

Pre-disaster Self-evacuation Transport Network Design under Uncertain Demand and Connectivity Reliability: A Novel Bi-level Programming Model



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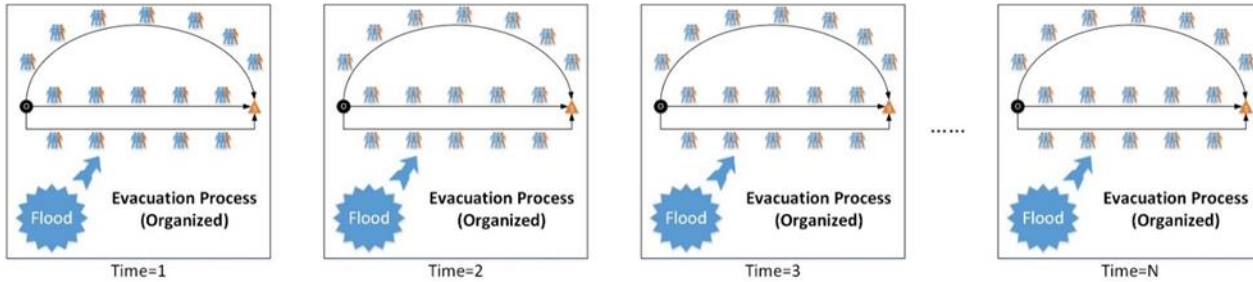
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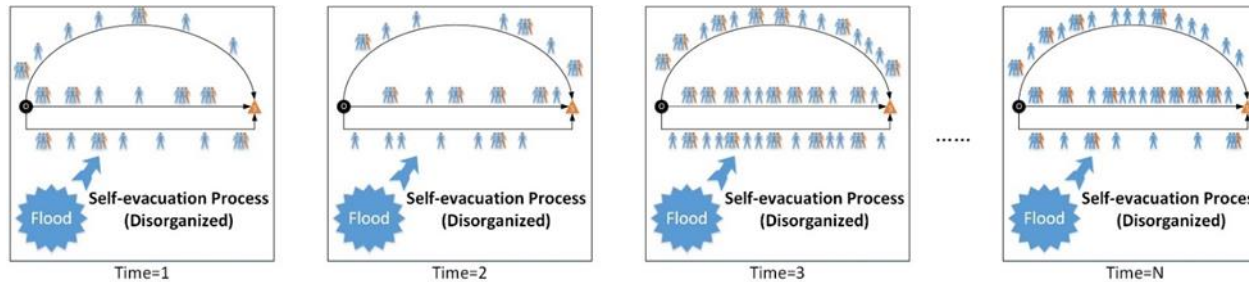
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◆ Evacuation and self-evacuation

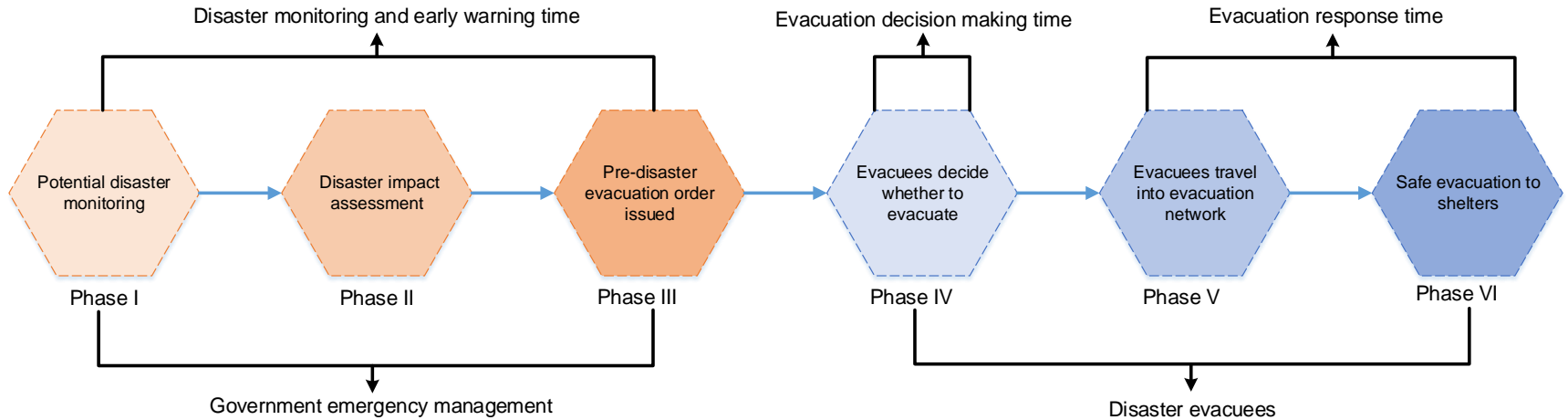


Scenarios of the evacuation process over time



Scenarios of the self-evacuation process over time

◆ Evacuation and self-evacuation

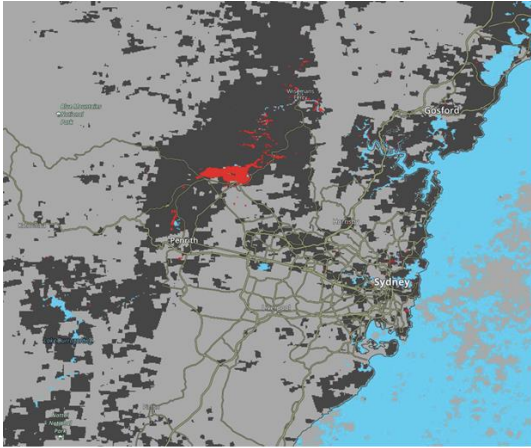


Pre-disaster self-evacuation process diagram

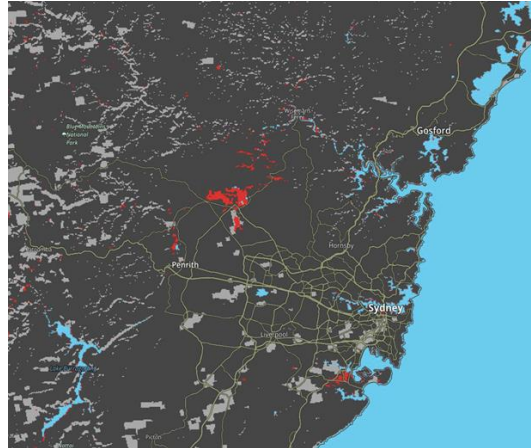
◆ Evacuation and self-evacuation

Comparison content	Evacuation	Self-evacuation
1. Whether the government issue evacuation orders?	√	√
2. Whether the government organizes the evacuation process?	√	
3. Whether evacuees can choose an evacuation route on their own?		√
4. Whether evacuees can choose the start time of evacuation?		√
5. Whether the evacuation process is orderly at any one time?	√	
6. Whether evacuees are fully aware of the traffic conditions of the evacuation network?	√	
7. Whether the overall time of evacuation can be estimated in advance?	√	
8. Whether evacuation demand can be estimated in advance?	√	
9. Whether the number and location of shelters are known by evacuees in advance?	√	√
10. Whether the capacity of the shelter can be known by evacuees?	√	√
11. Whether the evacuation process can occur in the pre-disaster phase	√	√

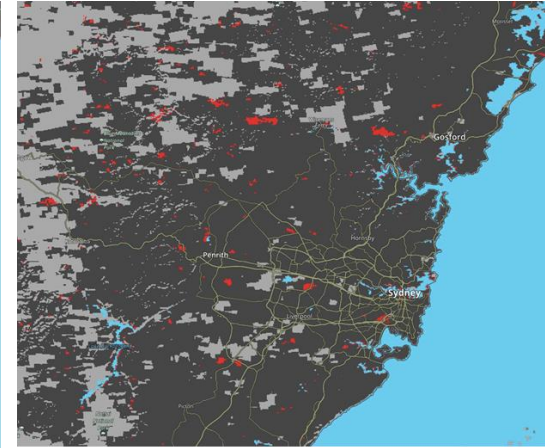
1. Background and motivation



Remote Sensing Imagery of Flood Disasters in the Greater Sydney Area **(03/2022)**



Remote Sensing Imagery of Flood Disasters in the Greater Sydney Area **(07/2022)**



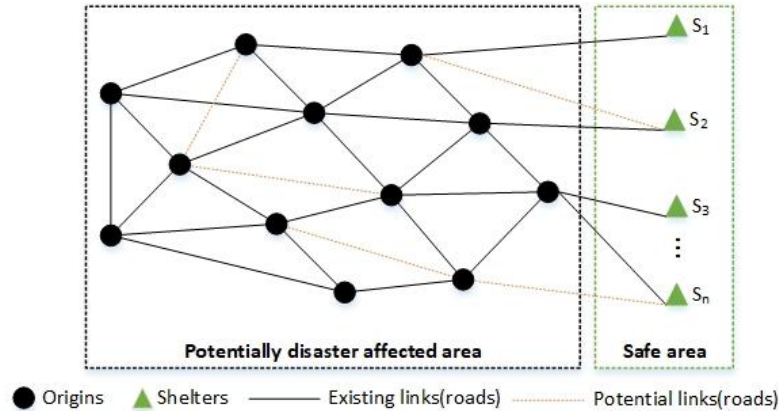
Remote Sensing Imagery of Flood Disasters in the Greater Sydney Area **(09/2022)**

- (1) Focus on the self-evacuation process and design a pre-disaster transport network with high efficiency.
- (2) Develop a novel bi-level programming model to solve network design problems under uncertain factors.
- (3) Innovate an improved user equilibrium, considering the psychological behavior of evacuees.

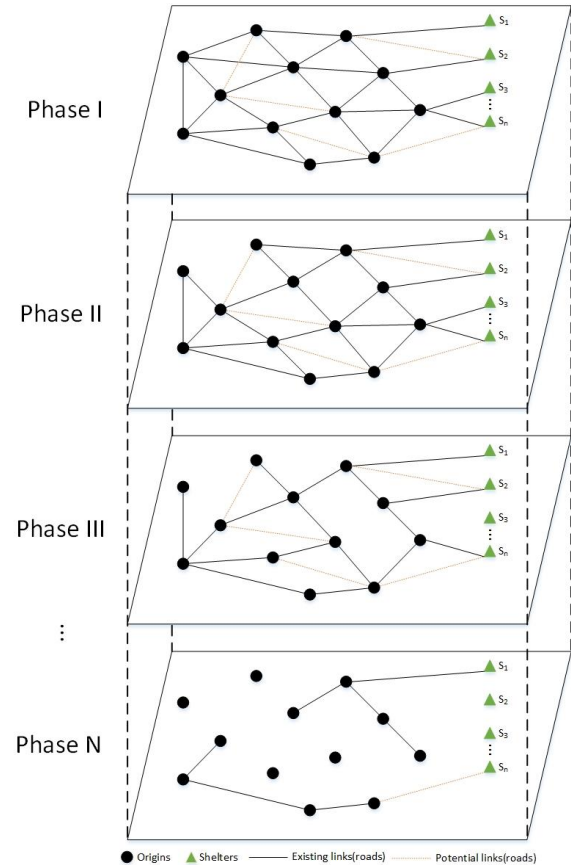
2. Literature review

Author/s	Problem type	Model type	Objective/s	Network structure	Solution approach	Disaster type
Ng and Waller (2009)	Certainty	Single level	Minimize the evacuation time and congestion	Static	Data simulation	Flood
Stepanov and Smith (2009)	Certainty	Single level	Minimize the evacuation time and congestion	Static	Exact algorithm and data simulation	NA
Hadas and Laor (2013)	Certainty	Single level	Minimize the evacuation time and construction cost	Static	Heuristic algorithm	NA
Marcianò et al. (2015)	Certainty	Single level	Minimize the evacuation time	Dynamic	Exact algorithm	Man-made disaster
Nahum et al. (2017)	Uncertainty	Single level	Minimize the evacuation time and construction cost	Dynamic	Evolutionary algorithm-based heuristic algorithm	Earthquake
Zhang et al. (2020)	Certainty	Single level	Minimize the evacuation time	Static	Exact algorithm based on K shortest path	Natural disaster
Xie et al. (2010)	Certainty	Bi-level	Upper-level: Maximize network performance Lower-level: Dynamic user equilibrium model	Dynamic	Lagrange relaxation and contraindicated search methods	Man-made disaster
Hua et al. (2015)	Uncertainty	Bi-level	Upper-level: Maximize network performance Lower-level: User equilibrium model	Static	Improved genetic algorithm	Natural disaster
Apivatanagul et al. (2012)	Certainty	Bi-level	Upper-level: Minimize network risk and evacuation time Lower-level: Dynamic user equilibrium model	Static	Exact algorithm based on dynamic user balancing	Hurricane
Yao et al. (2009)	Uncertainty	Single level	Minimize the evacuation time and construction cost	Static	Exact algorithm	Man-made disaster
Lv et al. (2015)	Uncertainty	Single level	Minimize the evacuation time	Static	Interactive heuristic algorithm	Man-made disaster
Afkham et al. (2022)	Uncertainty	Bi-level	Upper-level: Minimize network congestion and evacuation time Lower-level: Dynamic user equilibrium model	Dynamic	Benders decomposition and heuristic accelerator	Bushfire
Liu et al. (2022)	Certainty	Bi-level	Upper-level: Minimize the risk and construction cost Lower-level: User equilibrium model	Dynamic	Ant colony algorithm and NSGA-II	Man-made disaster
Li et al. (2022)	Certainty	Bi-level	Upper-level: Minimize network evacuation time Lower-level: User equilibrium model	Static	Cellular transport-based heuristic algorithm	Man-made disaster
He et al. (2018)	Certainty	Single level	Optimal number of shelters and optimal traffic flow assignment	Static	Benders decomposition and heuristic accelerator	Natural disaster
Niu et al. (2023)	Certainty	Bi-level	Upper-level: maximize the road network capacity-based functionality and reliability Lower-level: User equilibrium model	Dynamic	Empirical data analysis	Extreme events

3. Problem description



Basic topology diagram of evacuation transport network design (ETNDP)



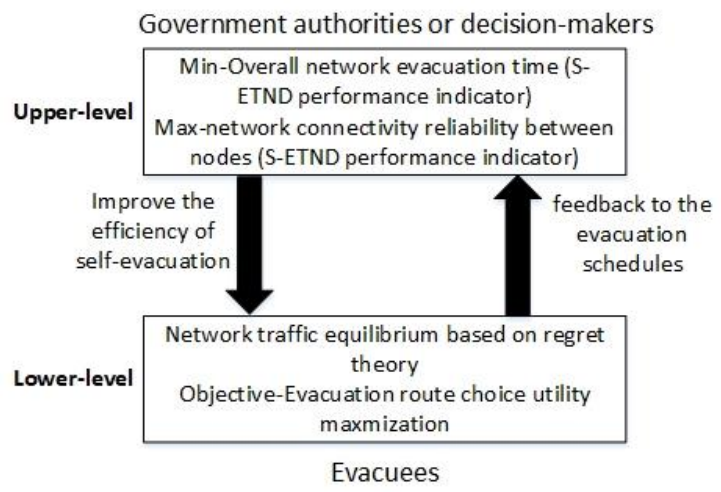
Basic topology diagram of Self-evacuation transport network design (S-ETNDP)

4. Modeling characteristics

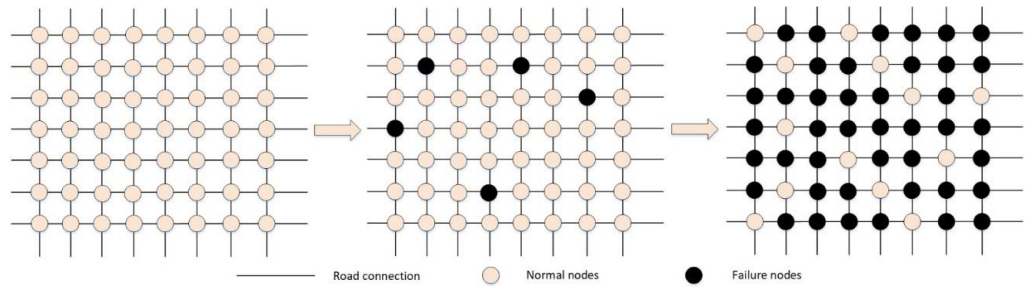
- Disaster features
- Topological features
- Transport modes
- Evacuation features
- Evacuation target
- Budget cost
- Self-evacuation behavior

Parameter names	Parameter definitions
N	The set of all nodes in the network, $N = \{1, 2, \dots, n\}$
S	The set of all roads in the network, $S = \{1, 2, \dots, s\}$
ω	Any OS(Origin-Shelter) pair in the network
r	Any evacuation route in the network between ω
R	The set of all evacuation routes, $r \in R$
X_s	Uncertainty parameter, the actual traffic flow on the road s
t_s^0	The free flow travel time for each road s
α_s^0, β	Regarding road impedance parameters, which indicate road congestion, the Federal Highway Administration (FHWA) recommends a value of $\alpha_s^0 = 0.15, \beta = 4.0$
C_s	The capacity of each road s
g_s	0-1 decision variable, that is 1 if the road s is interrupted by a flood attack, and 0 otherwise
$T_r(X_s)$	The actual travel time value of road s , it can also be called the impedance value of road s
$T_r(X_s)'$	Improved impedance value for road s
ρ	The network connectivity reliability
$\rho(L_s)$	The route connectivity reliability
τ_{sr}	0-1 decision variable, that is 1 if the road s is part of the route r , and 0 otherwise
ξ_s	The road connectivity reliability
a	average node degree in the network
k_i	The node degree of the node i
pt_i	The percolation threshold of the node i
λ	Non-negative risk aversion parameter, $\lambda > 0$
C_r^w	Utility function considering evacuation time impedance and regret feelings
η	Regret aversion degree parameter, $\eta > 0$
d^w	Uncertainty parameter, total demand in a self-evacuation network
f_r^w	Uncertainty parameter, traffic flow on route r between OS pair ω
v_j	0-1 decision variable, that is 1 if the node j is assigned to be a shelter and 0 otherwise
m	The number of shelters in the network
z_s	Construction cost per kilometer of potential equipped road s
D_s	Distance of potential equipped road s
Y_s	0-1 decision variable, that is 1 if the potential road s is selected to be equipped and 0 otherwise
B	The total investment budget for self-evacuation transport network
g_j	The capacity of the node j which is assigned as a shelter

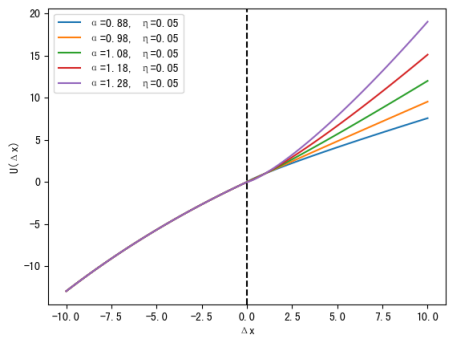
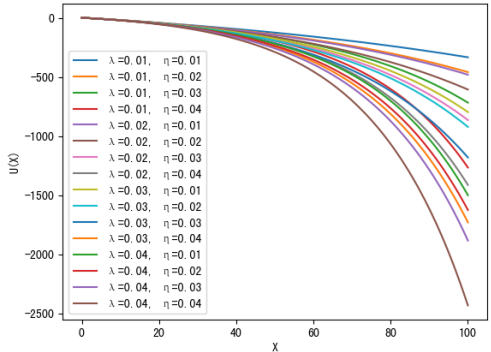
5. A novel Bi-level programming model



(1) Modeling approach



(2) Highlight 1: Quantifying network connectivity reliability based on percolation theory



(3) Highlight 2: Proposing a regret-risk utility function to describe the equilibrium conditions for the lower-level model

5. A novel Bi-level programming model

Upper-level model of S-ETNDP:

$$\min Z_1 = \sum_{s \in S} X_s T_s(X_s) = \sum_{s \in S} X_s \cdot t_s^0 \cdot \left[1 + \alpha_s^0 \cdot \left(\frac{X_s}{C_s \cdot (1 - \theta_s)} \right)^{\beta} \right] \quad (1)$$

The objective function (1) of the upper-level model and represents the minimized total evacuation time in the self-evacuation network.

$$\max Z_2 = \sum_{i=1}^R \prod_{s \in S} [P(p_{t_i} | \bar{k}_i) \cdot P(p_{t_j} | \bar{k}_j)]^{\tau_{rs}}, \forall i, j \in N \quad (2)$$

The objective function (2) of the upper-level model represents the maximized network connectivity reliability.

Subject to:

$$P(p_{t_i} | \bar{k}_i) = \frac{1}{\sqrt{2\pi\sigma(\bar{k}_i)}} \cdot \exp\left[-\frac{(p_{t_i} - \mu(\bar{k}_i))^2}{2\sigma(\bar{k}_i)^2}\right] = \frac{1}{\sqrt{2\pi\sigma(\bar{k}_i)}} \cdot \exp\left[-\frac{\left(\frac{\bar{k}_i}{a} - \mu(\bar{k}_i)\right)^2}{2\sigma(\bar{k}_i)^2}\right], \forall i, j \in N \quad (3)$$

$$P(p_{t_j} | \bar{k}_j) = \frac{1}{\sqrt{2\pi\sigma(\bar{k}_j)}} \cdot \exp\left[-\frac{(p_{t_j} - \mu(\bar{k}_j))^2}{2\sigma(\bar{k}_j)^2}\right] = \frac{1}{\sqrt{2\pi\sigma(\bar{k}_j)}} \cdot \exp\left[-\frac{\left(\frac{\bar{k}_j}{a} - \mu(\bar{k}_j)\right)^2}{2\sigma(\bar{k}_j)^2}\right], \forall i, j \in N \quad (4)$$

(3) and (4) represent the expressions of the node percolation threshold probability functions.

$$\sum_{j \in N} v_j = m \quad (5)$$

Ensure that a certain number of shelters are selected.

$$\sum_{s \in S} z_s Y_s D_s \leq B \quad (6)$$

Represents the constraint of the total investment budget for the self-evacuation transport network.

$$0 \leq X_s \leq C_s, \forall s \in S \quad (7)$$

$$\tau_{rs} \in \{0, 1\}, \forall s \in S, r \in R \quad (8)$$

$$v_j \in \{0, 1\}, \forall j \in N \quad (9)$$

$$Y_s \in \{0, 1\}, \forall s \in S \quad (10)$$

5. A novel Bi-level programming model

Lower-level model of S-ETNDP:

$$\max Z_3 = \sum_{s \in S} \int_0^{X_s} \left\{ \frac{1 - \exp[-\lambda \cdot T_s(X_s)^*]}{\lambda} + \frac{1 - \exp[\eta \cdot (T_s(X_s)^* - T_s(X_s)_{\min}^*)]}{\eta} \right\} dX_s \quad (11)$$

The objective function of the lower-level model.

Subject to:

$$f_r^\omega = d^\omega \cdot \left\{ \frac{\exp \left\{ \frac{1 - \exp[-\lambda \cdot T_r(f_r^\omega)]}{\lambda} + \frac{1 - \exp[\eta \cdot (T_r(f_r^\omega) - T_r(f_r^\omega)_{\min})]}{\eta} \right\}}{\sum_{l \in R} \exp \left\{ \frac{1 - \exp[-\lambda \cdot T_l(f_l^\omega)]}{\lambda} + \frac{1 - \exp[\eta \cdot (T_l(f_l^\omega) - T_l(f_l^\omega)_{\min})]}{\eta} \right\}} \right\} \quad (12)$$

A traffic equilibrium condition based on the Regret-risk function.

$$d^\omega = \sum_{r \in R} f_r^\omega \quad (13)$$

Represents the equilibrium relationship between demand and route flow in the self-evacuation network.

$$X_s = \sum_{\omega} \sum_{r \in R} f_r^\omega \cdot \tau_{sr}, \forall s \in S, \tau_{sr} \in \{0,1\} \quad (14)$$

Represents the equilibrium relationship between road flow and route flow.

$$\sum_{r \in R} f_r^\omega \leq \sum_{j \in N} g_j v_j, \forall j \in N, v_j \in \{0,1\} \quad (15)$$

The shelter capacity constraint

$$f_r^\omega \geq 0, \forall r, l \in R, 0 < \lambda < 1, 0 < \eta < 1 \quad (16)$$

$$T_r(f_r^\omega) = \sum_{s \in S} T_s(X_s)^* \tau_{sr}, T_s(X_s)^* = t_s^0 \cdot \left[1 + \alpha_s^0 \cdot \left(\frac{X_s}{C_s \cdot (1 - \beta_s)} \right)^\theta \right], \forall s \in S, r \in R \quad (17)$$

The basic road impedance and route impedance function definition.

5. A novel Bi-level programming model

Robust Optimization Approach—Just show the results

Upper-level model:

$$\min Z_1 = \sum_{s \in S} X_s T_s(X_s)^* = \sum_{s \in S} (X_{s0} + \bar{X}_s \|s^o\|) \cdot t_s^o \cdot \left[1 + \alpha_1^o \cdot \left(\frac{X_{s0} + \bar{X}_s \|s^o\|}{C_s \cdot (1 - \varrho_s)} \right)^{\rho} \right] \quad (70)$$

$$\max Z_2 = \sum_{r \in R} \prod_{s \in S} [P(p_{r1}|k_1) \cdot P(p_{rj}|k_j)] \tau_r, \forall i, j \in N \quad (71)$$

Subject to:

$$\sum_{j \in N} v_j = m \quad (72)$$

$$\sum_{i \in S} \tau_i D_i \leq B \quad (73)$$

$$\frac{\partial (X_{s0} + \bar{X}_s \|s^o\|)}{\partial (d_0^o + d^o \|s^o\|)} + 2\omega_1 \left(\frac{d^o \|s^o\|}{d_0^o + d^o \|s^o\|} \right) = 0, \forall s \in S \quad (74)$$

$$\omega_1 \left[1 - \sum_{\sigma} \left(\frac{d^o \|s^o\|}{d_0^o + d^o \|s^o\|} \right)^2 \right] = 0 \quad (75)$$

$$\frac{\partial (X_{s0} + \bar{X}_s \|s^o\|)}{\partial (d_0^o + d^o \|s^o\|)} - \frac{\partial C_s}{\partial (d_0^o + d^o \|s^o\|)} + 2\omega_2 \left(\frac{d^o \|s^o\|}{d_0^o + d^o \|s^o\|} \right) = 0, \forall s \in S \quad (76)$$

$$\omega_2 \left[1 - \sum_{\sigma} \left(\frac{d^o \|s^o\|}{d_0^o + d^o \|s^o\|} \right)^2 \right] = 0 \quad (77)$$

$$\tau_r \in \{0, 1\}, \forall s \in S, r \in R \quad (78)$$

$$v_j \in \{0, 1\}, \forall j \in N \quad (79)$$

$$I_r \in \{0, 1\}, \forall s \in S \quad (80)$$

$$\omega_1, \omega_2 \geq 0 \quad (81)$$

Lower-level model:

$$\max Z_1 = \sum_{s \in S} \int_0^{\infty} \left\{ \frac{1 - \exp[-\lambda \cdot T_s(X_s)]}{\lambda} + \frac{1 - \exp[-\eta \cdot (T_s(X_s) - T_s(X_s)_{max})]}{\eta} \right\} dX_s \quad (82)$$

$$\frac{\partial \left(\frac{\exp \left[\frac{1 - \exp[-\lambda \cdot T_s(f^o)]}{\lambda} + \frac{1 - \exp[-\eta \cdot (T_s(f^o) - T_s(f^o)_{max})]}{\eta} \right]}{\sum_{s \in S} \exp \left[\frac{1 - \exp[-\lambda \cdot T_s(f^o)]}{\lambda} + \frac{1 - \exp[-\eta \cdot (T_s(f^o) - T_s(f^o)_{max})]}{\eta} \right]} \right)}{\partial d^o} - \sum_{r \in R} \frac{\partial (f_{r0}^o + \bar{f}_r^o \|r^o\|)}{\partial (d_0^o + d^o \|r^o\|)} \quad (83)$$

$$+ 2\omega_r \left(\frac{d^o \|r^o\|}{d_0^o + d^o \|r^o\|} \right) = 0, \forall r \in R, d^o \in \mathcal{Q}$$

$$\omega_r \left[1 - \sum_{\omega} \left(\frac{d^o \|r^o\|}{d_0^o + d^o \|r^o\|} \right)^2 \right] = 0 \quad (84)$$

$$\sum_{r \in R} \frac{\partial (f_{r0}^o + \bar{f}_r^o \|r^o\|)}{\partial (d_0^o + d^o \|r^o\|)} + 2\omega_r \left(\frac{d^o \|r^o\|}{d_0^o + d^o \|r^o\|} \right) = 1, d^o \in \mathcal{Q}, f^o \in \mathcal{Q} \quad (85)$$

$$\omega_r \left[1 - \sum_{\omega} \left(\frac{d^o \|r^o\|}{d_0^o + d^o \|r^o\|} \right)^2 \right] = 0 \quad (86)$$

$$\sum_{\sigma} \frac{\partial \left[(f_{\sigma 0}^o + \bar{f}_{\sigma}^o \|s^o\|) \cdot \tau_{\sigma} \right]}{\partial (d_0^o + d^o \|s^o\|)} - \frac{\partial (X_{s0} + \bar{X}_s \|s^o\|)}{\partial (d_0^o + d^o \|s^o\|)} + 2\omega_s \left(\frac{d^o \|s^o\|}{d_0^o + d^o \|s^o\|} \right) = 0, \forall s \in S, \tau_{\sigma} \in \{0, 1\}, f^o \in \mathcal{Q}, I_r \in \mathcal{Q} \quad (87)$$

$$\omega_s \left[1 - \sum_{\omega} \left(\frac{d^o \|s^o\|}{d_0^o + d^o \|s^o\|} \right)^2 \right] = 0 \quad (88)$$

$$\sum_{r \in R} \frac{\partial (f_{r0}^o + \bar{f}_r^o \|r^o\|)}{\partial (d_0^o + d^o \|r^o\|)} - \sum_{r \in R} \frac{\partial g_r v_r}{\partial (d_0^o + d^o \|r^o\|)} + 2\omega_v \left(\frac{d^o \|r^o\|}{d_0^o + d^o \|r^o\|} \right) = 0, \forall j \in N, f^o \in \mathcal{Q} \quad (89)$$

$$\omega_v \left[1 - \sum_{\omega} \left(\frac{d^o \|r^o\|}{d_0^o + d^o \|r^o\|} \right)^2 \right] = 0 \quad (90)$$

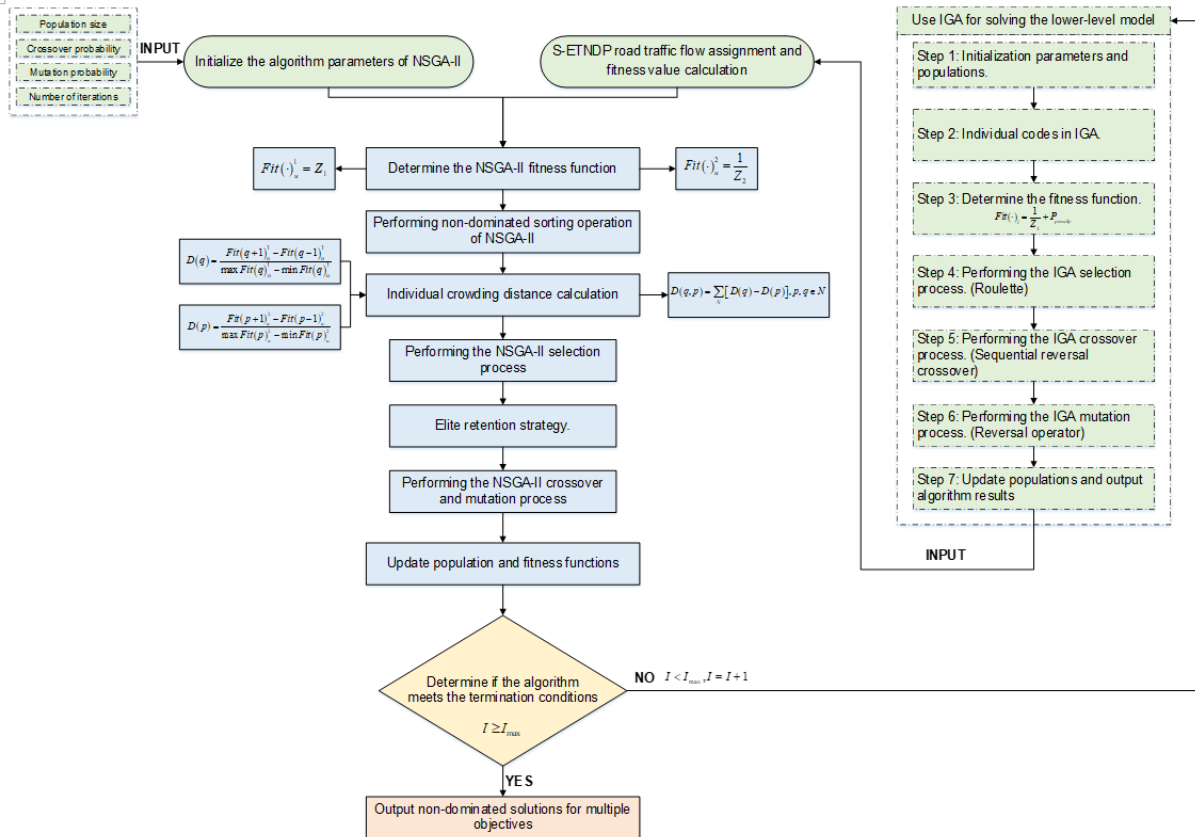
$$\forall r, l \in R, 0 < \lambda < 1, 0 < \eta < 1, v_r \in \{0, 1\}, \tau_r \in \{0, 1\} \quad (91)$$

$$T_s(X_s)^* = t_s^o \cdot \left[1 + \alpha_1^o \cdot \left(\frac{X_{s0} + \bar{X}_s \|s^o\|}{C_s \cdot (1 - \varrho_s)} \right)^{\rho} \right], T_s(f^o) = \sum_{s \in S} \left\{ t_s^o \cdot \left[1 + \alpha_1^o \cdot \left(\frac{X_{s0} + \bar{X}_s \|s^o\|}{C_s \cdot (1 - \varrho_s)} \right)^{\rho} \right] \cdot \tau_{rs} \right\}, \forall s \in S, r \in R \quad (92)$$

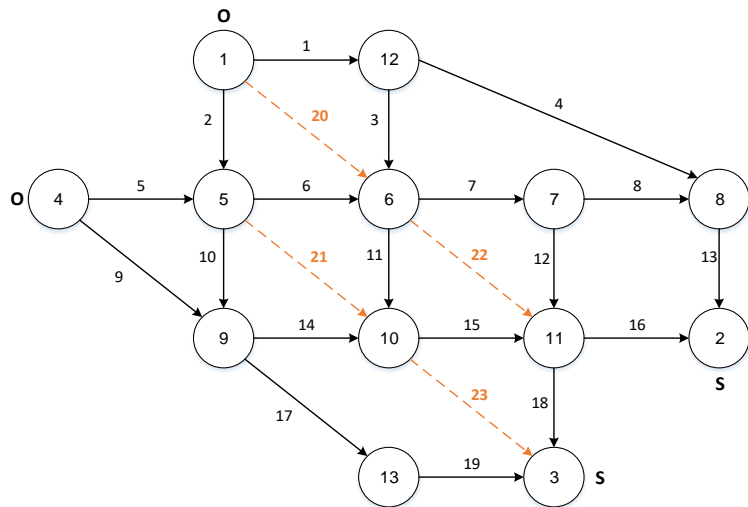
$$\omega_1, \omega_r, \omega_s, \omega_v \geq 0 \quad (93)$$

6. Algorithm design: IGA-NSGA-II

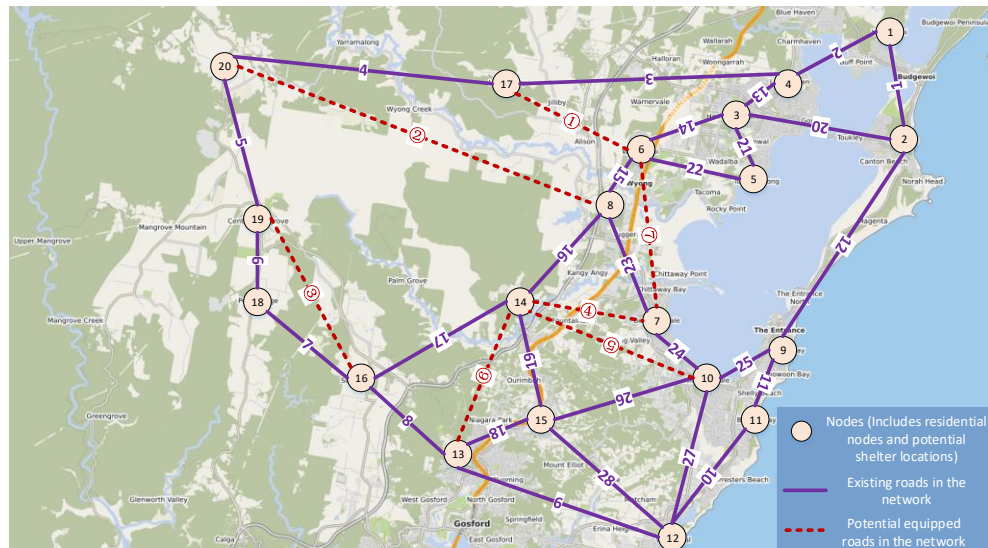
<p>Name: Improved Genetic Algorithm Combined with Non-dominated Sorting Genetic Algorithm II, IGA-NSGA-II</p> <p>Lower-level model</p> <p>Input:</p> <p>Parameter settings, fitness function, and algorithm rules</p> <ol style="list-style-type: none"> 1. Population Size: Q_n 2. Crossover Probability: p_c' 3. Mutation Probability: p_m' 4. Fitness Function: $Fit(\cdot) = \frac{1}{Z_1} + P_{penalty} = \frac{1}{\sum_{i \in S} \left[\frac{1 - \exp[-\lambda \cdot T_i(X_i)]}{\lambda} + \frac{1 - \exp[-\eta (T_i(X_i)' - T_i(X_i)'_{min})]}{\eta} \right]} + P_{penalty}$ <ol style="list-style-type: none"> 5. Crossover Rules: sequential reversal crossover operator 6. Mutation Rules: reversal operator <p>Output:</p> <p>Optimal route choice option and objective function value</p> <ol style="list-style-type: none"> 1. Initialized population size: Q_n' 2. Value of fitness function: $Fit(\cdot)$ 3. Road flow in equilibrium: X_i 4. Route flow in equilibrium: f_i^r
<p>Upper-level model</p> <p>Input:</p> <p>Parameter settings, fitness function, and algorithm rules</p> <ol style="list-style-type: none"> 1. Population Size: p_n' 2. Crossover Probability: p_c'' 3. Mutation Probability: p_m'' 4. Maximum Number of Iterations: I_{max} 5. Road flow from the lower-level model: X_i 6. Fitness Function: <ol style="list-style-type: none"> (1) $Fit(\cdot)'_1 = Z_1 = \sum_{i \in S} X_i T_i(X_i) = \sum_{i \in S} X_i \cdot t_i^0 \cdot \left[1 + \alpha_i^0 \cdot \left(\frac{X_i}{C_i - (1 - \theta_i)} \right)^{\beta_i} \right] + P_{penalty}$ (2) $Fit(\cdot)'_2 = \frac{1}{Z_2} = \frac{1}{\sum_{i=1}^r \prod_{k=1}^n [P(p_i, k_i) \cdot P(p_i, k_i)]}$ <p>Output:</p> <p>Multi-objective optimal solution set and objective function values</p> <ol style="list-style-type: none"> 1. Initialize population size p_n' and iteration counts $I = 0$ 2. Let $I = 1; I < I_{max}; I++$



7. Test network and case analysis

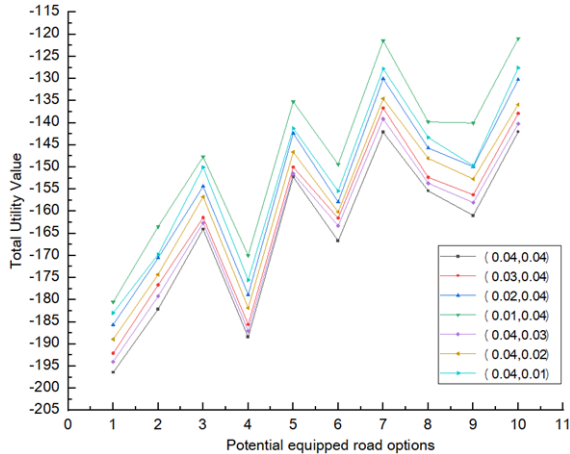


Nguyen-Dupuis network

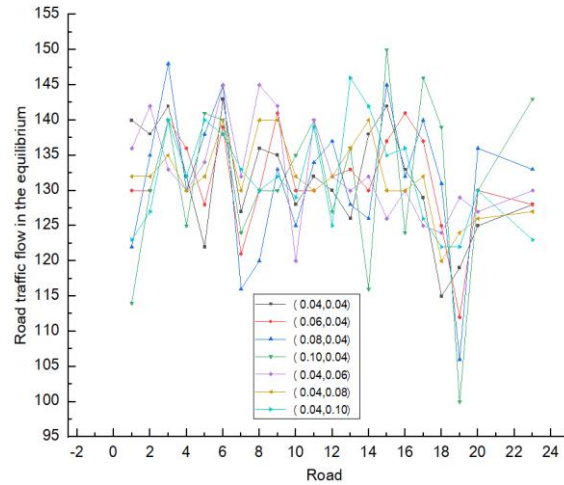


Case study (Central Coast area of Greater Sydney, Australia)

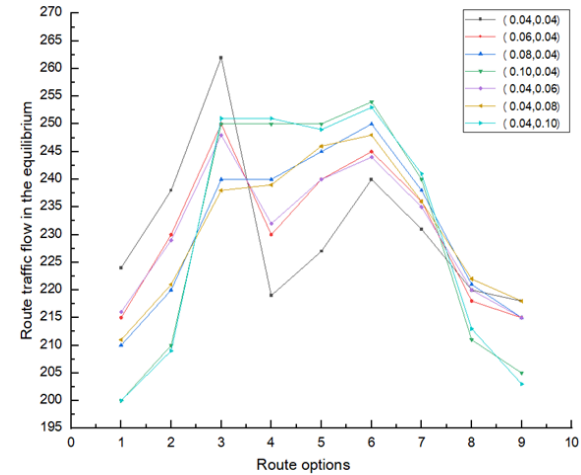
8. Research insights from N-D test network



Exploring the changes in risk aversion and regret aversion parameters on the route choice utility.

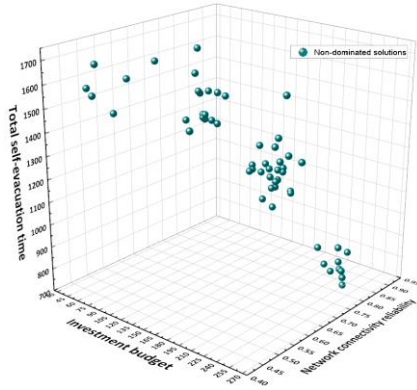


Exploring the changes in risk aversion and regret aversion parameters on the road traffic flow.

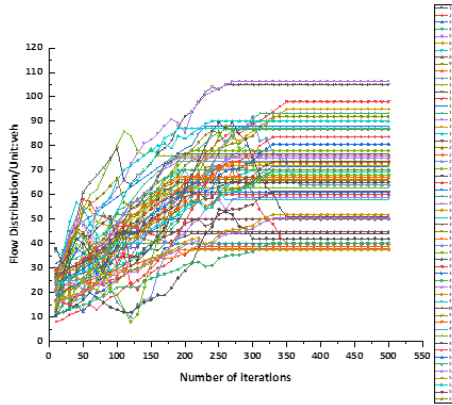


Exploring the changes in risk aversion and regret aversion parameters on the route traffic flow.

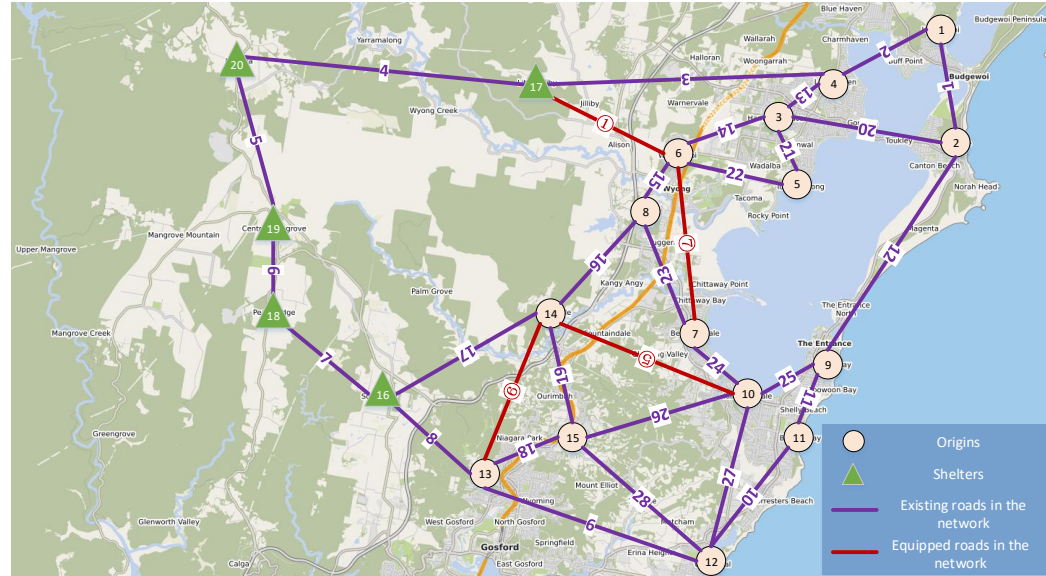
9. Research insights from case analysis network



Bi-objective non-dominated solutions under budget constraints



The lower-level model traffic equilibrium process during IGA-NSGA- II execution



Design of a pre-flood self-evacuation transport network for the Central Coast region of New South Wales, Australia

◆ Research contributions

- (1) A novel bi-level nonlinear programming model is developed to solve the self-evacuation transport network design problem under flood attacks.
- (2) An approach to quantifying the uncertain connectivity reliability based on percolation theory is proposed, and a robust optimization approach is used to transform the bi-level model with uncertain demand.
- (3) The model and algorithm in this paper can be applied to a real network of a certain size to give a solution that can directly answer the question of the potential equipped road construction option that should be chosen by the government authorities.
- (4) The values of the risk aversion parameter and regret aversion parameter are proved to have a great influence on the model solution, where the risk aversion parameter has a greater impact on the total network utility value and both parameters have almost the same impact on the route traffic flow in the equilibrium period.

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THANK YOU

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