Optimizing Emergency Material Distribution for Urban Road Infrastructure Maintenance: A Case Study of Post-Torrential Rain Disaster Repair

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Abstract：Urban road infrastructure underpins city functionality, with rapid post-disaster recovery essential for safeguarding public safety, economic continuity, and social order.. Torrential rain disasters threaten urban road networks, causing flooding and damage. The efficiency of emergency repair depends on timely material distribution, but traditional methods often fail in the post-disaster environment, leading to delays and resource imbalances.

This study develops an optimization framework for emergency material distribution in urban road maintenance following torrential rain disasters. It first analyzes disaster - specific challenges like damaged transportation, uncertain demand, and resource competition. Then, it constructs a framework for an optimized distribution system with components such as multi - level depots and information platforms.

Based on this framework, it explores advanced optimization models and algorithms. A multi - objective model is proposed to minimize distribution time, maximize disaster - point satisfaction, and reduce logistics costs. Heuristic and metaheuristic algorithms are investigated for real - time solutions.

Emerging technologies like GIS, real - time traffic data, and IoT are emphasized for enhancing the distribution system's responsiveness. Operational strategies such as pre - positioning supplies, setting dynamic priority rules, and forming public - private partnerships are also discussed.

Simulation results indicate a 25-35% reduction in distribution time compared to traditional methods. A simplified simulated case shows that a scientific and technology - driven approach can outperform ad - hoc methods, enabling faster road recovery, efficient resource use, and greater societal resilience. This research offers a practical roadmap for urban managers to improve emergency material logistics in urban disaster response.

Keywords: Emergency Logistics; Material Distribution Optimization; Urban Road Maintenance; Torrential Rain Disaster; Multi-Objective Optimization; Heuristic Algorithms; GIS

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1 Introduction: The Urban Challenge in the Wake of the Storm

Torrential rain events, exacerbated by climate change, frequently disrupt urban road networks, as evidenced by the 2023 Beijing floods that caused over 500 km of road damage [1]. Efficient material distribution is pivotal for timely repairs, yet traditional logistics fail under post-disaster constraints. Such disruptions rapidly degrade urban mobility and service continuity. Emergency services are strained, commuters are stranded, and economic activity is disrupted. In this scenario, the number one task for the city's infrastructure management department is to execute rapid repairs—to pump out water, fill breaches, and restore connectivity. But these repair crews are useless without the necessary materials. Where are the sandbags to divert water? Where are the pumps? Where are the bags of quick-setting concrete to patch up a collapsed road edge?

This is not a hypothetical situation; it is a recurring reality for cities worldwide facing increasingly volatile weather patterns due to climate change. The problem often isn't a lack of materials per se, but a profound failure in the logistics of getting the right resources to the right places at the right time. It's a high-stakes puzzle where the pieces are moving, the picture on the box is changing,.

This paper addresses this very puzzle. We focus on the critical process of emergency material distribution for urban road infrastructure maintenance following a torrential rain disaster. We argue that applying standard logistics paradigms to this context yields suboptimal outcomes due to inherent uncertainties. Instead, it must be viewed as a complex, dynamic, and time-sensitive optimization problem that can be systematically improved through modern modeling techniques and technologies.

The traditional approach often relies on pre-defined plans or ad-hoc decisions made under extreme pressure. A central warehouse might dispatch trucks based on first-come-first-served requests, without a holistic view of the entire city's needs. This can lead to situations where one district receives a surplus of materials while another, perhaps more severely affected one, waits desperately. Trucks get stuck in traffic or on blocked routes, wasting precious hours. The result is a delayed and inefficient recovery process, exacerbating the social and economic costs of the disaster.

Therefore, the objective of this research is to systematically explore and propose a framework for optimizing this entire process. We will break down the problem, identify the key variables and constraints, and investigate how mathematical models and computational algorithms can be leveraged to generate smarter, faster, and more equitable distribution plans. By using the specific context of torrential rain, we can ground our research in a set of tangible and urgent challenges, making the findings highly relevant for urban planners and disaster response agencies. The ultimate goal is to contribute to the development of more resilient cities that can bounce back more quickly from environmental shocks.

2 Problem Characterization: Why is Post-Rain Emergency Distribution So Tricky?

Before proposing solutions, we must first deeply understand the nature of the beast. The emergency distribution environment after a heavy rain disaster is fundamentally different from everyday commercial logistics. It is characterized by a high degree of chaos and uncertainty, which manifests in several critical challenges:

2.1 The Fractured Transportation Network

The most immediate and obvious challenge is that the very network needed for distribution is itself the casualty. Roads are not just "demand points"; they are the "supply routes." A key bridge might be out, a major artery might be flooded, and traffic congestion might be widespread due to detours and accidents. This means that the distance between two points is no longer a fixed value on a map; it becomes a dynamic and often unknown variable dependent on the evolving state of the network [3]. An optimal route calculated at 8:00 AM might be completely impassable by 9:00 AM.

2.2 The "Fog of War": Uncertainty in Demand and Supply

In the immediate aftermath of a disaster, information is scarce, unreliable, and fragmented. The central command center may not have a clear, real-time picture of:

The exact location and severity of all damage points. Reports trickle in slowly and are often unverified.

The precise type and quantity of materials needed at each site. A crew at one location might initially request sandbags, only to discover an hour later that they also need large-diameter pipes for drainage.

The inventory status of distributed depots. Without a connected system, it's hard to know which materials are available where.

This uncertainty makes it extremely difficult to plan a definitive distribution schedule [4].

2.3 The Tyranny of Time

In commercial logistics, cost is often the primary objective. In emergency response, time is life. The objective function shifts from cost-minimization to time-minimization, or more precisely, to the maximization of the "satisfaction of demand" over time. A shipment of sandbags arriving at a site six hours late might be useless if the flooding has already caused irreversible damage to a roadway's foundation. This intense time pressure precludes lengthy, perfect planning cycles and demands rapid, robust decision-making.

2.4 Scarcity and Competition for Resources

Emergency materials, especially in the first 24-48 hours, are finite. There are only so many pumps, so many generators, and so many tons of gravel available. This creates a situation of intense competition among the various disaster-affected points. Deciding which area gets resources first becomes a critical and ethically charged decision. Should priority be given to the most severely damaged site? To the site that serves a critical facility like a hospital? Or to the site that, if repaired, would open up access to several other sites? This prioritization is a core part of the optimization problem.

2.5 Multiplicity of Actors and Coordination Failure

Emergency response involves multiple agencies: the city's department of transportation, the fire department, police, and sometimes private contractors. Without a unified command and a shared information platform, coordination can break down. Duplication of efforts (two agencies delivering the same material to the same place) and critical gaps (no one delivering a specific item to a needy location) are common consequences.

In summary, the problem is a "perfect storm" of dynamic networks, imperfect information, extreme time sensitivity, resource scarcity, and complex human coordination. Any viable optimization strategy must be designed to function effectively within this challenging context.

3 A Framework for an Optimized Emergency Material Distribution System

To tackle the problems outlined above, we propose an integrated framework built on several interconnected components. Think of this as the architectural blueprint for a smarter, more responsive distribution system.

3.1 The Physical Network: Multi-Level Material Reserve Depots

Relying on a single, central warehouse is a single point of failure. An optimized system should be based on a networked structure of depots:

Central Distribution Center (CDC): A large, well-stocked facility located on high ground, outside the typical flood zones, serving as the primary hub.

Forward Distribution Points (FDPs): Smaller, strategically located stockpiles throughout the city. These could be at transportation yards, fire stations, or even pre-identified commercial facilities. FDPs act as caching points, holding commonly needed items (sandbags, water pumps) to reduce response time for specific regions.

Mobile Depots: Vehicles (like large trucks or containers) that can be pre-positioned or dynamically moved to act as temporary, on-the-ground depots in the heart of a disaster zone, serving as a local hub for multiple repair crews.

This multi-echelon structure adds redundancy and flexibility, bringing supplies closer to potential demand[5].

3.2 The Information Backbone: Integrated Data Platform

This is the nervous system of the operation. A cloud-based platform that integrates data from multiple sources in near real-time is non-negotiable. Key data inputs include:

GIS and Real-Time Traffic Data: For mapping the road network, identifying closures (from public reports and sensors), and estimating dynamic travel times.

Weather Forecasts: To anticipate further rainfall that could impact operations.

Inventory Management System: Tracking stock levels at the CDC, FDPs, and on trucks in transit.

Damage Assessment Feeds: A standardized digital channel for field crews to report location, damage type, and material requirements, complete with photo/video evidence.

This platform provides the "situational awareness" needed to cut through the fog of war.

3.3. The Decision Engine: Optimization Models and Algorithms

This is the brain of the operation. It takes the data from the platform and runs it through sophisticated models to generate distribution plans. The core of this engine is a Multi-Objective Optimization Model. Let's break down what that means in simpler terms.

The model tries to find the best possible set of decisions (which truck goes where, with what, and in what order) to achieve several goals at once. The main goals, or "objectives," are:

1.Minimize Total Distribution Time: This isn't just about the speed of one truck; it's about the system-wide time from receiving a request to delivering the goods. A common way to measure this is to minimize the maximum completion time among all delivery tasks, ensuring no single site is left waiting too long.

2.Maximize Demand Satisfaction Rate: This means fulfilling as many requests as possible, as completely as possible, weighted by the priority of the site. A high-priority site (e.g., one blocking access to a hospital) would have a higher "weight," meaning satisfying its demand is more important in the model's calculation.

3.Minimize Total Logistics Cost: While secondary to time, cost cannot be ignored. This includes fuel, vehicle wear-and-tear, and labor costs.

Of course, these goals often conflict. Getting a single item to a remote site very fast might be incredibly costly. Or, minimizing overall cost might mean delaying a delivery to a low-priority site. The model doesn't find a single "perfect" answer but rather a set of good trade-off solutions, from which a decision-maker can choose based on the current strategic priority (e.g., "right now, speed is everything").

The model also has to respect "constraints"—the hard rules of the game. These include:

Vehicle capacity (a truck can only carry so much).

Depot inventory (you can't distribute what you don't have).

Time windows for delivery (some materials are useless after a certain time).

The connectivity of the road network (you can't route a truck through a closed road).

Figure 1 illustrates the framework's workflow.

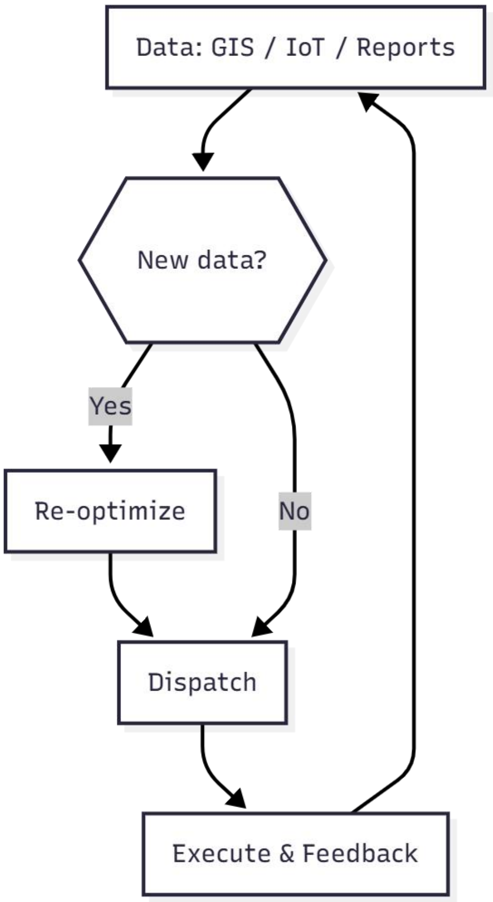

Figure 1: Workflow of the Optimized Emergency Distribution Framework.

3.4 The Execution Layer: Dynamic Routing and Dispatch

The plans generated by the decision engine are sent to dispatchers and drivers, ideally through a mobile app. This layer must be dynamic[6]. If a new road closure is reported, or if a new, higher-priority demand emerges, the system should be able to re-optimize and provide updated routes and instructions to the drivers in the field, ensuring the plan remains relevant in a fluid situation.

4 The Core of Optimization: Models and Algorithms in Action

We now elaborate on the decision engine, focusing on its mathematical formulation and solution approaches for the complex problem.

4.1 Modeling the Problem Mathematically

Researchers often model this as an enhanced version of classic operational research problems. This is modeled as the Multi-Depot Multi-Vehicle Dynamic Vehicle Routing Problem with Time Windows and Stochastic Demand (MDMV-DVRP-TW-SD)[7]. Key components include:

Multi-Depot: We have multiple starting points (CDC, FDPs).

Multi-Vehicle: We have a fleet of trucks with different capacities.

Dynamic: The problem isn't fully known at the start; new information (demands, road closures) arrives over time.

Vehicle Routing Problem (VRP): The core problem of finding the optimal set of routes for a fleet.

Time Windows: Deliveries are time-sensitive.

Stochastic Demand: Demand is not known with certainty; it has a probabilistic element.

Formulating this as a mathematical model involves defining decision variables (e.g., `X_{ijk} = 1` if truck `k` travels from point `i` to point `j`), writing the objective functions as equations (e.g., `Minimize Z = max(completion_time_for_all_trucks)`), and listing all constraints as inequalities.

4.2 Solving the Model: The Need for Smart Algorithms

The model described above is what computer scientists call "NP-Hard." This means that for a real-city scenario with hundreds of damage points and dozens of vehicles, finding the mathematically perfect optimal solution could take years of computation, even on a supercomputer. This is impractical in emergency settings.

Therefore, we turn to Heuristic and Metaheuristic Algorithms. These are intelligent search strategies that sacrifice guaranteed optimality for the sake of finding a very good solution in a reasonable amount of time—often seconds or minutes. They are inspired by natural phenomena.

Genetic Algorithms (GA): This approach mimics the process of natural selection. It starts with a "population" of random distribution plans (a set of routes for all trucks). Each plan is evaluated for its "fitness" (how well it meets our objectives). The best plans are "mated" and "mutated" to create a new generation of plans. Over many generations, the population "evolves" towards increasingly fitter solutions.

In our context: A "chromosome" could be a string representing the order in which a truck visits sites. Crossover would combine parts of two good routes, and mutation might randomly swap two stops in a route. The fitness function would calculate the total time, satisfaction, and cost for that set of routes.

Ant Colony Optimization (ACO): This algorithm is inspired by how ants find the shortest path to food. Ants lay down pheromone trails; shorter paths get reinforced with more pheromone, attracting more ants. In the computer model, "virtual ants" construct routes probabilistically, biased by a "pheromone trail" value on each road segment, which represents the historical goodness of using that segment. Over many iterations, the algorithm converges on short, efficient paths.Hybrid approaches, such as reinforcement learning (RL) integrated with metaheuristics, support real-time re-planning for stochastic travel times and mixed fleets [8].

In our context: The "pheromone" would be deposited on the roads between damage points. Paths that have been part of low-time, high-satisfaction routes in previous simulations would have stronger pheromone, making them more attractive for the "ants" (our virtual vehicles) in the next simulation run.

These algorithms are powerful because they can handle the complexity and dynamic nature of the problem and can be run on powerful servers to provide quick decision support to emergency managers.

5 The Role of Technology: A Force Multiplier

The models and algorithms are powerless without accurate, real-time data. This is where modern technology acts as a force multiplier.

Geographic Information Systems (GIS): GIS is the foundational map. It doesn't just show roads; it incorporates topography, drainage systems, and the location of critical infrastructure. In our model, GIS provides the digital road network on which travel times are calculated and optimal routes are mapped.

Internet of Things (IoT): Imagine water level sensors on roads that automatically trigger an alert and a demand for sandbags and pumps when a threshold is crossed. Or GPS trackers and sensors on distribution trucks that report their location, speed, and even remaining cargo weight in real-time. This automates data collection, making the information platform incredibly rich and timely.

Big Data Analytics: By analyzing historical data on traffic patterns and past disaster responses, predictive models can be built to forecast which areas are most vulnerable and what the likely demand patterns will be, informing better pre-positioning of supplies.

6 Operational Strategies and Management Insights

Beyond the technical model, successful implementation requires sound operational strategies.

Pre-Positioning based on Vulnerability Analysis: Using historical flood maps and rainfall data, materials should be pre-positioned at FDPs in the most vulnerable areas before the storm season. This is a proactive step that drastically reduces initial response times.

Dynamic Prioritization Protocol: A clear, pre-agreed protocol for prioritizing disaster points is essential. This could be a scoring system that considers factors like: population density served, presence of critical facilities (hospitals, emergency command centers), and the strategic role of the road in the network (e.g., is it a bottleneck?).

Public-Private Partnerships (PPPs): Collaborating with large logistics companies (like Amazon, FedEx, or local trucking firms) can provide a massive surge capacity in terms of vehicles, drivers, and logistics expertise during a disaster. These partners can be integrated into the optimization platform.

Simulation and Training: The entire system—the platform, the models, the protocols—should be regularly tested through simulation exercises and tabletop drills. This ensures that human operators are familiar with the system and can use it effectively under pressure.

7 A Simplified Case Study Illustration

Let's conceptualize a simplified example to see how this would work in practice.

Scenario: A district of a city is hit by a severe storm. The initial damage assessment identifies 15 critical road damage points (R1 to R15). We have:

1 Central Depot (CD) and 2 Forward Depots (FD1, FD2).

A fleet of 5 trucks of varying capacities.

Materials required: Sandbags (S), Pumps (P), Quick-dry Concrete (C).

Steps:

1.Data Integration: The integrated platform pulls in the locations of R1-R15, the inventory at CD, FD1, FD2, and real-time traffic data showing that two roads leading to R5 and R12 are flooded.

2.Demand Input: Field crews report their needs. For example, R1 (a flooded underpass) needs 10 units of S and 2 units of P. R7 (a washed-out shoulder) needs 5 units of C.

3.Prioritization: The system automatically scores each site. R1 is near a hospital and gets a high priority. R7 is on a major highway and also gets a high score.

4.Model Execution: The dispatcher runs the optimization algorithm (e.g., a Genetic Algorithm). The inputs are: all demands, all depot inventories, all vehicle locations and capacities, the live road network, and the priority scores.

5.Output - The Optimized Plan: The algorithm outputs a plan in 30 seconds. It might look like this:

Truck 1 (starting at FD1): Go to R3 (Medium Priority, deliver S), then to R1 (High Priority, deliver P). Estimated completion: 85 minutes.

Truck 2 (starting at CD): Load with C. Go directly to R7 (High Priority). Then, if possible, proceed to R10. Estimated completion: 110 minutes.

Truck 3... and so on.

The plan ensures that the highest-priority sites are served first by the most suitable vehicles, taking into account the blocked roads.

6.Dynamic Update: As Truck 2 is en route to R7, a new request comes in from R16, which is even higher priority. The system immediately re-runs the model. The new instruction is sent to Truck 2: "After R7, proceed to R16. Ignore R10 for now." Another truck is reassigned to R10.

In this simulated scenario, the optimized system demonstrates a clear advantage over a manual, first-in-first-out approach, ensuring that critical resources are deployed where they are needed most, efficiently and swiftly.

8 Conclusion and Future Directions

The maintenance of urban road infrastructure in the chaotic aftermath of a torrential rain disaster is a monumental task. The efficiency of the emergency repair effort is inextricably linked to the performance of the underlying material distribution system. As we have argued, relying on instinct and ad-hoc methods in this complex environment leads to suboptimal outcomes, prolonged disruption, and increased risk.

This paper has presented a comprehensive case for treating emergency material distribution as a sophisticated optimization problem solvable through an integrated framework. By combining a resilient physical network of depots, a robust real-time information platform, and intelligent decision-support tools powered by multi-objective models and metaheuristic algorithms, cities can transform their emergency logistics from a reactive chore into a proactive, strategic capability.

The proposed approach acknowledges and directly addresses the core challenges: dynamic networks, demand uncertainty, and extreme time pressure. It leverages technology not as a gimmick, but as a fundamental enabler for situational awareness and computational decision-making.

Future research avenues include UAV integration for rapid assessment and micro-deliveries, machine learning-enhanced demand prediction, and blockchain-secured resource tracking to bolster inter-agency trust. Furthermore, advances in Machine Learning can improve the predictive accuracy of demand forecasting and network degradation. Finally, exploring Blockchain technology for creating tamper-proof and transparent logs of resource requests, allocations, and deliveries could enhance accountability and trust among the various responding agencies.

In an era of climate uncertainty and growing urban density, building resilience is not an option but a necessity. Optimizing the flow of critical resources when the city is at its most vulnerable is a cornerstone of that resilience. By embracing the principles and methods outlined in this paper, city managers can ensure that when the next storm hits, they are not just reacting to chaos, but are actively managing it, guiding their city back to normalcy with speed, efficiency, and purpose.

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