# Flood-Aware Routing Optimization for Jeddah's Rainy Days

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## Abstract
Climate change has intensified the frequency and severity of floods, especially in urban areas like Jeddah, Saudi Arabia. This study aims to optimize flood-aware routing to enhance the city's resilience during such events. We formulated an optimization problem to select safe transportation routes based on road quality, drainage efficiency, and flood depth, ensuring route continuity. Two optimization methods were applied: Exact Optimization using linear programming and Approximate Optimization using Simulated Annealing. While the Exact Optimization method guarantees optimal routes, making it suitable for small-scale, high-stakes scenarios, it becomes computationally expensive for large datasets. Simulated Annealing, a heuristic method, provides near-optimal solutions with faster computation times, making it more suitable for larger, real-time applications. Comparative analysis showed that Exact Optimization is optimal for critical evacuations, while Simulated Annealing excels in scalability and efficiency for large urban networks. This study emphasizes the importance of choosing the appropriate optimization method based on application scale and urgency, contributing to effective flood management strategies for Jeddah and similar urban areas.

**Keywords**
Flood Management, Optimization, Route Optimization, Exact Optimization, Simulated Annealing, Climate Change

## 1. Introduction
Climate change continues to pose significant challenges globally, with floods emerging as one of the most destructive natural disasters. Annually, floods claim the lives of approximately 2,000 individuals and cause widespread devastation to infrastructure, economies, and communities. The increasing frequency and intensity of floods, driven by shifting climate patterns, have underscored the need for proactive flood management strategies.

Jeddah, a vibrant coastal city in Saudi Arabia, is particularly vulnerable to flash floods due to its rapid urban expansion and unique topographical features. Situated between the Red Sea and mountain chains, the city experiences frequent flood events, which have historically led to severe damage to infrastructure, loss of life, and disruption of daily activities.

This project analyzes Jeddah's flood-prone areas and formulates an optimization problem to address these challenges. The study evaluates both exact and approximate optimization methods to identify the most effective approach for managing Jeddah's transportation network during flood crises. By doing so, the project contributes to a resilient urban infrastructure capable of mitigating the impacts of climate-induced flood events, ultimately safeguarding lives and livelihoods in Jeddah.

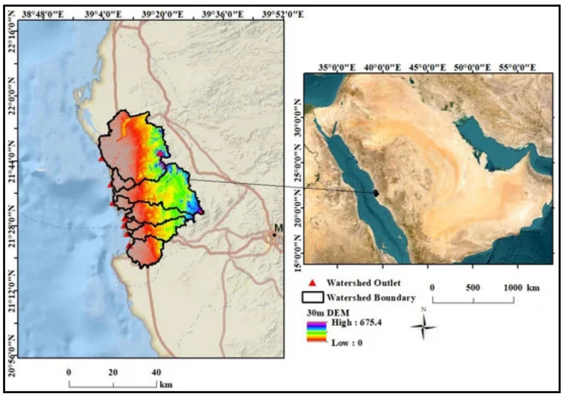


Figure 1. Study Area Location Map: Geographic Representation of the Jeddah Region.

## 2. Mathematical Formulation
The flood-aware routing optimization problem is structured as a standard mathematical optimization model, where the objective is to maximize the safety of routes during flood events while adhering to constraints related to route continuity, road quality and drainage efficiency, flood depth and the avoidance of main roads.

- **Objective Function :**

$$\text{Maximize } S = \sum_i \sum_j (w_1 q_{ij} + w_2 e_{ij} - w_3 d_{ij}) \cdot x_{ij}$$

The objective function aims to **Maximize** the total safety score (S) of the selected route during flood events. Each road segment i-j contributes to the safety score based on three factors:

- **Road Quality (q):** Roads with better quality are safer to travel on during floods. w1 is a weight to prioritize this factor.
- **Drainage Efficiency (e):** Roads with better drainage systems are less likely to be severely impacted by flooding. w2 emphasizes the importance of this factor.
- **Flood Depth (d):** Roads with lower flood depth are safer. This factor is subtracted to penalize roads with high flood levels, with w3 representing its impact.

The binary decision variable **x** ensures that only the selected road segments contribute to the total safety score

## 3. Constraints

### 3.1. Route Continuity:

$$\boxed{\sum_j x_{ij} - \sum_k x_{ki} = \begin{cases} 1 & \text{if } i = \text{source} \\ -1 & \text{if } i = \text{destination} \\ 0 & \text{otherwise} \end{cases}}$$

This constraint ensures the route is continuous from the source to the destination:

- At the source, exactly one road segment is selected to leave (+1).
- At the destination, exactly one road segment ends (-1).
- At all intermediate nodes, the number of entering and exiting road segments must balance (0).

### 3.2. Road Quality and Drainage Efficiency:

$$\boxed{x_{ij} = 0 \quad \text{if } q_{ij} < q_{\min} \text{ or } e_{ij} < e_{\min}}$$

This constraint excludes road segments that do not meet the minimum standards for road quality $(q\min)$ or drainage efficiency $(e\min)$.. These conditions ensure that unsafe roads are never included in the solution.

### 3.3. Flood Depth:

$$\boxed{x_{ij} = 0 \quad \text{if } d_{ij} > d_{\max}}$$

This constraint excludes road segments where the flood depth $(dij)$ exceeds a maximum allowable threshold $(d\max)$ . This ensures that roads submerged beyond safe levels are not considered as part of the route.

## 4. Data-Driven Approach to Optimization

In designing the flood-aware routing optimization model, realism and practicality were critical. To ensure the model reflects the actual conditions of Jeddah during flood events, we utilized a combination of research studies, spatial analysis, and geospatial data. The flood risk map, developed through satellite imagery, urban extension zone overlays, and hydrographic network mapping, provided the foundation for segmenting Jeddah into distinct risk zones.

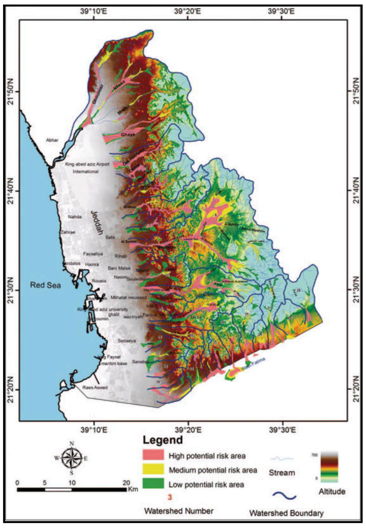


Fig 2. Flood Risk Map of Jeddah

### 4.1. Flood Risk Zones:

1. **High-Risk Zone:** Areas in direct contact with wadis and urban regions most prone to severe flooding.
2. **Moderate-Risk Zone:** Areas bordering high-risk zones, facing significant flooding during extreme events.
3. **Low-Risk Zone:** Areas farther from the hydrographic network, with minimal exposure to .

**Thus, The weights we picked for the objective function are:**

- ***w1 = 0.2:***
  Quality is given the least weight, as it is secondary to flood-related factors.

- ***w2 = 0.6:***
  Drainage is moderately weighted, as it indicates a road's ability to handle water runoff.

- ***w3 = 0.7:***
  Flood Depth is prioritized the most, as it directly impacts safety and feasibility of travel.

## 5. Explanation of Methods Used

When addressing the challenge of optimizing flood-safe routing in urban networks, we implemented two distinct methodologies:

- Exact Optimization.
- Simulated Annealing.

These approaches offer complementary strengths, allowing us to compare their efficacy under varying conditions and network scales.

### 5.1. Exact Optimization Method

Exact optimization relies on **linear programming** to mathematically model and solve the routing problem. By systematically evaluating all possible routes while adhering to constraints such as road quality, drainage efficiency, and flood depth, this method ensures that the solution is not only feasible but also optimal.

- **Advantages**:
  - Guarantees an optimal solution, ensuring maximum safety for chosen routes.
  - Provides precision, making it ideal for small-scale or critical applications where accuracy is paramount.
- **Limitations**:
  - Computationally expensive, as evaluating all possible routes can become infeasible for larger datasets.
  - Requires significant processing power and time as the network complexity increases.

This method's rigorous nature makes it a powerful tool when precision outweighs computational limitations, such as in planning critical evacuation routes during extreme flood events.

### 5.2. Simulated Annealing

Simulated annealing, inspired by the process of **annealing in metallurgy**, is a heuristic optimization approach. Unlike exact methods, it does not exhaustively search all possible solutions but instead iteratively explores potential routes, favoring those with better scores while avoiding being trapped in local optima.

- **Advantages:**
  - Scalable for large, complex transportation networks.
  - Computationally efficient, making it suitable for real-time or near-real-time applications.
  - Can adapt to dynamic inputs, allowing for flexibility during rapidly evolving flood scenarios.
- **Limitations:**
  - Does not guarantee a globally optimal solution, especially in highly complex networks.
  - The quality of the solution depends on factors such as cooling rate and the number of iterations.

This method excels in balancing computational efficiency with solution quality, providing a near-optimal routing framework adaptable to Jeddah's urban sprawl.

```
Results for Constraint: {'D': 6, 'Q': 5, 'E': 4}
Linear Programming Results for Dataset 1 (Small dataset):
       S  i  j  Q  E  D      x  Selected
0  (1,2)  1  2  8  7  3  x_1_2       1.0
1  (2,3)  2  3  6  5  4  x_2_3       1.0
2  (3,4)  3  4  7  6  5  x_3_4       1.0
3  (4,5)  4  5  9  8  6  x_4_5       1.0
Execution Time (Linear Programming): 0.0193 seconds

Simulated Annealing Results for Dataset 1 (Small dataset):
Optimized Route Indices: [1, 2, 3, 0]
Execution Time (Simulated Annealing): 0.0048 seconds
```

Fig 3. Linear Programming vs. Simulated Annealing Dataset 1

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Linear Programming Results for Dataset 2 (Large dataset):
          S   i   j  Q  E  D       x  Selected
0     (1,2)   1   2  8  7  3    x_1_2      1.0
3     (2,3)   2   3  5  4  5    x_2_3      1.0
5     (3,4)   3   4  6  5  4    x_3_4      1.0
7     (4,5)   4   5  7  6  5    x_4_5      1.0
9     (5,6)   5   6  8  7  4    x_5_6      1.0
11    (6,7)   6   7  9  8  3    x_6_7      1.0
13    (7,8)   7   8  8  7  5    x_7_8      1.0
14    (8,9)   8   9  7  6  3    x_8_9      1.0
16   (9,10)   9  10  8  7  5   x_9_10      1.0
18  (10,11)  10  11  9  8  4  x_10_11      1.0
19  (11,12)  11  12  8  7  5  x_11_12      1.0
20  (12,13)  12  13  7  6  3  x_12_13      1.0
21  (13,14)  13  14  9  8  4  x_13_14      1.0
22  (14,15)  14  15  8  7  5  x_14_15      1.0
23  (15,16)  15  16  7  6  3  x_15_16      1.0
24  (16,17)  16  17  9  8  4  x_16_17      1.0
25  (17,18)  17  18  8  7  5  x_17_18      1.0
26  (18,19)  18  19  7  6  3  x_18_19      1.0
27  (19,20)  19  20  9  8  4  x_19_20      1.0
28  (20,21)  20  21  8  7  5  x_20_21      1.0
Execution Time (Linear Programming): 0.0343 seconds

Simulated Annealing Results for Dataset 2 (Large dataset):
Optimized Route Indices: [3, 26, 19, 7, 25]
Execution Time (Simulated Annealing): 0.0058 seconds
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```

Fig 4. Linear Programming vs. Simulated Annealing Dataset 2

## 6. Detailed Results and Analysis

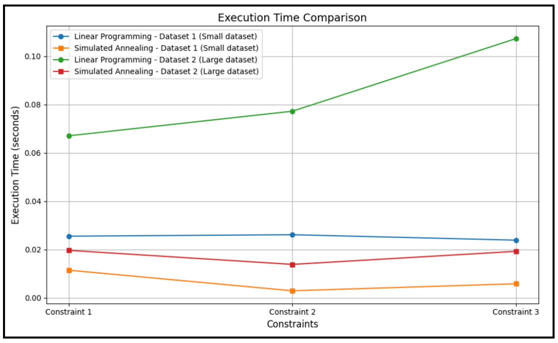


Fig 5. Execution Time Comparison: Linear Programming vs Simulated Annealing Across Constraints and Datasets

The comparative analysis of these methods revealed important insights into their performance and applicability:

- **Exact Optimization:**
  - Delivered optimal solutions for smaller, less complex networks.
  - However, the time required to compute these solutions increased exponentially with network size. For large-scale applications, this method became impractical due to its computational demands.
- **Simulated Annealing:**
  - Provided near-optimal solutions in a fraction of the time required by exact methods.
  - Its ability to scale and maintain computational efficiency made it well-suited for real-time flood management scenarios.

### 6.1. Key Findings:

- For **small-scale, high-stakes routing problems**, such as evacuating critical areas, exact optimization remains the preferred choice due to its precision.
- For **large networks** or situations requiring rapid decision-making, simulated annealing emerges as the more practical solution, achieving good results with minimal computational overhead.

By demonstrating the trade-offs between accuracy and computational efficiency, this study underscores the importance of selecting an appropriate methodology based on the specific needs and constraints of flood management in Jeddah.

## 7. Conclusion and Future Improvements

This study highlights the critical role of optimization in enhancing urban resilience to climate-induced disasters. By applying both exact and approximate optimization methods, we have established a robust framework for flood-aware routing tailored to the unique challenges of Jeddah.

### 7.1. Key Takeaways:

- **Exact Optimization**:
  - Ideal for small-scale, critical scenarios where accuracy is paramount.
  - Provides a benchmark for evaluating the performance of heuristic methods.
- **Simulated Annealing**:
  - Offers a scalable, computationally efficient alternative for large networks.
  - Enables dynamic adaptability, essential for real-time applications during flood events.

### 7.2. Future Improvements:

- **Integration with Real-Time Data:**
  - Incorporating live weather data and traffic conditions could enhance the adaptability of the routing framework, ensuring it responds dynamically to evolving flood scenarios.
- **Machine Learning Integration:**
  - Developing predictive models to anticipate flood risks based on historical and geospatial data can improve the reliability and accuracy of routing decisions.
- **Algorithm Scalability:**
  - Further optimizing the simulated annealing algorithm to handle larger, more complex networks will extend its applicability to metropolitan-scale planning.
- **Public Engagement:**
  - Creating a user-friendly application to disseminate real-time route recommendations to residents during flood events can bridge the gap between research and community impact.

By addressing these areas, the framework can evolve into a comprehensive decision-support system, safeguarding Jeddah's infrastructure and communities against future flood crises. This study not only provides a pathway for immediate implementation but also sets the stage for continuous innovation in urban disaster management.

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**Appendices**

[1] Flood-Aware Routing Optimization.ipynb

[2] datasets_small_large.xlsx