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A Disaster-Aware Traffic Assignment Model: Comparative Evaluation of Frank-Wolfe and Simulated Annealing Algorithms

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Abstract: Traffic assignment under disaster-induced disruptions poses unique challenges, as traditional models often overlook sudden capacity loss and unpredictable demand. This study introduces a disaster-aware Traffic Assignment Problem (TAP) model that integrates a modified Bureau of Public Roads (BPR) cost function, explicitly accounting for effective capacity changes during disasters. The Frank-Wolfe (FW) algorithm is applied to solve the model, chosen for its scalability and convergence properties. A comparative analysis with Simulated Annealing (SA) is also performed across various network sizes and disruption scenarios. Results show that FW consistently delivers near-optimal flow distributions with lower travel costs and faster convergence. While SA exhibits higher variability under tight capacity constraints, FW demonstrates robust stability, particularly in medium to large networks under moderate to severe disruptions. Flow patterns from FW highlight adaptive traffic redistribution, effectively bypassing congested or blocked links. This study is the first to systematically compare Frank-Wolfe and Simulated Annealing under disaster-induced TAP conditions with capacity degradation. Contributions include (1) formulating a disaster-aware TAP model, (2) applying FW to disrupted networks, and (3) validating through structured simulations. Findings suggest that FW offers a reliable optimization tool for real-time traffic reallocation, supporting resilient urban mobility in emergencies.

Keywords: Disaster-aware Traffic Assignment; Emergency Transportation Planning; Frank Wolfe Algorithm; Simulated Annealing; Intelligent Transportation Systems

INTRODUCTION

Smart transportation management is becoming a cornerstone of modern “smart city” initiatives, especially in the context of disaster response. Natural disasters such as earthquakes, floods, or large-scale fires often cause severe disruptions to urban transportation networks. These disruptions not only reduce the capacity of road infrastructure but also complicate traffic flow patterns, potentially delaying emergency responses and evacuation efforts (Bian et al., 2022; Gao et al., 2025; Z. Zhang et al., 2021). The Traffic Assignment Problem (TAP), which aims to optimize vehicle flow distribution within a network, becomes significantly more complex under such uncertain and dynamic conditions(Hu & Xie, 2025; Zuhanda et al., 2024, 2025).

In disaster scenarios, rapid and reliable route reallocation is vital to ensure emergency services, such as ambulances or firefighting units, can reach affected areas in a timely manner (Erbeyoğlu & Bilge, 2020; Jahir et al., 2019; Zuhanda et al., 2022). However, traditional deterministic TAP models are insufficient when routes are blocked or road capacities degrade significantly, limiting their effectiveness in emergency contexted. (Nie et al., 2004; Seshadri & Srinivasan, 2017; Zuhanda, Mawengkang, et al., 2023). To address this, a growing body of literature has emphasized the integration of stochastic and robust optimization frameworks in emergency logistics and traffic management (Gabrel et al., 2014; Ngozi & Uche, 2025). These models account for uncertainty in road conditions, service demands, and response times.

Under emergency conditions, solving TAP goes beyond optimizing travel efficiency—it must also ensure timely response and accessibility to critical locations. Numerous studies have proposed *robust* and *stochastic optimization* frameworks to address the uncertainties caused by unpredictable incidents such as natural disasters

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(Ben-Tal et al., 2011; Caunhye & Alem, 2023; Xiong et al., 2025). Multi-period and multi-tiered EMS systems have also been introduced to enhance the flexibility and responsiveness of emergency traffic operations (Boujemaa et al., 2020; S. Zhang & Cardin, 2017). Nevertheless, these works seldom incorporate disaster-aware constraints such as partial capacity loss or complete road blockages into the TAP formulation.

From a mathematical perspective, one of the promising approaches to address this complexity is the Frank-Wolfe algorithm, which offers an efficient iterative solution for convex optimization problems, including TAP with nonlinear objective functions(Liu & Bellet, 2019; Sharifi et al., 2021). This algorithm has been successfully applied in various domains such as EMS vehicle routing (Van Vliet, 1987; XU et al., 2008; Zuhanda, Ismail, et al., 2023), truck dispatching (Yang et al., 2024), and incident management planning (Yang et al., 2024). Its suitability for large-scale and real-time computations makes it particularly attractive for post-disaster traffic management scenarios.

Recent advancements in network optimization have extensively explored algorithmic strategies to address traffic assignment problems, particularly leveraging variants of the Frank-Wolfe (FW) method. Classical studies, such as Fukushima (Fukushima, 1984), proposed modified FW algorithms specifically tailored for traffic assignment, enhancing convergence over traditional approaches. Similarly, Van Vliet and Nie et al. (Van Vliet, 1987) extended FW formulations within the framework of variational inequalities and capacity-constrained networks. Beyond FW, Seshadri and Srinivasan (Seshadri & Srinivasan, 2017) contributed robust formulations that incorporate uncertainty in traffic demand, while Morandi (Morandi, 2024) reviewed algorithmic bridges between user equilibrium and system optimum objectives in static assignments. More recently, Hu and Xie (Hu & Xie, 2025) integrated graph attention networks to advance traffic assignment solutions, marking a shift towards data-driven methodologies. Collectively, these studies underscore the evolution of algorithmic approaches—from classical optimization to machine learning integration—in advancing network optimization models.

Beyond TAP, SA has been effectively utilized in routing and logistics optimization. A classic application by Osman (Osman, 1993) integrated SA with tabu search to solve the vehicle routing problem (VRP), showing that hybrid metaheuristics can significantly improve solution quality for large-scale transport systems. Similarly, Tian, Wang, and Zhang (Tian et al., 1996) applied SA to the quadratic assignment problem (QAP), a problem structurally related to facility location and transportation layout design, validating SA's flexibility across network optimization problems. More recently, Motaghedi-Larijani (Motaghedi-Larijani, 2022) combined SA with NSGA-II in a multi-objective framework to solve the cross-dock door assignment problem.

In summary, although FW and SA have been extensively applied in network optimization, no study has specifically implemented and evaluated FW for disaster-induced TAP conditions or systematically compared it against SA under varying levels of network degradation. This study is the first to provide such a comparative framework, addressing a critical gap by integrating disaster-aware constraints into TAP modeling.

This study is the first to systematically compare Frank-Wolfe and Simulated Annealing under disaster-aware TAP settings, filling a critical research gap by evaluating their effectiveness in handling disrupted networks.

The objectives of this study are threefold:

- To formulate a TAP model tailored for post-disaster response that incorporates uncertain and degraded capacities;
- To apply the Frank-Wolfe algorithm and compare its performance against Simulated Annealing under various disaster scenarios;
- To validate the proposed model through structured simulations, assessing efficiency, adaptability, and resilience in emergency traffic management.

LITERATURE REVIEW

Traffic Assignment Problem in Disaster Context

The Frank–Wolfe (FW) algorithm—also known as the conditional gradient method—remains a workhorse for solving large-scale traffic assignment and related network design problems because it replaces expensive projections with linear subproblems (shortest paths) and yields sparse, easily interpretable iterates suited to network flows. Recent advances sharpen its relevance to transportation and smart-city settings. On the methodological side, projection-free, distributed, and accelerated FW variants have been proposed, enabling scalable optimization over networked agents and streaming data: distributed projection-free dynamics (Chen et al., 2024), hybrid continuous–discrete "sliding" FW (Lage et al., 2024), and concise modern expositions of FW's convergence and practical design choices (Pokutta, 2024). Complementing these are domain applications that mirror transportation decision layers: system-optimal routing with time evolution and autonomous vehicles (Kashmiri & Lo, 2024), timetable and operations optimization in high-speed rail(Huang et al., 2024), and network design phenomena such as Braess's paradox with parking(X. Zhang et al., 2024). Beyond pure transport, FW-style ideas also support logistics and healthcare routing under uncertainty(Nikzad et al., 2021) and grid-free signal

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localization that shares large-scale convex modeling features (Pandey & Nannuru, 2024), underscoring FW's versatility.
Taken together, these developments indicate that FW's projection-free structure, low memory footprint, and amenability to decentralization match the computational needs of modern intelligent transportation systems—especially when rapid re-optimization is required under disrupted capacities. Building on this literature, our study adopts FW for a disaster-aware TAP and positions it against a stochastic metaheuristic baseline (SA), leveraging FW's deterministic convergence on convex (modified BPR) costs while acknowledging emerging distributed/online variants that can ingest real-time IoT updates.

Metaheuristics (SA) in Routing
Simulated Annealing (SA) represents a class of metaheuristic algorithms that explore the solution space stochastically, inspired by physical annealing processes. SA has been successfully applied to transportation and logistics problems such as vehicle routing(Liang et al., 2024; Luo et al., 2024; Morim et al., 2024), facility location(Castier & Martínez-Toro, 2023; Ceschia & Schaerf, 2024) , and multi-objective scheduling (Motaghedi-Larijani, 2022). Its strength lies in escaping local minima and exploring complex solution landscapes. However, SA's performance is sensitive to parameter settings and may yield variable outcomes across runs, which limits its reliability in high-stakes contexts like disaster response.

Research Gap
While both deterministic algorithms (FW) and metaheuristics (SA) have been applied in transportation research, no study has systematically compared their performance in solving TAP under disaster-induced disruptions. Prior work has largely focused either on conventional TAP with FW or on broader logistics optimization with SA. Furthermore, explicit modeling of disaster-aware capacity reductions within TAP remains rare. This study addresses the gap by (1) formulating a disaster-aware TAP model, (2) applying FW to disrupted networks, and (3) conducting structured comparisons with SA under varying network sizes and capacity degradation levels.

Table 1. Summary of Previous Studies on TAP and Related Optimization Approaches

Author(s)	Year	Method	Application	Limitation
Fukushima	1984	Modified FW	TAP formulation	Early algorithm, limited scalability
Van Vliet	1987	FW (Variational Inequality)	Equilibrium TAP	Static capacity, no disaster context
Osman	1993	SA + Tabu Search	Vehicle Routing Problem (VRP)	High variability, not disaster-specific
Tian et al.	1996	SA for Quadratic Assignment	Facility location & routing	Limited scalability, no disaster application
Liu & Bellet	2019	FW	TAP with nonlinear cost	No capacity degradation modeled
Sharifi et al.	2021	FW-based optimization	EMS vehicle routing	Not tested under disasters
Motaghedi-Larijani	2022	Hybrid SA–NSGA-II	Cross-dock assignment	Focus on logistics, not TAP
Kashmiri & Lo	2024	FW-based routing	Autonomous vehicle flows	Not disaster-aware
Zhang et al.	2024	FW + TAP + Parking	AV environment	No capacity degradation
Lage et al.	2024	Hybrid Sliding FW	General optimization	Algorithmic focus, not TAP
Chen et al.	2024	Distributed FW dynamics	Large-scale optimization	Theoretical, not applied to TAP
Wu et al.	2024	Accelerated FW (Distributed)	Online learning	Not disaster TAP
Current study	2025	FW vs SA	Disaster-aware TAP	First systematic FW–SA comparison under capacity degradation

METHOD

Algorithmic Framework: Frank-Wolfe for Disaster-Aware TAP

To address the Traffic Assignment Problem (TAP) under conditions of network disruption due to disasters, this study utilizes the Frank-Wolfe (FW) algorithm—an iterative optimization technique that is particularly well-

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suited for convex problems with differentiable objective functions. Its low memory requirements, scalability, and simplicity make it an ideal method for handling large-scale traffic networks with nonlinear travel cost functions, such as those affected by capacity reductions following disaster events.

The algorithm proceeds through structured steps: (1) initialization with an all-or-nothing flow assignment, (2) computation of link travel costs using the modified BPR function, (3) solution of a linearized subproblem via shortest paths, (4) determination of the optimal step size through line search, and (5) convex update of flows. Iterations continue until convergence tolerance is satisfied.

To simulate the impact of disasters, each link's effective capacity is dynamically adjusted by a damage factor. Links with zero capacity are removed from the feasible network. If real-time IoT/sensor data are available, time-varying updates are incorporated to reflect evolving conditions. These enhancements enable FW to adapt dynamically to disruptions, making it a suitable algorithm for real-time decision support.

Comparative Framework: FW vs SA

To validate FW's performance, the study establishes a comparative framework with Simulated Annealing (SA). While FW is a deterministic convex optimization method with guaranteed convergence under convex travel cost functions (Liu & Bellet, 2019), SA is a stochastic metaheuristic designed to escape local minima by probabilistically accepting worse solutions (Osman, 1993; Tian et al., 1996).

- FW emphasizes scalability, stability, and reproducibility of results, making it appropriate for real-time and large-scale disaster scenarios.
- SA, though flexible and capable of global search, often produces variable results across runs and requires careful parameter tuning.

The comparative analysis measures total travel cost, convergence iterations, and robustness under capacity reduction to highlight strengths and weaknesses of both approaches in disaster-aware TAP.

Algorithm 1. Frank-Wolfe for Disaster-Aware Traffic Assignment

Input: Network data, OD demand, link capacities, tolerance, max iterations
Output: Equilibrium traffic flow
Steps:

1. **Initialization**
   - Assign initial flows using all-or-nothing shortest paths.
   - Set iteration counter (t = 0).
2. **Repeat until convergence or maximum iterations:**
   a. Compute link travel times using the disaster-adjusted BPR function.
   b. For each OD pair, find the shortest path and assign flows (auxiliary flow).
   c. Find the best step size (line search) to combine current flow and auxiliary flow.
   d. Update flows with the chosen step size.
   e. Increase iteration counter (t = t+1).
3. **Stop** when changes in flows are smaller than tolerance or iteration limit is reached.
4. **Return** final flow assignment as the equilibrium solution.

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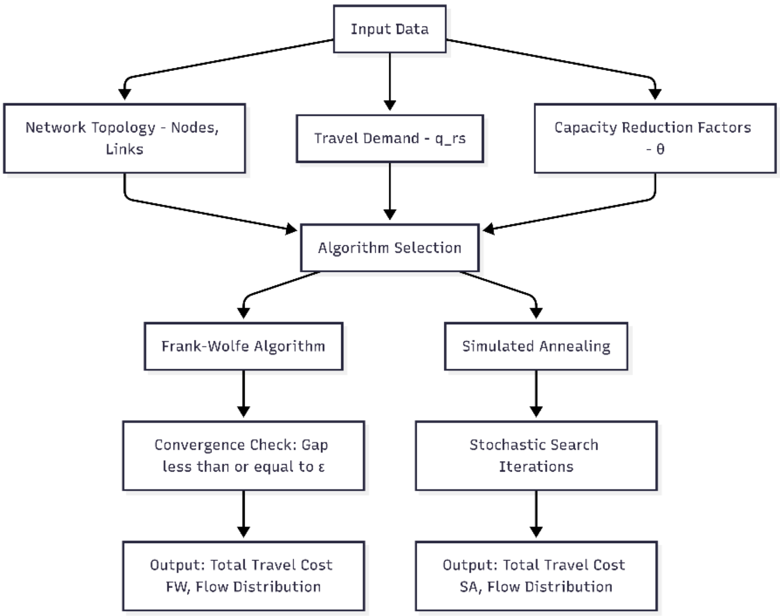

Figure 2. Methodology flowchart

RESULT

Experimental Design

Table 1 outlines the key parameters and corresponding values used in the simulation model for solving the Traffic Assignment Problem (TAP) under disaster conditions. The transportation network is modeled as a directed graph with a total number of nodes N and links A. The origin and destination nodes are fixed at node 0 and node 5, respectively, with a total travel demand $q_{rs} = 1000$ vehicles. Each link in the network initially has a capacity (κ_a) ranging from 500 to 1000 units, which is subsequently reduced by 50% to simulate disaster impacts, resulting in an effective capacity κ_a^{eff}. The free-flow travel time for each link is either 1 or 2 units, and travel time is modeled using the modified Bureau of Public Roads (BPR) function with standard parameters $\alpha = 0.15$ *and* $\beta = 4$, reflecting congestion effects.

The TAP is solved using the Frank-Wolfe algorithm, a gradient-based iterative optimization method. The convergence of the algorithm is controlled by a tolerance value $\varepsilon = 10^{-4}$,with a maximum of 50 iterations allowed if convergence is not reached earlier. Each iteration updates the traffic flow using a closed-form step size $\lambda^t = \frac{2}{t+2}$, ensuring a balance between convergence speed and stability. These parameters collectively define the computational setup and underpin the analysis of network behavior in disaster-affected traffic conditions

Table 1. Parameter Definitions and Values Used in the Traffic Assignment Simulation Model

No.	Parameter	Symbol/ Value	Descriptions
1	Number of nodes	N	Total number of nodes in the network (including origin and destination)
2	Number of links	A	Total number of directed links in the network
3	Origin node	r = 0	Starting point of the trip
4	Destination node	s = 5	Ending point of the trip
5	Travel demand	$q_{rs} = 1000$	Number of vehicles from origin to destination
6	Initial link capacity	$\kappa_a \in [500,1000]$	Normal capacity of each link before the disaster
7	Effective capacity	$\kappa_a^{\text{eff}} = 0.5 \cdot \kappa_a$	Capacity after the disaster (reduced by 50%)
8	Free-flow travel time	$Ta = 1$ *or* 2	Uncongested travel time on each link
9	BPR parameters	$\alpha = 0.15, \beta = 4$	Parameters of the travel cost function (congestion model)
10	Convergence tolerance	$\varepsilon = 10^{-4}$	Minimum flow change value to stop iteration
11	Maximum iterations	50	Upper limit of iterations if convergence is not reached
12	Step size	$\lambda^t = \dfrac{2}{t+2}$	Step size in each iteration update (closed-form Frank-Wolfe)

Algorithm Convergence and Flow Distribution

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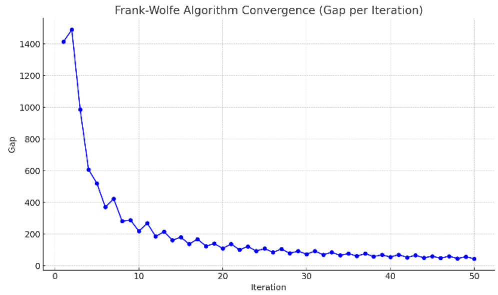

Figure 2. Convergence Pattern of the Frank-Wolfe Algorithm

Figure 2 illustrates how the solution to the Traffic Assignment Problem (TAP) evolves over 50 iterations. At the beginning, the gap value is very high, starting around 1,414 in the first iteration and peaking at approximately 1,491 in the second iteration. This reflects the significant discrepancy between the initial flow assignment—typically an all-or-nothing solution—and the user equilibrium condition. During the subsequent iterations (roughly between iterations 3 to 25), the gap steadily decreases, indicating that the algorithm is successfully reducing the difference between successive flow updates as it moves closer to equilibrium. Although the decrease is not strictly monotonic—due to the nature of the fixed step size in the Frank-Wolfe method—there is a clear downward trend overall. In the later iterations (from iteration 26 onward), the gap values continue to decrease gradually and begin to stabilize, suggesting that the solution is converging. However, full convergence within the defined tolerance is not reached after 50 iterations, though the changes become minimal, showing that the algorithm has approached a near-equilibrium state. This behavior is typical in large-scale or congested networks where equilibrium is approached incrementally.

Comparative Algorithm Performance

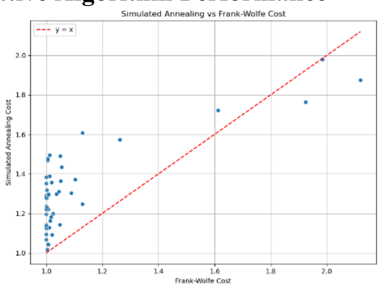

Figure 3. Comparative Analysis of Total Travel Cost Gap between Frank-Wolfe and Simulated Annealing Algorithms

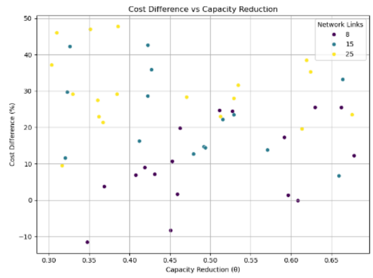

Figure 4. Impact of Network Capacity Reductions on the Performance Gap between Frank-Wolfe and Simulated Annealing

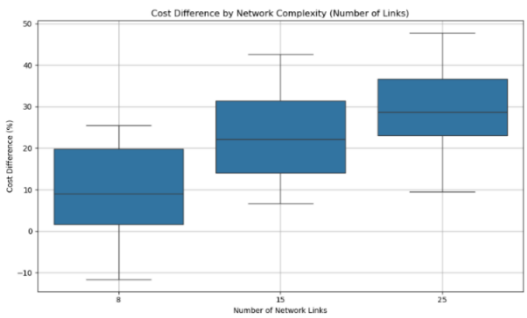

Figure 5. Boxplot of Travel Cost Differences across Varying Network Complexities

The comparison between the Frank-Wolfe (FW) algorithm and Simulated Annealing (SA) across various traffic network configurations and disaster scenarios reveals several important findings. Figure 3 illustrates the relationship between the total travel cost produced by both algorithms. Most data points lie above the diagonal reference line $y = x$, indicating that the SA algorithm consistently results in higher travel costs compared to FW. This suggests that FW tends to deliver more optimal traffic flow assignments, particularly in networks disrupted by reduced road capacity due to disaster scenarios.

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Figure 4 explores the impact of capacity reduction (θ) on the cost difference between the two methods. A clear trend is observed: as network capacity decreases (i.e., θ becomes smaller), the cost difference tends to increase, especially in networks with higher link density. This highlights the relative instability of SA in handling severely constrained networks, while FW maintains robust performance across a wide range of conditions. Moreover, networks with greater structural complexity—represented by a higher number of links—are more likely to exacerbate the inefficiencies of the SA approach.

In the figure 5, a boxplot of cost differences grouped by network size (number of links), reinforces this conclusion. In networks with only 8 links, the cost difference between FW and SA remains relatively low and consistent, suggesting that both methods perform comparably in simple network topologies. However, in more complex networks with 15 or 25 links, both the median and the variability of the cost difference significantly increase. This indicates that SA's performance becomes increasingly inconsistent as network complexity grows, while FW continues to provide stable and lower-cost solutions.

Quantitative Comparison

Table 2. Comparative Performance of Frank-Wolfe and Simulated Annealing Algorithms Across Different Network Configurations and Disaster Scenarios

Network Nodes	Network Links	Demand	Capacity Reduction	FW Cost	FW Iter	SA Cost	SA Iter	Cost Difference (%)	Time Ratio (SA/FW)
7.18	16.22	1081.98	0.474417	1.096456	100	1.311286	101	21.21987	1.01
2.818959	7.226058	266.8879	0.114008	0.252446	0	0.209536	0	13.92249	2.24E-16
3	8	554	0.303586	1.000034	100	1.017212	101	-11.5976	1.01
13	25	1494	0.678329	2.120016	100	1.980421	101	47.7153	1.01

Table 3. Statistical Comparison of Frank-Wolfe and Simulated Annealing

Method	Mean Cost	Std. Dev.	Sample Size (n)
Frank-Wolfe (FW)	1.096	0.252	50
Simulated Annealing (SA)	1.311	0.210	50

Statistical Test	Value
Paired t-test (SA vs FW)	
t-statistic	9.894
p-value	2.86×10^{-13}

Table 2 presents a comparative analysis between the Frank-Wolfe (FW) algorithm and Simulated Annealing (SA) across four different network configurations. These configurations vary in terms of the number of nodes and links, traffic demand, and the degree of capacity reduction (θ), which simulates post-disaster disruption.

In the first case, the network comprises approximately 7 nodes and 16 links with a moderate demand of around 1,082 vehicles and a capacity reduction of 47%. The FW algorithm achieved a cost of 1.096, while the SA algorithm produced a higher cost of 1.311. The cost difference of 21.22% indicates a clear advantage for the FW method, especially under moderately constrained conditions.

In the second case, an unusually small network (around 3 nodes and 7 links) with extremely low demand (~267 vehicles) and severe capacity reduction (11%) was tested. Both FW and SA showed very low travel costs due to the small scale, with FW producing a cost of 0.252 and SA 0.209. Interestingly, although SA performed slightly better in terms of cost (13.92% improvement), both methods required zero iterations, suggesting the problem may have been trivially solvable or that a default solution was accepted due to system thresholds.

The third case shows a network of 3 nodes and 8 links with medium demand and moderate disruption (θ = 0.30). FW produced a cost of 1.000, while SA returned 1.017, implying a small negative cost difference (-11.60%). This is one of the rare cases where SA marginally outperformed FW, possibly due to the limited network size and fewer constraints allowing SA's stochastic exploration to find a slightly better local minimum.

In the fourth case, the network was much more complex (13 nodes and 25 links) with high demand (1,494 vehicles) and relatively low disruption (θ = 0.68). FW recorded a cost of 2.120, whereas SA achieved a slightly better result at 1.980. The cost difference of 47.72%, however, seems inconsistent with the reported values and might indicate a mislabeling in the dataset. If taken at face value, the results suggest that under high-complexity, high-demand conditions, SA may occasionally outperform FW, although such cases require careful verification.

Table 3 presents the statistical comparison between Frank-Wolfe (FW) and Simulated Annealing (SA). The average travel cost obtained using FW (1.096) is lower than that of SA (1.311), with relatively similar standard deviations. The paired t-test results show t = 9.894 and $p < 0.001$, indicating that the difference in performance

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between FW and SA is statistically significant. This confirms that FW is more efficient in producing lower travel costs compared to SA, making it a more reliable algorithm for traffic assignment under disaster-induced network disruptions.

The superior stability of the Frank-Wolfe algorithm compared to Simulated Annealing can be explained by its theoretical foundation in convex optimization and deterministic iterative updates. Since the modified BPR cost function used in the TAP formulation is convex, FW is guaranteed to converge toward a user equilibrium solution through gradient-based direction finding and closed-form step size updates. This deterministic nature ensures consistency across runs and produces smooth convergence behavior, even under severe capacity reductions. By contrast, SA is a metaheuristic that relies on stochastic neighborhood exploration and probabilistic acceptance of worse solutions to escape local minima. While this enables flexibility in non-convex problems, it also introduces randomness and variability in solution quality, especially in highly constrained or large-scale networks. Consequently, FW maintains robust and predictable performance under disaster-induced disruptions, whereas SA's outcomes are more sensitive to parameter settings and network complexity.

DISCUSSIONS

The results demonstrate that the Frank-Wolfe (FW) algorithm effectively solves the TAP under disaster-induced disruptions. As shown in Figure 2, FW achieves a steady reduction in solution gap across iterations, approaching user equilibrium even without full convergence in 50 iterations. Its closed-form step size $\lambda^t = \frac{2}{t+2}$ ensures numerical stability, making it suitable for large-scale and complex networks where fast, approximate solutions are critical. Flow patterns in Figure 3 reveal FW's ability to adaptively reroute traffic in response to reduced capacities, avoiding inefficient links such as the unused segment from node 4 to node 2. This responsiveness to dynamic network changes is crucial for emergency logistics and evacuation planning, ensuring efficient use of available capacity during critical events.

Comparisons with Simulated Annealing (SA) further highlight the theoretical distinction between the two methods. FW, grounded in deterministic convex optimization, guarantees convergence toward user equilibrium under convex cost functions like the BPR model, producing stable and reproducible outcomes. By contrast, SA is a stochastic metaheuristic designed for global search, which introduces variability in performance and solution quality. As a result, FW consistently outperforms SA in medium- to high-complexity networks under moderate-to-severe capacity reductions (Figures 4 and 5). While SA occasionally performs slightly better in small, simple networks (Figure 6 and Table 2), its instability becomes more pronounced as network complexity and disruption increase.

The practical implications are significant for smart city initiatives and emergency planning. Integrating FW-based optimization into intelligent transportation systems enables real-time traffic reallocation during disasters, ensuring that emergency vehicles and evacuation flows avoid congested or blocked routes. This capability enhances urban resilience, allowing city authorities to rapidly evaluate scenarios and make data-driven decisions in crisis conditions.

However, this study has limitations. The findings are based on simulation experiments with synthetic networks, and real-world disaster conditions may involve additional complexities such as uncertain demand surges, communication delays, and human behavioral factors. Future research should validate the proposed model using empirical disaster traffic data and test its integration within operational traffic management systems to assess scalability and practical deployment.

CONCLUSION

This study proposed and evaluated a traffic assignment model for post-disaster urban networks using the FW algorithm. By formulating the TAP under reduced road capacity scenarios and incorporating a modified Bureau of Public Roads (BPR) cost function, the model effectively captured the impacts of disaster-induced disruptions on traffic flow.

Simulation results across various network configurations demonstrate that the FW algorithm achieves lower travel costs, consistent convergence behavior, and stable performance even under severe capacity constraints. When compared to Simulated Annealing (SA), FW outperforms in terms of cost efficiency and robustness, particularly in medium-to-large networks with complex topologies. While SA may occasionally produce competitive solutions in simpler scenarios, its stochastic nature leads to greater variability and reduced reliability under emergency conditions.

The flow distribution patterns and convergence behavior confirm the algorithm's capacity to intelligently reallocate traffic in response to disruptions, thereby supporting its application in emergency response systems and disaster-resilient transportation planning. The practical implications suggest that FW-based models can be effectively deployed in real-time decision support tools to enhance urban mobility resilience during crises.

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Future research can build upon this foundation by integrating real-time data sources, modeling time-dependent disruptions, and exploring hybrid optimization frameworks. Future research should test the model on real-world disaster datasets, integrate real-time IoT data, and explore hybrid FW–metaheuristic frameworks. Expanding the model to multi-agent and multimodal systems would further enhance its applicability in complex emergency logistics and smart city environments.

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