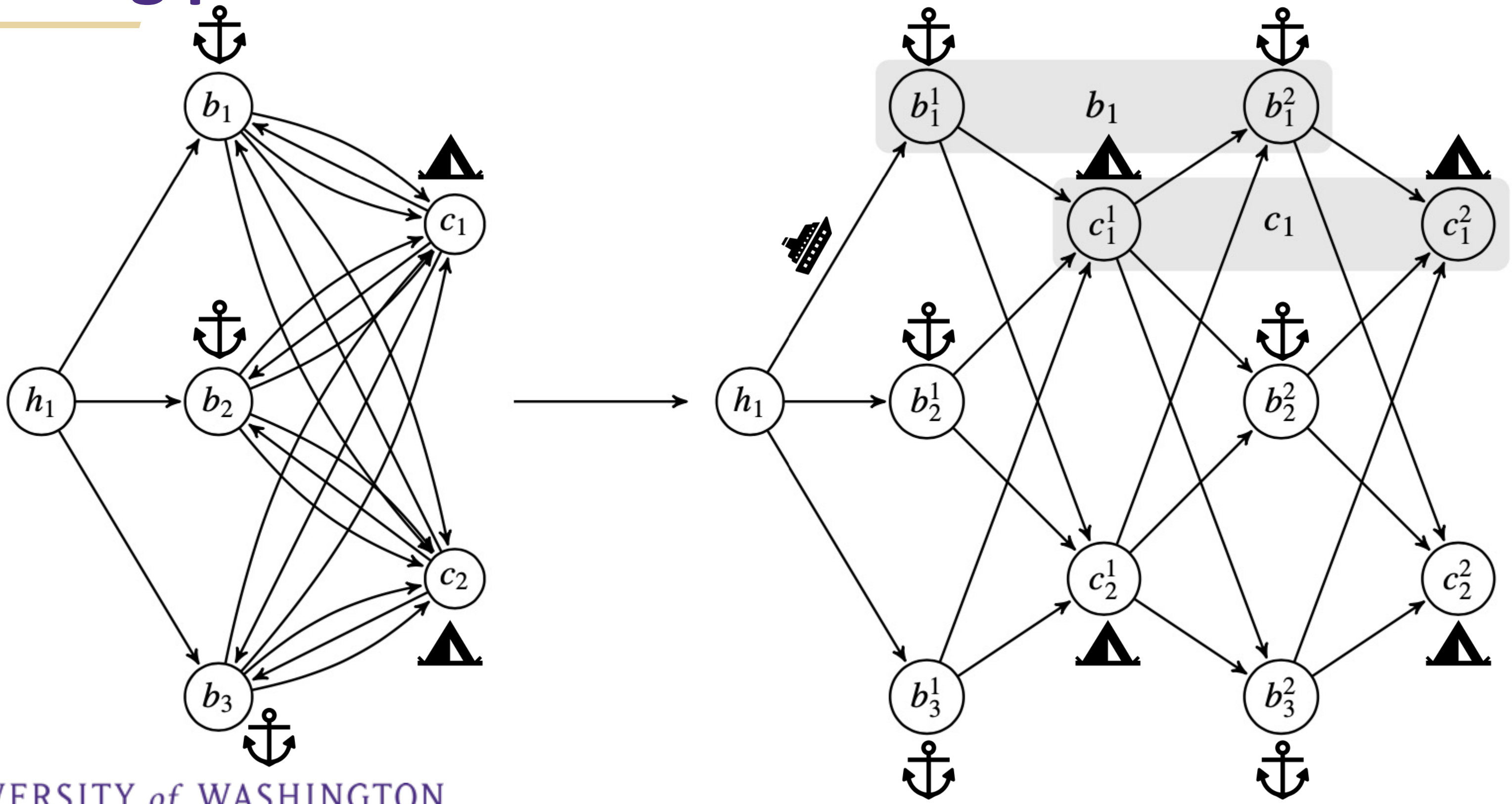
Drop-off location (shelter)

Evacuation resource

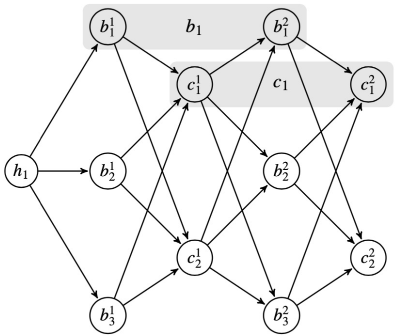
Non-linear
Multiple tours
Heterogeneous fleet

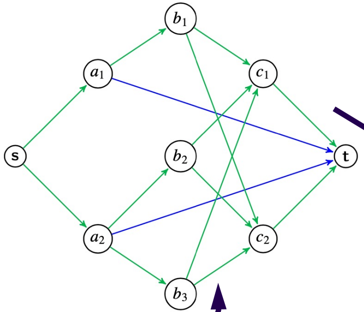
Routing problem

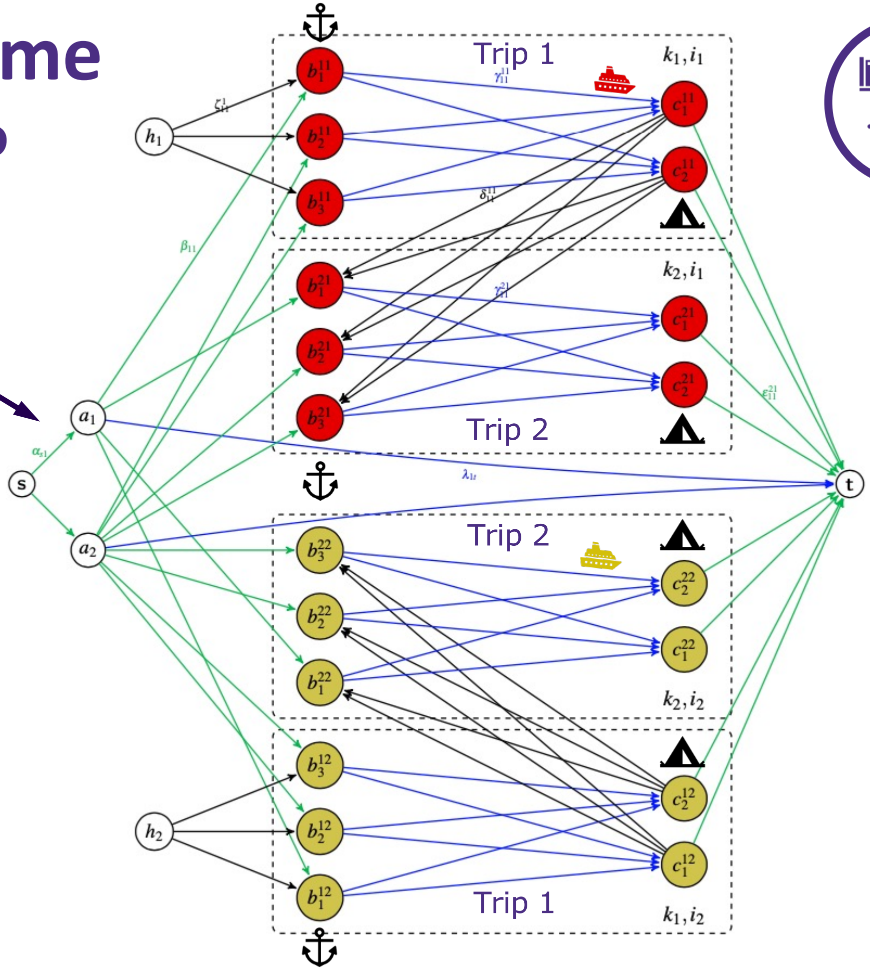
Evacuation area
Pick-up location (dock)
Drop-off location
Evacuation resource



Minimize Evacuation Time with Deterministic ICEP







Evacuation area

Pick-up location (dock)

Drop-off location

Evacuation resource 1

Evacuation resource 2

Contributions of D-ICEP and S-ICEP Formulations

> Developed routing formulation to evacuate an isolated community without land-based evacuation routes
> Developed scenario-based evacuation planning tool from D-ICEP
> Validated as appropriate evacuation planning tool with emergency responders and coordinators (Bowen Island Municipality)
> Developed and tested constructive greedy heuristic
> Published in:

ISSN: 1366-5545

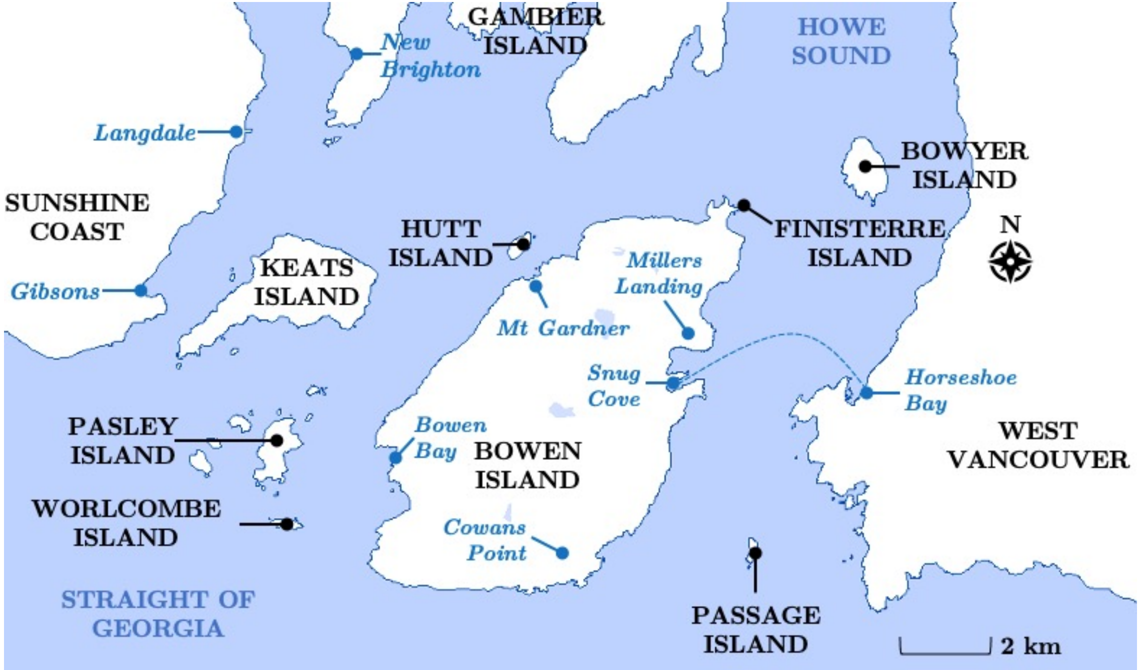
Transportation Research Part E: Logistics and Transportation Review

CiteScore	Impact Factor
9.3	6.875

Time to First Decision	Review Time
4.6 weeks	9.2 weeks

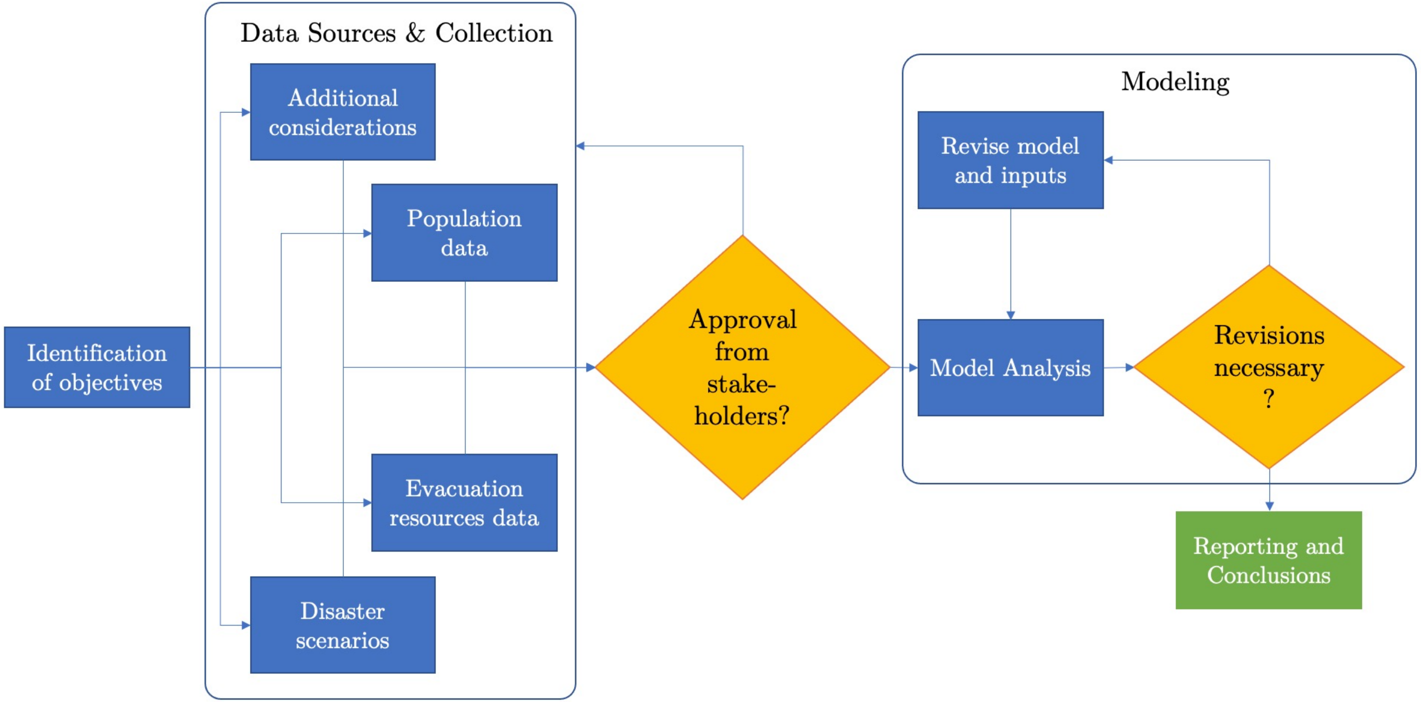
Case Study for Planning Evacuations

Bowen Island



Source of image: Bowen Island Municipality

Study Process



Contributions of the Case Study

- > **Validated suitability of S-ICEP for evacuation planning with practitioners in emergency management**
- > **Detected high solution sensitivity**
  - – **Close collaboration with stakeholders necessary**
  - – **End-to-end data-modeling integration valuable**
- > **Published in:**

ISSN: 2212-4209

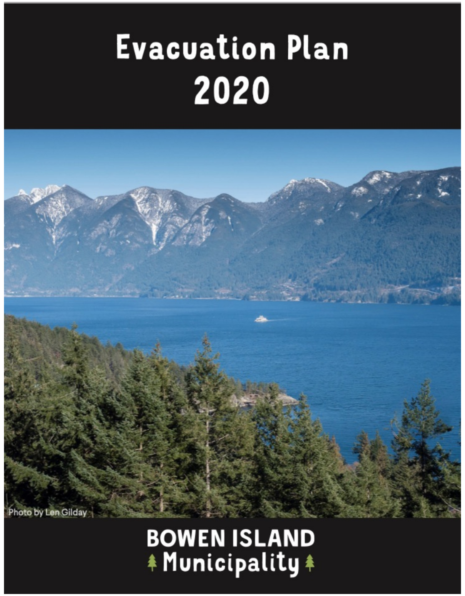
International Journal of Disaster Risk Reduction

CiteScore 5.5

Impact Factor 4.32

Review Time 11.3 weeks

Publication Time 1.2 weeks



Meta-Heuristic Solution Approach

How to solve the ICEP?

Commercial solvers (e.g. CPLEX, Gurobi)

> Challenges:
  - Routing problems are NP-complete
  - Problem is very complex in structure and objective
  - Trip expansion generates many binary variables

> Consequences:
  - For many instances commercial solver takes very long

Greedy heuristics (from previous section)

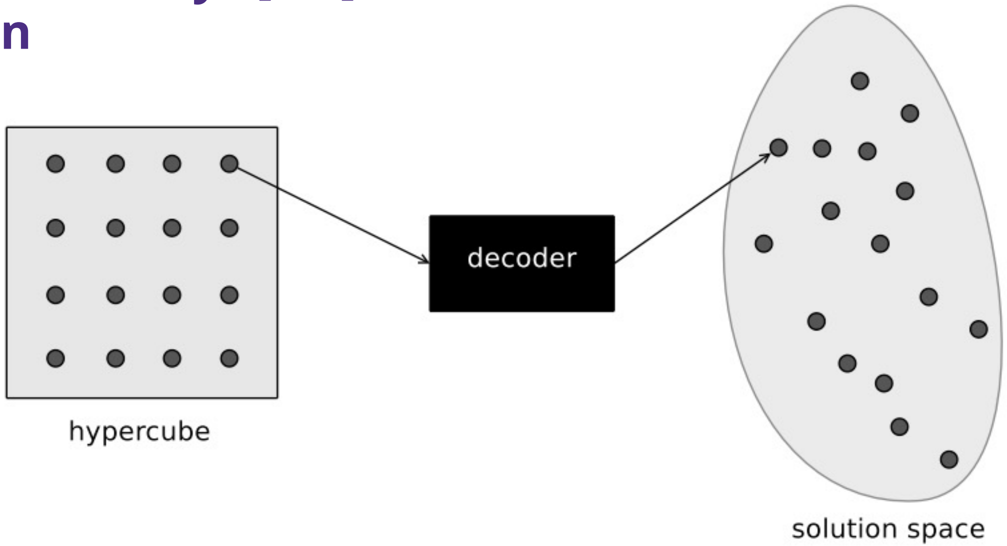
> Challenges:
  - Unreliable solution quality especially for S-ICEP

Chosen Methodology: Multi Parent Biased Random Key Genetic Algorithm (MP-BRKGA)

> **Reasons:**
  - Feasible region of ICEP very complex
  - MP-BRKGA generates feasible solution in every iteration
  - Population based structure is promising to avoid local minima effectively
  - Proven track record for solving routing problems

Random-Key Genetic Algorithm (Bean, 1994)

- Simplification of solution representation
- Use random keys [0,1] instead of variable values to represent solution



Source: Gonçalvez and Resende, 2011

Developed Chromosome Decoder Logic
Step 1

1	2	…	s	s+1	s+2	…	t	t+1	…	n
0.2	0.9	…	0.8	0.4	0.6	…	0.3	0.2		0.3

Scenario level

1	2	…	s	s+1	s+2	…	t
0.2	0.9	…	0.8	0.4	0.6	…	0.3

Resource level

s+1	s+2	t-1	t
0.4	0.6	0.1	0.3

Mapping	Index	Dock
0	0	None
0.167	1	Evac Dock 1
0.333	2	Evac Dock 2
0.5	3	Safe Dock 1
0.667	4	Safe Dock 2
0.833	5	Safe Dock 3

Route plan Resource 1
Evac Dock 2
Safe Dock 1
None (Stay)
Evac Dock 1

Developed Chromosome Decoder Logic Step 2

Route plan Resource 1
Evac Dock 2
Safe Dock 1
None (Stay)
Evac Dock 1

Route plan Resource 2
Evac Dock 1
Evac Dock 2
Safe Dock 1
None (Stay)

1. Order all arrivals

Ordered arrivals	Arrival time
R2: initial loc → Evac Dock 1	3:00 pm
R1: initial loc → Evac Dock 2	3:05 pm
R2: Evac Dock 1 → Evac Dock 2	3:20 pm
R1: Evac Dock 2 → Safe Dock 1	3:25 pm
R2: Evac Dock 2 → Safe Dock 1	3:40 pm

2. Allocate evacuees

Evacuees allocated
min(remaining evac. at ED1, remaining cap. R2)
min(remaining evac. at ED2, remaining cap. R1)
min(remaining evac. at ED2, remaining cap. R2)
Unload all evacuees on R1
Unload all evacuees on R2

3. Delete all trips after full allocation

4. Evaluate fitness of plan

Experiment Results

Data label	No. resources	No. docks	Scenarios	Gurobi		MP-BRKGA (concurrent)		MP-BRKGA (parallelized)	
				Solution time	Objective	Solution time	Objective	Solution time	Objective
Test 1	6	7	2	5.51s	101.03	109.77s (last imp.)	172.00	142.42s	124.00
Test 2	4	5	2	2.36s	56.67	188.13s (last imp.)	56.67	17.65s	56.67
Test 3	2	5	2	116.15s	229.00	375.28s (last imp., ran for 3600s)	324.00	928.2s	232.64
Test 4	5	8	3	3600s (aborted)	313.04	805.57s (last imp., ran for 3600s)	291.39	671.39s	259.73
Test 5	20	6	4	3600s (aborted)	178.04	1217.39s (last imp.)	218.25	908.63s	108.03

Conclusions and Learnings

- MP-BRKGA quicker than Gurobi for large instances
- Possibility to run longer allows convergence in expectation
- Evolution in MP-BRKGA is too slow to compete with Gurobi for small instances, even in parallelized case

Contributions of MP-BRKGA and Decoder

- MP-BRKGA helps in solving large scale problems
- Important step towards more efficient solution methods for ICEP
- Invited submission to:
  Winter Simulation Conference 2022

ICEP for Evacuation Response

Develop a response version of ICEP for evacuations with uncertain evacuees

- Goal: Make ICEP useful as a disaster response tool
- Relax assumption on certainty over evacuee numbers in D-ICEP upon start of evacuation
- Two solution approaches:
  - Use historic data:
    - Cardinality-Constrained Robust Optimization
  - Use data based on availability:
    - Rolling-Horizon Optimization

Robust Optimization (cardinality constrained)
(Soyster, 1973; Bertsimas and Sim, 2004)

> **Start with D-ICEP**

> **Create demand uncertainty sets from historic data or preliminary information with mean and max values** $\{\overline{d_a}, \overline{d_a} + \widehat{d_a}\}, \forall a \in A$

> **Introduce parameter** Γ**, where** $\Gamma \in [0, |A|]$ **is the number of locations where the demand can vary from mean values** $\overline{d_a}$

> **Introduce variable** $l_a, \forall a \in A$**, which models decision in robust subproblem**

> **Add constraint:** $\vec{l} = \underset{\{V \subseteq A, |V| = \Gamma\}}{\operatorname{argmax}} \sum_{a \in V} \widehat{d_a} l_a$

> **Modify first flow conservation constraint in D-ICEP to obtain R-ICEP:**

$$d_a = fl_{at} + \sum_{\beta_{jb}^{ki} \in \bar{B}: j=a} fl_{ab}^{ki} \quad \forall a \in A \rightarrow \quad \overline{d_a} + \widehat{d_a} l_a = fl_{at} + \sum_{\beta_{jb}^{ki} \in \bar{B}: j=a} fl_{ab}^{ki} \quad \forall a \in A$$

Formulation Changes

D-ICEP -> R-ICEP

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

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

$$s_i = \sum_{\zeta^{1i}_{hb} \in \bar{Z}} (t^i_{hb} w^{1i}_{hb}) + \sum_{\gamma^{ki}_{bc} \in \bar{\Gamma}} (t^i_{bc} x^{ki}_{bc}) + \sum_{\delta^{ki}_{cb} \in \bar{\Delta}} (t^i_{cb} y^{ki}_{cb}) + \sum_{\zeta^{1i}_{hb} \in \bar{Z}} (u_i w^{1i}_{hb}) + \sum_{\zeta^{1i}_{hb} \in \bar{Z}} (o_i w^{1i}_{hb}) + \sum_{\delta^{ki}_{cb} \in \bar{\Delta}} (o_i y^{ki}_{cb}) + \sum_{\gamma^{ki}_{bc} \in \bar{\Gamma}} (p_i x^{ki}_{bc}) \qquad \forall i \in I \tag{5.3}$$

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

$$fl^{ki}_{bc} \leq q_i(x^{ki}_{bc}) \qquad \forall \gamma^{ki}_{bc} \in \bar{\Gamma} \tag{5.5}$$

$$1 = \underset{\{V \subseteq A, |V| = \Gamma\}}{\arg\max} \sum_{a \in V} \hat{d}_a l_a \tag{5.6}$$

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

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

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

$$\sum_{\zeta^{1i}_{hb} \in \bar{Z}} w^{1i}_{hb} \leq 1 \qquad \forall i \in I \tag{5.10}$$

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

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

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

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

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

$$fl_{at} \geq 0 \qquad \forall \lambda_{at} \in A \tag{5.16}$$

$$fl^{ki}_{ab} \geq 0 \qquad \forall \beta^{ki}_{ab} \in \bar{B} \tag{5.17}$$

$$fl^{ki}_{bc} \geq 0 \qquad \forall \gamma^{ki}_{bc} \in \bar{\Gamma} \tag{5.18}$$

$$fl^{ki}_{ct} \geq 0 \qquad \forall \epsilon^{ki}_{ct} \in \bar{E} \tag{5.19}$$

$$s_i \geq 0 \qquad \forall i \in I \tag{5.20}$$

$$r \geq 0 \tag{5.21}$$

$$w^{1i}_{hb} \in \{0, 1\} \qquad \forall \zeta^{1i}_{hb} \in \bar{Z} \tag{5.22}$$

$$x^{ki}_{bc} \in \{0, 1\} \qquad \forall \gamma^{ki}_{bc} \in \bar{\Gamma} \tag{5.23}$$

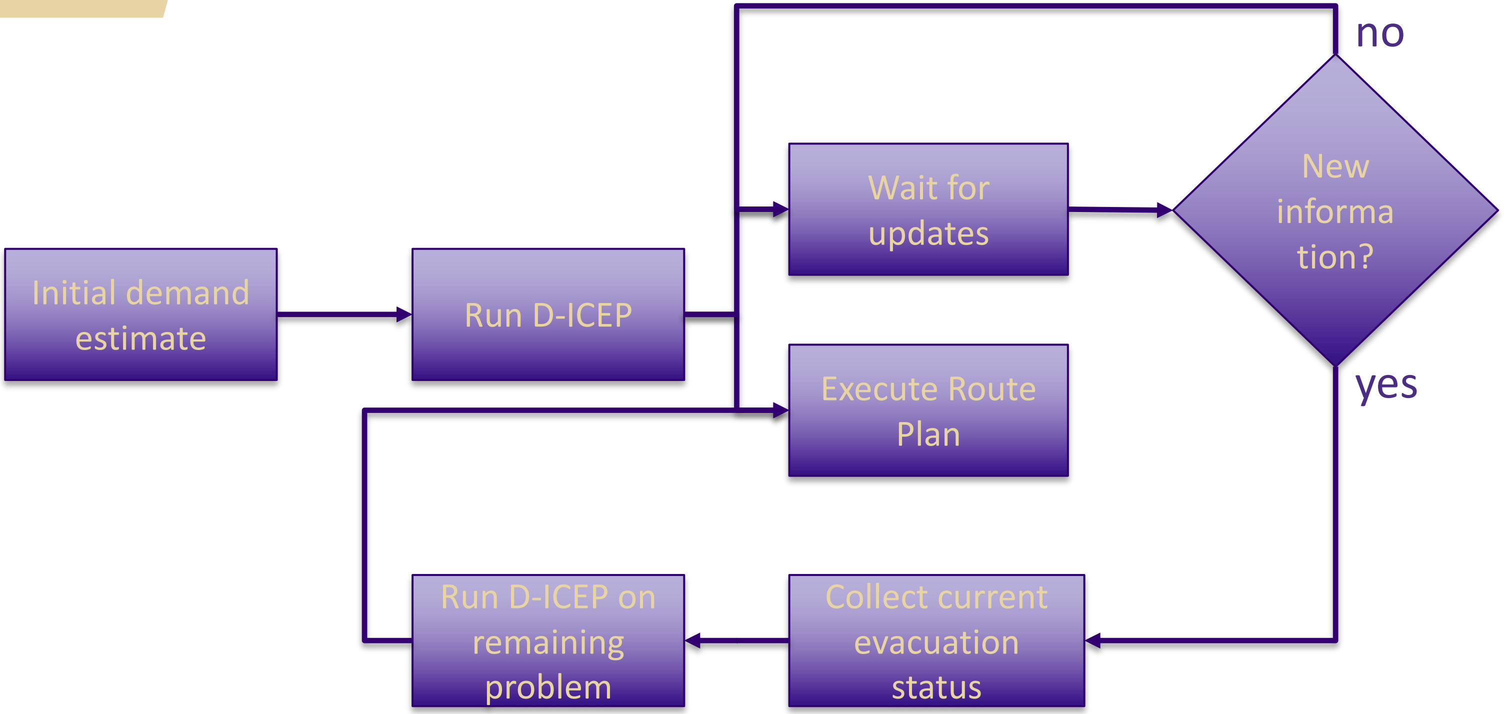
$$y^{ki}_{cb} \in \{0, 1\} \qquad \forall \delta^{ki}_{cb} \in \bar{\Delta} \tag{5.24}$$

$$l_a \in \{0, 1\} \qquad \forall a \in A \tag{5.25}$$

Advantages of this Robust Optimization Implementation

- Relatively simple model expansion
- No budgets for uncertainty need to be considered since feasibility is not affected
- Model can be solved through two simple steps:
  - Solve sub-problem
  - Use outputs from sub-problem to solve main problem deterministically
- Model maintains same complexity as D-ICEP

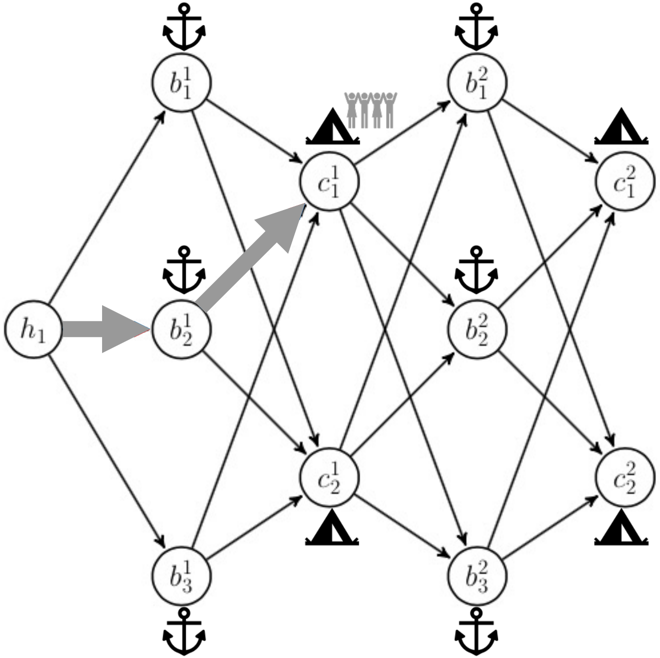
Rolling-Horizon Optimization
(Sethi and Sorger, 1991)



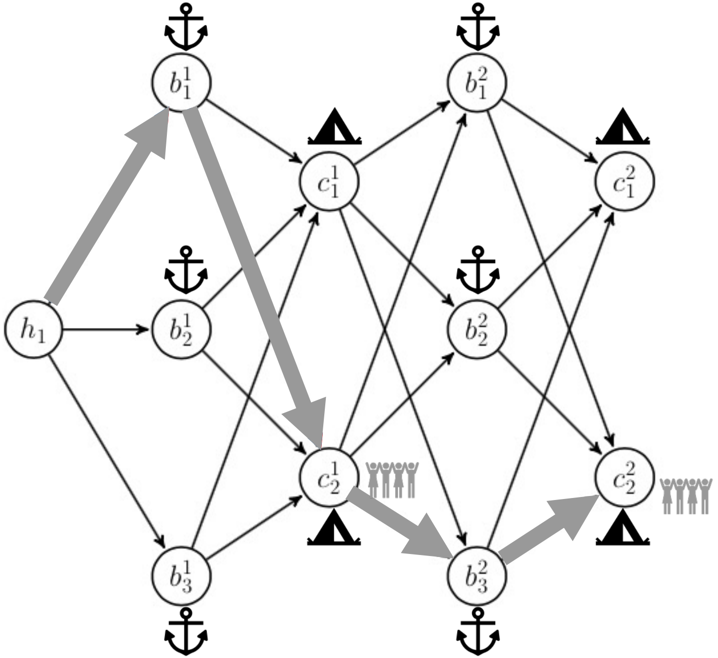
RH-ICEP Algorithm
Example

- initial route plan
- executed route segments
- updated information
- updated route plan

Resource 1



Resource 2



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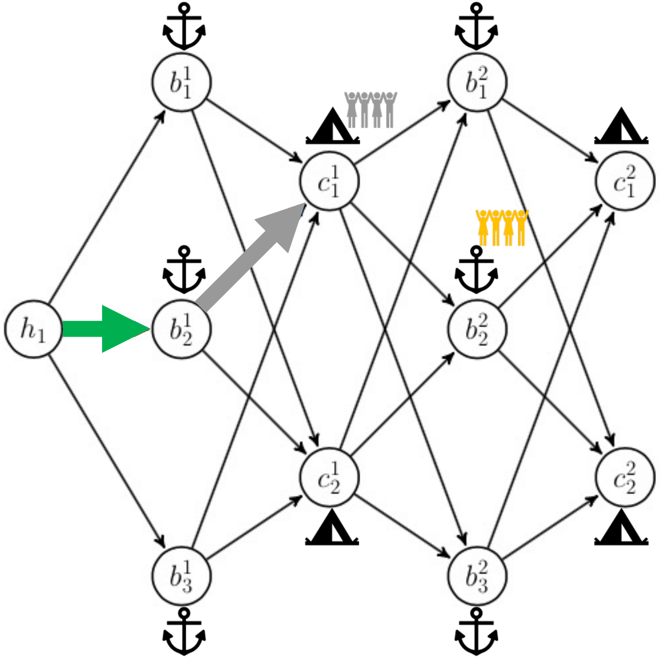
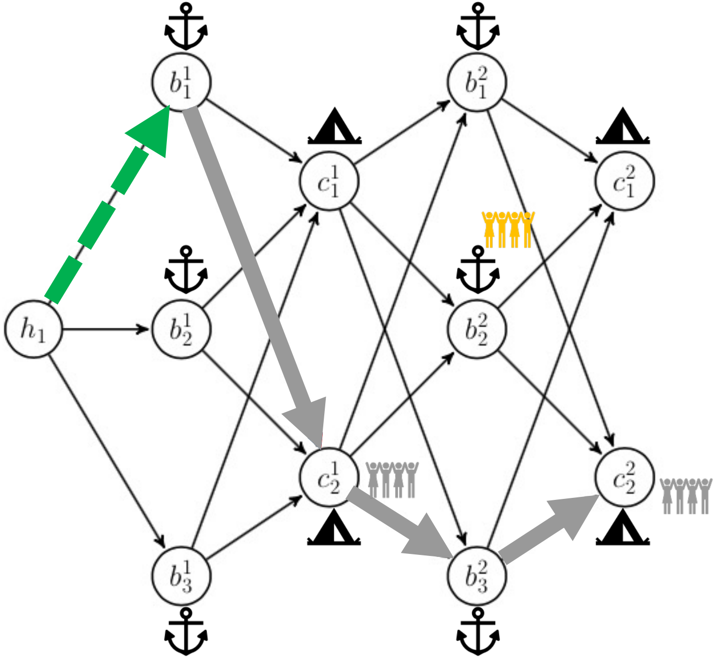


Resource 2



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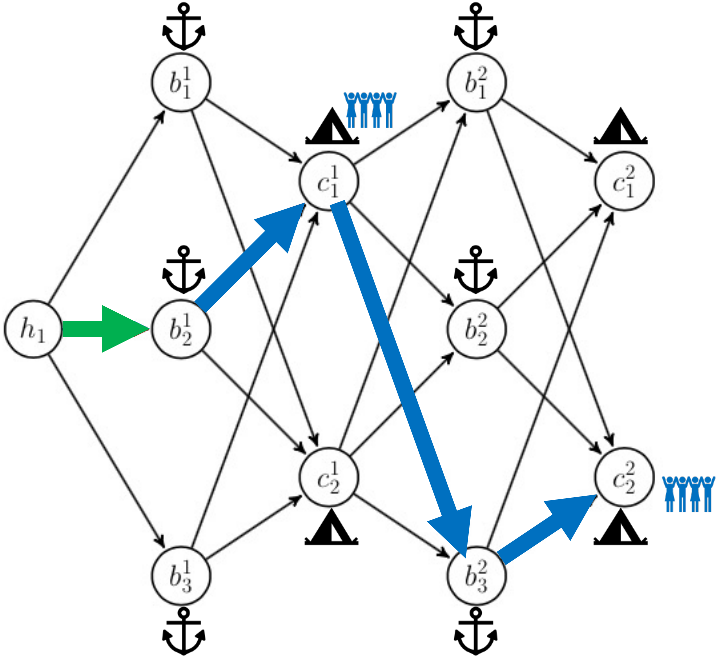
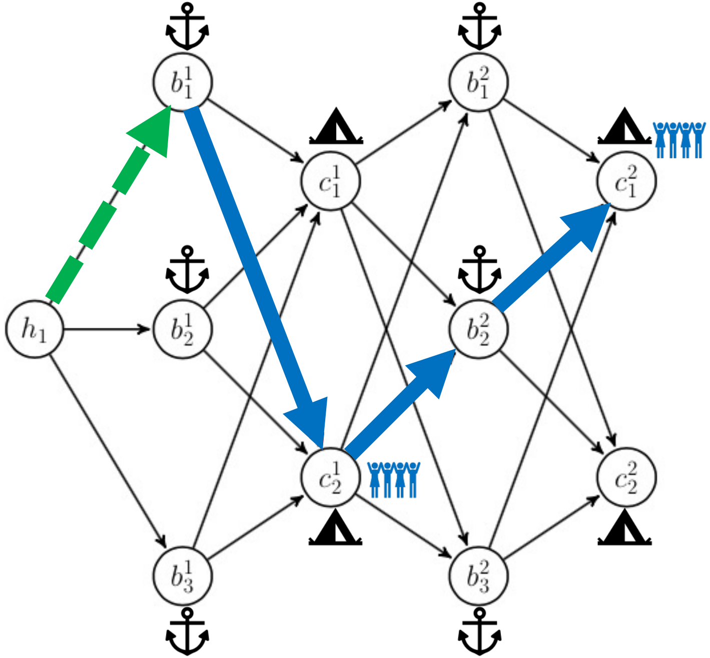


Resource 2



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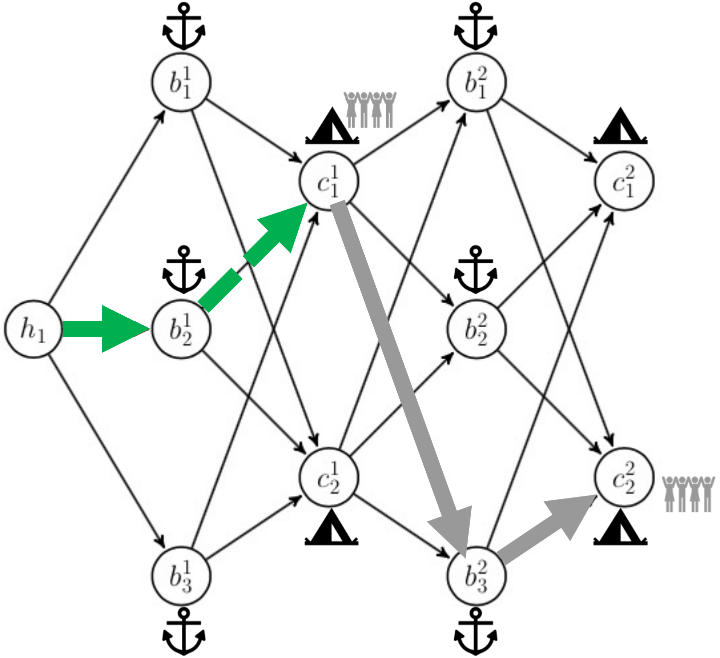
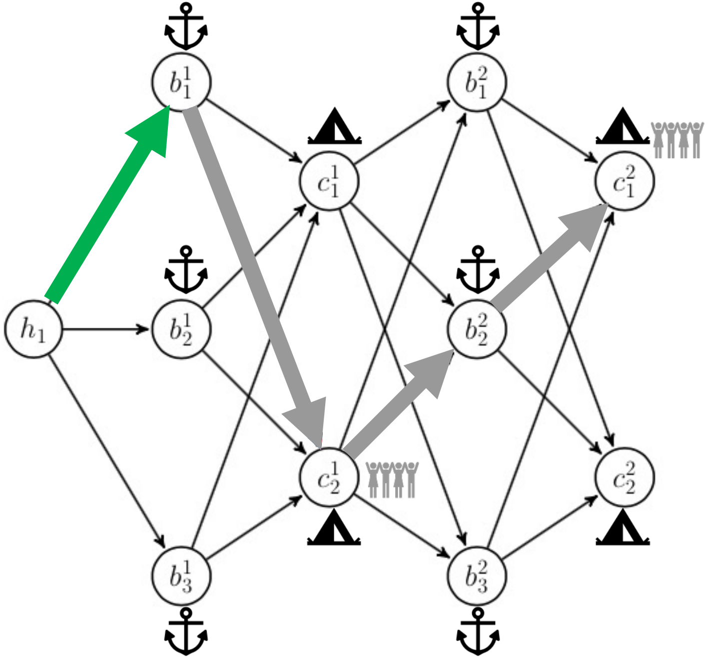


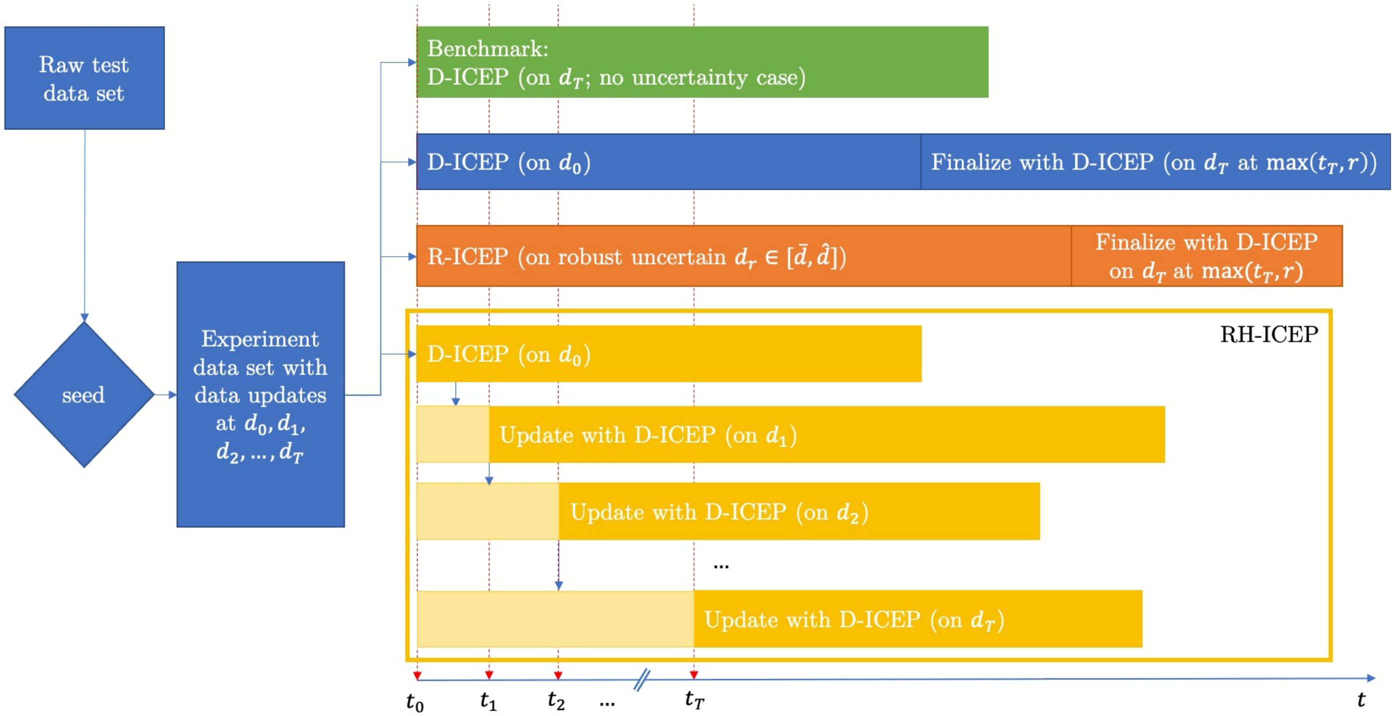
Resource 2



Advantages of RH-ICEP

- Incorporates new information that becomes available over time and improves route plan
- Can react dynamically to a shift in evacuation demand
- Every iteration, remainder becomes easier to solve as the problem size shrinks
- Complexity remains in worst case equivalent to D-ICEP

Simulation Experiment Set Up



Simulation Data

> Full factorial 3^k experiment design
> Defined multiple parameters to investigate behavior

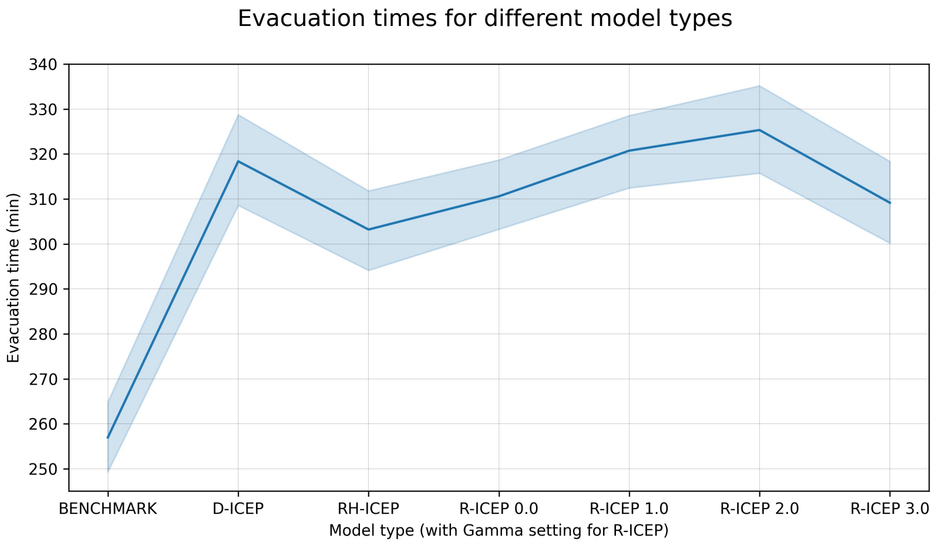
Table 5.2: Test Data Sets for RH-ICEP and R-ICEP Performance Benchmark

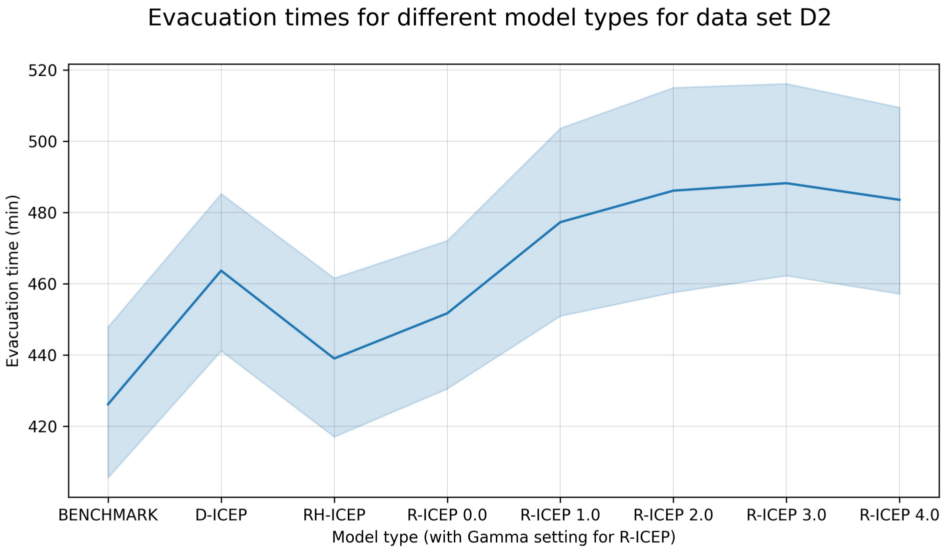
	D1	D2
Sets	*Set size*	
Evacuation resources	5	6
Initial storage locations	1	2
Evacuation locations	3	4
Evacuation pick-up points	6	6
Safe drop-off points	2	3
Compatibility between resources and nodes	Full	Limited
Resource Heterogeneity	1.22	38.08

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

Experiment Results





Conclusions

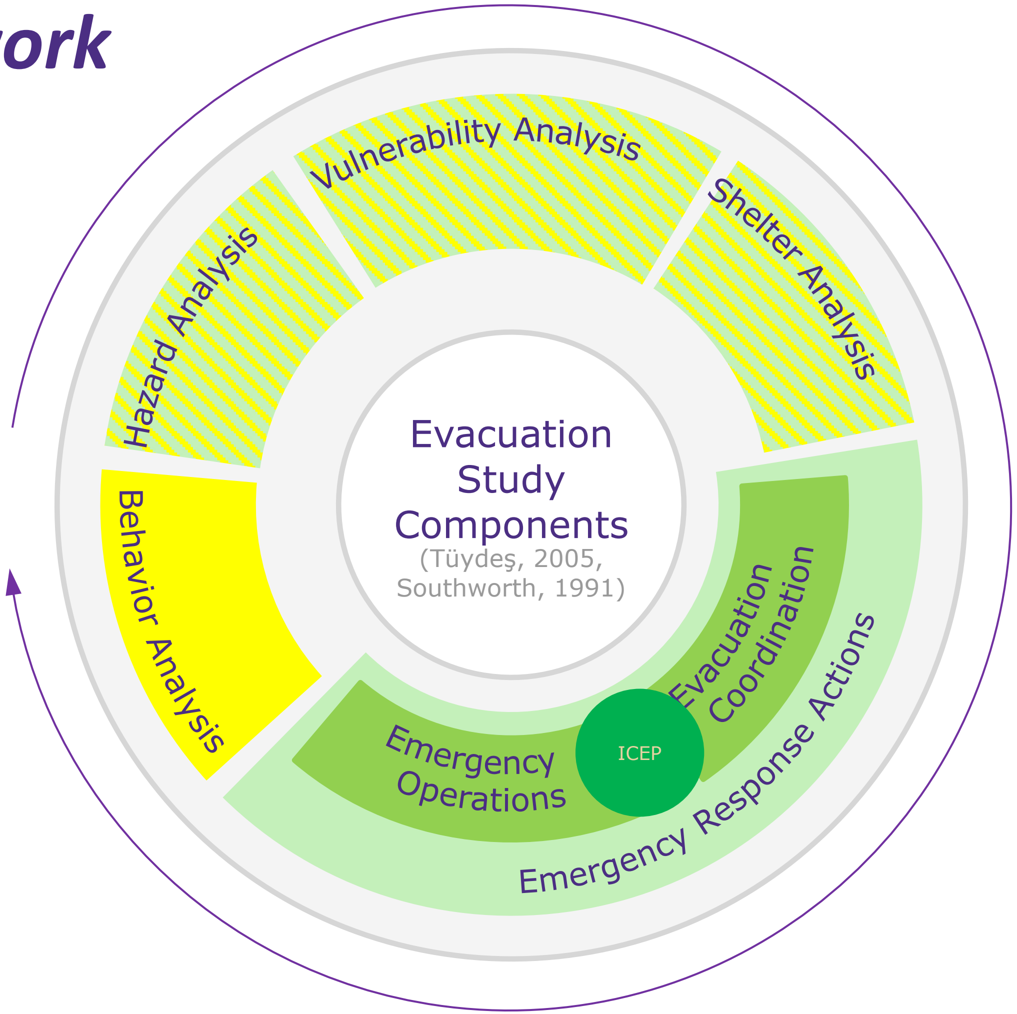
> RH-ICEP generally outperforms D-ICEP and R-ICEP
> Adaptiveness of rolling horizon implementation works efficiently
> R-ICEP only competitive for homogeneous data sets
> Performance ranking robust across simulated parameter settings
> Many parameters influence difference between algorithms

Contributions of RH-ICEP and R-ICEP

- RH-ICEP and R-ICEP both provide substantial improvements over D-ICEP for response (up to 12.5% improvement in evacuation time)
- Simple structure allows quick solution
- Planned submission to:

Final Conclusions and Future Work

Evacuation Framework Revisited



Challenges for Modeling Framework

> Interdependencies between model and on-land transportation
> Evacuation behavior plays a role in real-world scenarios

Future Work

> Integration with on-land transportation into large simulation framework
> Consideration of evacuation behavior
> Generalization of model for more routing options
> Prioritization features

Challenges for Efficient Solution Approaches

- Escaping local minima is an ongoing challenge
- Convergence difficult to time

Future Work

- Experiment with algorithm restarts on BRKGA, adaptive randomization rates and path relinking
- Adding bias to decoder
- Alternative solution approaches:
  - Other meta-heuristics
  - Column generation

Challenges for Response Tools

> RH-ICEP robustly outperforms other options but establishing competitive ratio is challenging

Future Work

> Exploration of more data set characteristics
> Real-world data set tests
> Combined robust and rolling-horizon optimization methods
> Incorporation of uncertainties in time components

Thank You for a Great Time!

- Thanks to my committee:
  - Prof. Linda Ng Boyle
  - Prof. Anne Goodchild
  - Prof. Chiwei Yan
  - Prof. Xuegang (Jeff) Ban
  - Prof. Michael R. Wagner

- Thanks to everyone else!
- Time for questions!