Operations Research Disaster Relief Logistics

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***Abstract*—This project studies two linked decisions in disaster relief: when a response operation can be completed, and how limited relief supplies should be distributed. We use PERT/CPM for nine dependent activities and a minimum-cost transportation linear program for three warehouses and four relief camps. Because the baseline contains 630 available units against 690 units of demand, we explicitly allow shortages and restrict total dispatch to truck capacity. The expected schedule lasts 17.67 days, with critical path A–B–E–F–G–H–I. With 12 trucks carrying 50 units each, the optimization delivers 600 units, leaves 90 unmet and has a penalized objective of 20,650 cost units. We test fleet, capacity and penalty sensitivity, and examine a Nashik-flood scenario using secondary demographic information and illustrative stocks. The study is a reproducible student application rather than a field-validated emergency plan.**

I. INTRODUCTION AND OBJECTIVES

During disasters, saving time can matter as much as saving money. Relief organizers must confirm needs, locate supplies, prepare routes, coordinate vehicles and decide which affected locations receive limited stock. An efficient allocation that ignores preparation delays may arrive too late; a timely schedule that ignores shortages may also fail to support some camps. Our purpose is to use established Operations Research methods in a way that can be understood and replicated. We first estimate activity durations and the critical path. We then optimize warehouse-to-camp flows, and finally test whether different fleet and stock assumptions change the recommended plan. The two methods are linked through planning decisions, not solved as a single time-indexed mathematical program.

Research questions

RQ1. Which response activities determine the critical path and expected project completion time?

RQ2. How can limited warehouse stock be allocated across relief camps while respecting fleet capacity?

RQ3. What happens to delivery shortfalls and cost when trucks, vehicle capacities or shortage penalties change?

RQ4. How does a flood-related geography-based scenario change the trade-off between cost and coverage?

Study design

We combine a 2010–2026 EBSCOhost literature search and Biblioshiny analysis with a synthetic baseline, independent LP implementations reported by the data team, and an illustrative Nashik application. This separation matters: bibliographic counts are observed database records, while model inputs and reported computational outcomes are illustrative scenario results.

II. RESEARCH METHOD AND BIBLIOMETRIC REVIEW

We searched EBSCOhost through the NMIMS library. The broad Boolean query included the compulsory operations AND research terms and disaster-relief, transportation, optimization and scheduling terms; the supplementary query targeted PERT, CPM, critical-path analysis and emergencies. Results were filtered to English, peer-reviewed academic journals for 2010–2026 and sorted by Date newest. The two searches returned 350 and 26 records. One overlapping reference was removed, leaving 375 unique exported references managed in Mendeley and processed with Biblioshiny. The 375 records represent a deduplicated search collection, not the final number of fully eligible studies. The screening workbook flags off-topic records and three case-type entries for review. Abstracts were present for 374 records, DOIs for 370; author-affiliation and cited-reference metadata were unavailable. Consequently, we interpret publication, journal and title-term patterns, but not country-coauthorship or automated reference-citation networks.

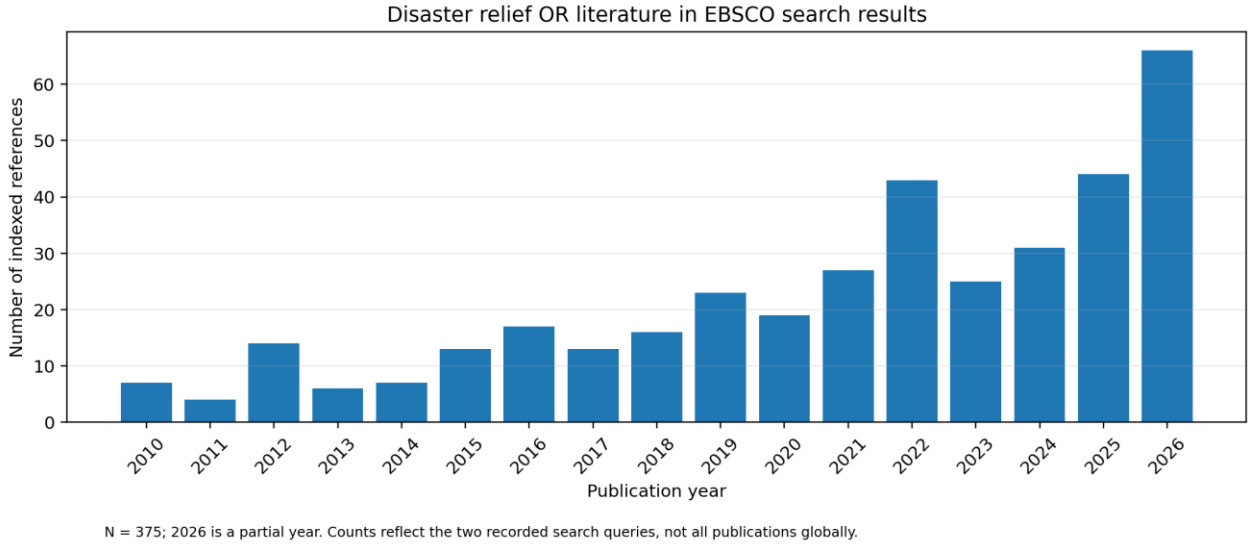

Figure 1. Annual publication records in the EBSCO search collection, 2010–2026. The final year is incomplete.

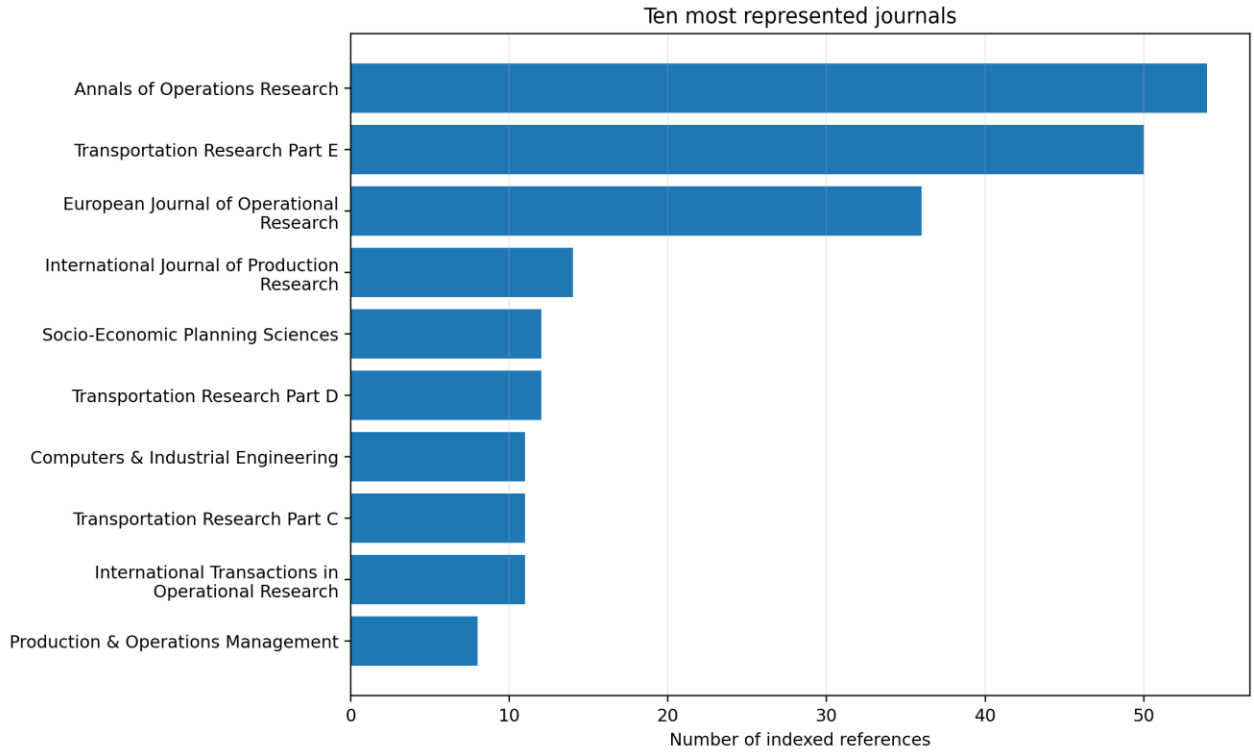

Figure 2. Most represented journals among 375 retrieved references (before final relevance screening).

The leading journals were Annals of Operations Research (54), Transportation Research Part E (50) and European Journal of Operational Research (36). Publication counts increased overall during the search window, although search wording and the incomplete 2026 year affect the observed pattern.

2.1 Literature synthesis and thematic findings

The reviewed papers fall into related streams. Caunhye et al. [1] and Kamyabniya et al. [4] organize emergency-logistics optimization around supply distribution, facilities and transport. Berkoune et al. [9], Afshar and Haghani [10] and Ahmadi et al. [11] address relief flows, operational constraints and

network disruptions. Scheduling studies by Zheng et al. [5] and Wang et al. [7] show how emergency-task precedence and critical paths can support coordination. Sabouhi et al. [6] and de Castro Pena et al. [8] illustrate that routing and scheduling have already been integrated in more advanced formulations.

Research stream	Selected papers	Connection to our model
Reviews & scope	Caunhye [1]; Kamyabniya [4]	Justifies explicit objectives and limits
Task scheduling	Zheng [5]; Wang [7]	Critical activities, duration and slack
Relief allocation	Berkoune [9]; Afshar [10]	Shipment quantities and supply restrictions
Uncertainty/equity	Ahmadi [11]; Ferrer [13]	Road damage, coverage and fairness gaps
Integrated planning	Sabouhi [6]; de Castro Pena [8]	Supports linking schedule and distribution

Our specific contribution is not a new algorithm or the first integrated disaster model. It is a transparent two-stage classroom framework showing how a PERT/CPM timetable can be interpreted alongside a transportation LP, and where the approach breaks down if humanitarian priorities and uncertain roads are omitted.

2.2 Theme and citation evidence

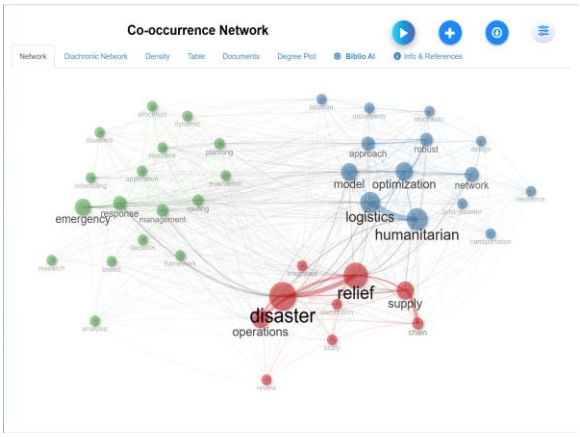

Figure 3. Biblioshiny co-occurrence clusters from article title terms (Louvain clustering).

The network groups disaster and relief operations, humanitarian logistics and optimization, and emergency planning and scheduling. Since the search itself contains several of these terms, clusters are descriptive associations, not proof of a gap. Google Scholar counts recorded by our group on 11 October 2026 cover 19 of 20 core papers: 3,903 citations in total (median 119). Caunhye et al. [1] had the most reported citations (1,264). These counts were manually recorded, vary over time and were not independently checked.

III. MATHEMATICAL MODEL AND SOLUTION LOGIC

3.1 PERT/CPM scheduling

For activity k, a_k is the optimistic duration, m_k the most likely duration and b_k the pessimistic duration (all measured in days). The estimated time is $t_k = (a_k + 4m_k + b_k)/6$, and the variance is $v_k = [(b_k - a_k)/6]^2$. The forward pass gives earliest start ES_k = maximum earliest finish of its predecessors, with $EF_k = ES_k + t_k$. The backward pass obtains latest start LS_k and latest finish LF_k. Slack is $LS_k - ES_k$; zero slack marks critical activities.

Under the simplifying assumption of independent activity durations, the critical-path variance is the sum of its activity variances. We use the normal approximation $P(T \leq \text{target}) \approx \Phi[(\text{target} - \text{mean})/\text{standard deviation}]$ as an indicative planning estimate rather than an operational guarantee.

3.2 Transportation linear program

Indices i = 1,3 denote warehouses; j = 1,4 denote relief camps. S_i is available stock, D_j is demand, c_{ij} is the relative shipping cost per unit, F is the number of trucks, K is units per truck and p is the penalty for each unmet unit. Decision variable $x_{ij} \geq 0$ is the number of relief units shipped from warehouse i to camp j, while $u_j \geq 0$ is unmet demand at camp j.

MINIMIZE $Z = \Sigma_i\Sigma_j c_{ij} x_{ij} + p \Sigma_j u_j$

SUBJECT TO $\Sigma_j x_{ij} \leq S_i$; $\Sigma_i x_{ij} + u_j = D_j$; $\Sigma_i\Sigma_j x_{ij} \leq F \times K$; $x_{ij}, u_j \geq 0$

The shortage variable is essential because baseline supply and fleet capacity are both below total demand. A pure balanced transportation tableau with every demand met would be infeasible. For manual comparison, Vogel's Approximation Method (VAM) constructs an initial tableau allocation and the Modified Distribution method (MODI) tests/improves it. The team used a balanced extension with unused-

stock and shortage dummy cells, subject to the fleet condition. In the computer model, linear programming handles the shortage and truck constraints directly.

3.3 Data and assumptions

The baseline has one homogeneous relief-kit unit, constant unit costs, deterministic requirements, divisible shipment quantities and pooled truck capacity.

It does not model individual vehicle routes, damaged roads, loading times, heterogeneous goods or camp-priority weights. The arbitrary costs are comparative cost units, not rupee freight rates.

Table 1. Baseline relative unit costs and warehouse/camp totals (illustrative student inputs).

Warehouse	C1	C2	C3	C4	Supply
W1	4	6	9	7	250
W2	5	4	6	8	200
W3	8	5	4	6	180
Demand	180	150	200	160	690

IV. PERT/CPM ACTIVITY RESULTS

Nine tasks were assigned three-time estimates. The reported activity calculations were checked against the precedence network. Critical path: A → B → E → F → G → H → I, with expected total completion of 17.67 days.

Table 2. PERT expected durations, earliest times and slack. All times are relative days from project start.

ID	Activity	Predecessor	a / m / b	t_e (days)	ES	EF	Slack
A	Needs assessment	—	1 / 2 / 3	2.00	0.00	2.00	0
B	Inventory / donors	A	2 / 3 / 4	3.00	2.00	5.00	0
C	Relief site selection	A	1 / 2 / 3	2.00	2.00	4.00	3.33
D	Road access mapping	B, C	1 / 2 / 3	2.00	5.00	7.00	2.33
E	Procurement / packing	B	3 / 4 / 7	4.33	5.00	9.33	0
F	Fleet allocation	D, E	1 / 2 / 3	2.00	9.33	11.33	0
G	Dispatch coordination	F	1 / 1 / 2	1.17	11.33	12.50	0
H	Last-mile delivery	G	2 / 3 / 5	3.17	12.50	15.67	0
I	Monitoring / close-out	H	1 / 2 / 3	2.00	15.67	17.67	0

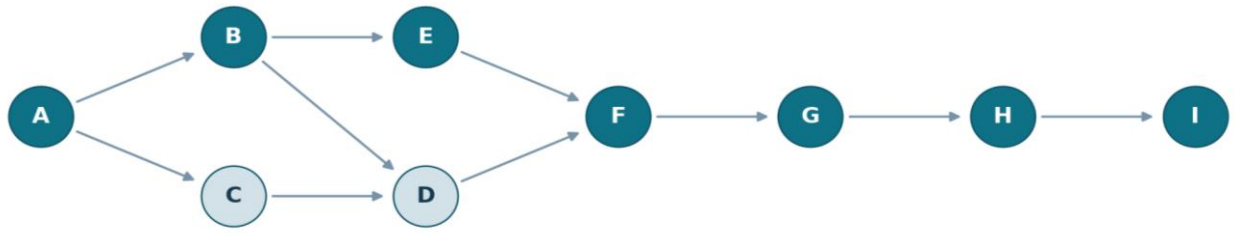

Figure 4. Activity precedence schematic. Dark nodes identify zero-slack activities.

The variance of the critical activities totals about 1.17 days², so their combined standard deviation is about 1.08 days. Using a target of 19 days gives a normal-approximation on-time probability of roughly 89%. This is illustrative and assumes independent durations. Site selection (C) and access mapping (D) have 3.33 and 2.33 days of slack respectively.

An important timing distinction: dispatch coordination is expected to finish at day 12.50; day 17.67 is the completion of the entire operation, including last-mile delivery and monitoring. These schedule outputs are interpreted alongside, rather than embedded as time constraints in, the LP allocation.

V. TRANSPORTATION SOLUTION: BASELINE

The baseline stock is 630 units, total camp demand is 690, and the 12-truck fleet can transport 600 units (12 × 50). Since the shortage penalty is 200 relative cost units per unmet unit, the solver makes full use of transport capacity, leaving 90 units unmet. The reported SciPy HiGHS solution has been reproduced from the supplied cost, supply and demand table.

Table 3. Baseline optimal shipping allocation (illustrative units).

From / to	C1	C2	C3	C4	Hub dispatched
W1	180	0	0	70	250
W2	0	150	20	0	170
W3	0	0	180	0	180
Delivered	180	150	200	70	600
Unmet	0	0	0	90	90

Indicator	Computed value	Interpretation
Inventory	630	30 units remain at W2
Demand	690	Four camps combined
Fleet throughput	600	Binding restriction
Delivered / unmet	600 / 90	87.0% demand covered
Shipping cost	2,650	Relative cost units
Shortage penalty cost	18,000	90 × 200
Total LP objective	20,650	Shipping + shortages

Camps C1–C3 are fully served, but C4 receives only 70 of 160 required units. That outcome minimizes the specified cost-plus-shortage objective; it should not be interpreted as the fair or medically best allocation. A real response model would need minimum service levels or differentiated penalties linked to urgency.

Checks across solution approaches

The implementation contribution describes three calculations of the baseline: SciPy HiGHS, OR-Tools GLOP and a manual VAM-to-MODI transport method.

They agree on the objective of 20,650 for this case. The last method uses dummy rows/columns to handle shortage and unused stock. Our accompanying small Python script independently recreates the baseline allocation, PERT early times and fleet/capacity/penalty sensitivities.

VI. SENSITIVITY ANALYSIS

We changed one parameter at a time, holding the baseline data and remaining assumptions fixed. Fleet-size tests identify a switch in the binding constraint: fewer trucks prevent shipment of available stock, while 14 trucks are enough to carry all 630 stock units. Additional trucks then do not increase delivery because stock, rather than trucks, is scarce.

Table 4. Fleet-size sensitivity at 50 units/truck and shortage penalty 200.

Trucks	Transport cap.	Delivered	Unmet	Shipping cost	Objective
8	400	400	290	1,600	59,600
10	500	500	190	2,000	40,000
12	600	600	90	2,650	20,650
14	700	630	60	2,890	14,890
16	800	630	60	2,890	14,890

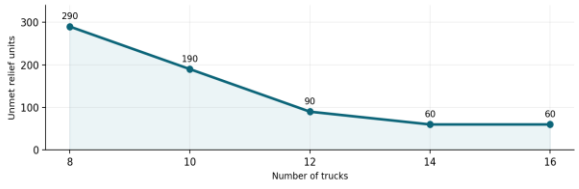

Figure 5. Unmet demand declines until inventory becomes the binding constraint.

At 12 trucks, increasing each truck's capacity from 40 to 50 and 60 units changes unmet demand from 210 to 90 and 60 respectively. Across penalty weights 25, 50, 100, 200, 500 and 1,000, the model still delivers 600 units with 90 unmet; the penalized objective changes because shortage carries more weight, not because extra stock or vehicles become available.

Test	Low setting	Baseline	High setting
Truck capacity	40 → 210 unmet	50 → 90 unmet	60 → 60 unmet
Penalty per unmet	25 → Z 4,900	200 → Z 20,650	1,000 → Z 92,650

A uniform penalty can encourage full fleet use but cannot automatically distribute hardship fairly across camps. A differentiated shortage-cost or service-floor model is the natural next step.

VII. DATA IMPLEMENTATION AND NASHIK EXTENSION

The data contribution describes four data groups: the synthetic 3 × 4 baseline, nine PERT activities, generated scale instances and a Nashik flood scenario. The team reports Python implementations using OR-Tools GLOP, SciPy HiGHS and a coded VAM/MODI method, plus an Excel Solver workbook. The original full repository and dataset generator were not among the materials provided for this compilation, so the claimed timing benchmarks cannot be independently rerun here. The accompanying script reproduces the small baseline and selected sensitivities only.

7.1 Scenario grounded in Nashik geography

The extension uses the August 2019 Nashik monsoon flood as a planning context, with six illustrative beneficiary zones: Nashik, Niphad, Trimbakeshwar, Igatpuri, Peint and Dindori. Population and household counts were drawn from secondary tables reproducing Census 2011 data; rainfall descriptions from a contemporaneous news account; and several road distances from OpenStreetMap-based routing. The share of affected households, available depot stocks and closure assumption are scenario choices, not observed relief requirements.

Table 5. Demand proxies constructed from secondary household figures and a 2% assumed affected-household rate.

Beneficiary zone	2011 households	Assumed kits, 2%
Nashik	389,061	7,781
Niphad	97,419	1,948
Trimbakeshwar	30,410	608
Igatpuri	46,129	923
Peint	24,119	482
Dindori	58,271	1,165
TOTAL	645,409	12,907

Four starting depots were considered: Bhiwandi (6,000 kits), Sinnar (3,500), Chandwad (2,000) and Malegaon (3,500), for 15,000 kits under the full-stock scenario. The model uses kit-kilometres as a distance-weighted cost proxy, not monetary expenditure. Some depot-to-zone distances are estimated using average detour factors rather than independently routed records, limiting geographic precision.

7.2 Nashik case results and interpretation

Table 6. Nashik geography-based scenario outcomes as reported by the implementation team.

Scenario	Stock	Delivered	Unmet	Cost (kit-km)	km per kit
S1: full stock	15,000	12,907	0	1,059,889	82.1
S2: Bhiwandi closed	9,000	9,000	3,907	586,802	65.2
S3: S2 + equal minimum fill	9,000	9,000	3,907	650,302	72.3

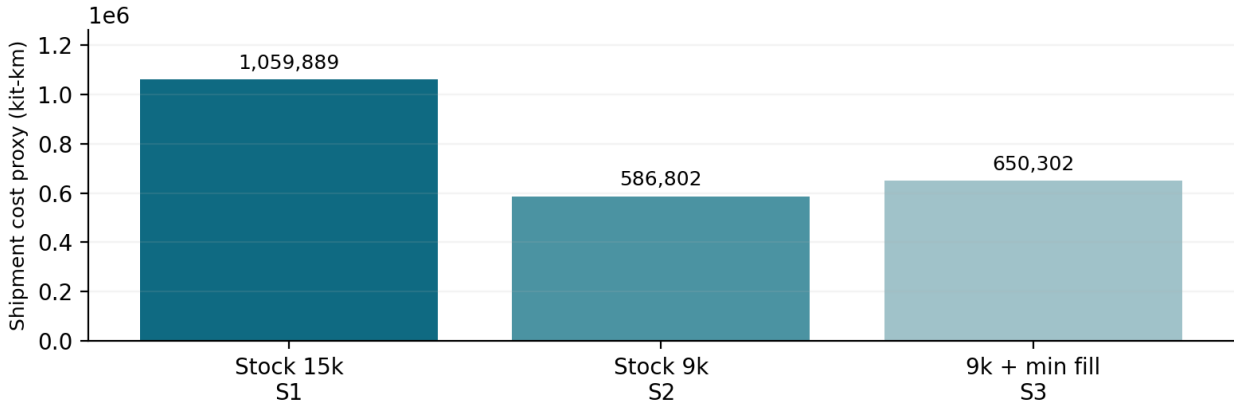

Figure 6. Transport-cost proxy for the three case-study scenarios.

With S1 stock, every zone can be supplied under the assumed inputs. Closing the Bhiwandi depot in S2 reduces stock to 9,000 kits and creates a 3,907-kit shortage. Under the least-cost S2 allocation, some zones receive nothing. S3 enforces a common minimum fill ratio of about 69.7%: the distribution

reaches all six zones but increases the kit-km objective by 63,500 (about 10.8%) relative to S2.

VIII. DISCUSSION AND MANAGERIAL IMPLICATIONS

Together the results show that timing, available stock and transport capacity have different roles. PERT/CPM identifies procurement/packing and the downstream activities that can delay completion. The baseline LP identifies the cost-minimizing allocation for a stated budget of transport capacity; fleet expansion helps only until inventory is exhausted. Nashik S3 illustrates a visible cost-versus-coverage trade-off when an equity constraint is added.

A relief manager could first protect zero-slack activities, then check whether transport or stock is binding before committing resources. A live system should re-estimate road access, supply, demand and delivery urgency as conditions change. Neither the baseline cost matrix nor the illustrative Nashik scenario justifies direct operational decisions without local validation.

Limitations

The LP is deterministic and continuous; it omits truck tours, loading bottlenecks, route failures, perishability, safety constraints and camp-level priority. The PERT normal approximation assumes independent activity durations. The Nashik extension uses older household data and partly estimated distances; all stock levels and affected shares are assumptions. Bibliometric search counts may include irrelevant matches and incomplete metadata. The students' scaled-runtime claims are not re-certified from the materials in this compilation.

IX. CONCLUSION

Our results show why a relief plan needs both a timeline and an allocation model. PERT/CPM gives an expected completion time of 17.67 days and identifies seven critical activities; dispatch coordination is complete by an expected 12.50 days. For the illustrative distribution instance, 12 trucks transport 600 of 690 demanded units at a shipping cost of 2,650 and a penalized objective of 20,650. The scenario tests distinguish fleet bottlenecks from inventory bottlenecks and demonstrate that lowest-cost delivery need not give equal coverage. In a Nashik-based simulation, protecting a minimum service level raises the distance-cost proxy by 10.8% relative to an unrestricted allocation. These findings support a useful educational decision framework, but not a field-ready disaster plan.

X. SOURCES AND REPRODUCIBILITY

The paper uses the group's two EBSCOhost result screenshots, 375-record Mendeley/BibTeX export, 20-paper abstract-grounded comparison matrix, manually collected Scholar counts and Biblioshiny charts. A small runnable script and data audit are supplied in the accompanying submission folder. The original teammate's full Google Colab/GitHub repository was not uploaded, so a live repository URL is still needed if the faculty specifically requires one.

The bibliography below cites selected works represented in the group's references and the documented Nashik case sources. The 20-paper shortlist and search-screening log remain available as separate supporting files. We have not treated all 375 search hits as screened, eligible full-text studies.

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SUPPLEMENTARY EVIDENCE REGISTER

Provided separately in the submission package: two EBSCO search-result screenshots; Mendeley BibTeX and RIS exports; 20-paper literature matrix; citation audit; Biblioshiny visualizations; reference-screening workbook; reproduction script for the small LP and PERT instance. Items are supplementary evidence rather than additional pages of the main report.

SUBMISSION AND SCOPE NOTE

The source materials from the four group members contained different model versions. This document reports the tested shortage-penalty LP for the baseline; distinguishes the Nashik scenario from observed relief operations; and replaces stale comments about incomplete EBSCO/Biblioshiny work with the supplied completed evidence. The scaled original program and a live repository link must still be supplied by the implementation lead if required for code reproducibility.