Journal of Scientific & Industrial Research
Vol. 83, July 2024, pp. 761-771
DOI: 10.56042/jsir.v83i7.7693

Optimizing Strategic Placement of Railroad Accident Relief Equipment: A Simulation-Based Decision Tool

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Received 31 December 2023; revised 03 March 2024; accepted 16 April 2024

This study presents a simulation based method for the comparative evaluation of solutions for location of relief equipment on railway networks—a domain that has been notably neglected in scholarly exploration. To fill this gap a comprehensive simulation framework is introduced that utilizes mathematical modelling and optimization techniques to evaluate the performance of the location solution in different real time circumstances over a long-time horizon. This transportation model considers the demand-supply problem for each instance of accident on a railway network. The model integrates constraints mirroring the practical and operational restrictions associated with moving relief equipment within the network. Application of this transportation model is demonstrated with historical data of accidents and the demand of equipment during each scenario, presenting a practical case study to validate the proposed methodology. Computational experiments are conducted to compare three existing location solutions available in the literature. These location solutions are critically examined to assess their efficacy in addressing the challenges of relief facility placement within a railway network along with analysis of their strengths and weaknesses. It is noted that there is approximately 1.5% less cost of attention and 60% less penalty in the case of the solution obtained through multi-objective problem when compared with two other solutions obtained through 'Set- Covering Model' and 'Existing locations' adopted by the railways considered in the study. By using real-life scenarios, advanced simulation techniques, and comparative analysis of existing solutions, this work not only addresses the current gap in academic research but also sets the stage for further advancements in the optimization of relief operations within complex railway networks.

Keywords: Train accidents, Relief-facilities, Monte carlo simulation, Transportation, Optimization

Introduction

Across the global landscape, railway systems have been diligently pursuing heightened speeds and streamlined transportation of goods and passengers. However, as we strive for greater speed, we are confronted with the pressing challenge of ensuring the safety of our trains. A myriad of dynamic factors come into play, each with the potential to precipitate a catastrophe, whether through increased velocity or other means. Among these factors are human error, technical malfunctions, natural calamities, and deliberate sabotage, all of which persist as constant threats to railway operations. While, concerted efforts are undertaken to uphold the safety standards of train operations, unfortunate incidents still occur with unpredictable frequency, intensity, and ramifications. These accidents manifest in varying forms and magnitudes, rendering their impact difficult to forecast. It is an acknowledged reality that the history of railway development has been marked by tragic accidents, underscoring the importance of ongoing vigilance and precautionary measures.

A head-on collision between a passenger train and a freight train in Greece has killed dozens of people and injured scores more.[1] In July 2013, a commuter train hurtled off the rails as it came around a bend near the north-western Spanish city of Santiago de Compostela, killing 80 and injuring 145 others. An investigation showed that the train was travelling at the rate of 179 kph (111 mph) on a stretch with an 80 kph (50 mph) speed limit when it left the tracks and smashed into a wall. The 2004 Sri Lanka tsunami train wreck is one of world history's deadliest rail disasters. It occurred on December 26, 2004, when a powerful tsunami triggered by the massive 9.1 magnitude Indian Ocean earthquake struck the coastal areas.[1] Similarly, in the devastating triple train accident in Odisha's Balasore recently, which claimed 288 lives and injured more than 1,000 people have caused innumerable loss to the property and prestige to the railways. In this unfortunate accident, the

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Coromandel Shalimar Express, running at 128 kmph, and the Yesvantpur-Howrah Super-fast, at 126 kmph, were nearing the speed limit of 130 kmph (Sharma)[2]. This accident has raised many flags and questioned the preparedness of Railways to handle such a disastrous accident efficiently and save precious human lives.

Indian Railways is one of the world's largest railway networks under single management. The gigantic size and its continuous operation pose various unique challenges. For this purpose, railway has a dedicated framework in place to handle accidents and disasters swiftly and efficiently. The primary objective is to minimize casualties, provide immediate medical assistance, and restore normalcy. A multi-tiered system is employed to manage these situations effectively. Staff members are trained to follow emergency protocols and coordinate with higher authorities to ensure a swift response.

In recent years, Railways has invested in modern technology and infrastructure to enhance safety and disaster management capabilities. This includes the implementation of advanced signaling systems, track maintenance practices, and the use of data analytics to detect potential issues and take proactive measures.[3] It is clear that the system recognizes the need for continuous improvement and learning from past incidents to boost safety measures and ensure agility to meet the challenge swiftly.

Following such incidents, the railway authorities have undertaken several measures to enhance safety and disaster response capabilities — (a) Strengthening safety protocols and guidelines for train operations, maintenance, and infrastructure; (b) Implementing advanced signaling systems, track monitoring technologies, and safety equipment; (c) Conducting regular safety audits, inspections, and risk assessments to identify potential vulnerabilities; (d) Enhancing training programs for railway staff, focusing on emergency response, evacuation procedures, and passenger safety.

Indian Railways maintains a robust disaster management system for accidents and disasters, including specialized stock such as Accident Relief Trains (ART) and Accident Relief Medical Equipment (ARME) vans. These rolling stocks are equipped with the necessary tools, medical supplies, and equipment to handle rescue operations, provide medical aid, and extricate passengers from derailed or damaged coaches. A team of officers and staff is also maintained at the location of the assets to handle and manage it during deployment at the site and keep it ever ready to move at short notice. The location of these vital assets becomes a critical and strategic decision for authorities. These locations are mostly governed by the operational needs like availability of trained manpower and other additional support needed to operate and maintain these critical assets. The speed and capacity of rolling stock to quickly reach the spot of event is also one of the important factors. But there has been very limited attempt to apply mathematical modeling in such a critical decision. Absence of mathematical model based logic and established decision support system has compelled authorities to adopt locations based on their experience. This approach ignores many factors which are capable of influencing the frequency and intensity of the events along with the capability of the disaster management to quickly respond to emergent call for relief. For instance, the location of ARME should be promptly done for the sections where passenger traffic is more than others and possibility of human casualty dominates over other sections. Similarly, the number of Assets needed to the cover the entire network also does not have a mathematical basis. Therefore, it is amply clear that despite the strategic location of accident relief resources being of utmost importance for a complex system like railways, there is a glaring lack of academic engagement. Bababeik *et al.* 2018 and Tripathi *et al.* 2022 are the only few known works who have tried to address the issue of locating accident relief assets to minimize the impact of an accident.[4,5] Mishra *et al*. 2022 have tried to decide the location based on the betweenness and centrality of the node where the siting of the equipment is proposed.[6] This study does not consider both operational parameters of the section of the network nor the parameters governing the ability of the equipment to perform the desired task. It is most simplistic study on such a critical decision.

However, these studies being conducted for different countries and for different operational requirement could not be compared for the efficacy of the result. Other academic engagements are primarily noticed in the rescue and relief operation by deployment of ambulances and other allied mechanisms unrelated to the railways own capabilities in handling the event. The efficacy of these results has been largely confined to the realms of debate and discussion, without actually being able to be evaluated for application in real life situation. The current study is an attempt to develop a tool for such comparison. Primarily, a mathematical method has been developed to conduct a comparative analysis between various solutions, which is the novelty of this work.

Through this work, a model for simulation of various accidents over a railway network is developed to explore the possibility of providing rescue and relief from the shortest possible path in the least possible time to minimize the impact of the accident. The possible scenarios are generated randomly choosing the accident and demand profile at a random location over the network. The demand is supplied from the predefined location as obtained by various mathematical models proposed in literature and a comparative analysis is presented after simulating the events for a large number of repetitions.

Literature Review

In recent years, disaster management has received much attention from academia and industries. The nature of the disaster varies in frequency, and so does the degree of impact it has on the overall surrounding environment. The severity of it also varies with relative effect on humans or material affected. Numerous studies have been done in the past for efficient emergency rescue operations, including the deployment of ambulances and the location of medical relief during various calamitous events.[7–12] Yan *et al.* (2021)[13] offer rescue plans for emergency vehicles on an arterial road caused by accidents. In this study rescue path plan for emergency vehicles based on Markov's decision process is proposed. The rescue route proposed in this work claims that the arrival time to the accident site is 67.1% faster. Similarly, Duan *et al*.[14] provides a swarm algorithm for emergency rescue of traffic accidents. In particular, the study proposes a bi-stage optimization model and algorithm to shorten the emergency response time and control the adverse impact of traffic evacuation on background traffic. Bešinović[15] has undertaken extensive literature survey on resilience of railway network and identifies the rising trend in the application of data driven approach in post disaster management in railways. This study sets the stage for future direction of research in the field of disaster management in railways. Ample research has been conducted in the field of analysis of the cause and impact of an accident on a rail network.

It has been observed from past railway-related accidents that the requirement of such rescue operations is quite different from road-related rescue operations. In particular, along with the unique and complex nature of operational requirements, the peculiarity of the accident and the accessibility of location during an accident in railways are the primary factors in rescue operations. Usually, the location is not accessible by any means other than the railway network itself.[16] So, the requirement for disaster management or accident attention also requires special treatment.

There have been a few attempts by academic scholars to address the issue of location of accident relief equipment over a railway network. In particular, Bababeik *et al*.[4] and Tripathi *et al*.[5] have proposed an optimization-based algorithm for optimization of location of accident relief equipment on a railway network. In the study conducted for Iran railways[4] the relief equipment is considered as single consist of train, which always moves as a single unit during an accident. It carries every asset to each location, even if it is not required at the specific site. Similarly, medical van will be taken to a site where a goods train is involved in an accident with no human casualty. The glaring deficiency of this study was rectified by Tripathi *et al*.[5] by considering movement of these units as a single consist of assets or as a consist of any combination of the assets. In this study, the problem has been dealt in more detail considering the equipment's demand variation with intensity and importance of the accident. This study has considered various factors influencing the specific demand of the resources and the effectiveness of the response during crises.

In this work, a complex problem of determining the optimal location for different types of accident relief facilities on a railway network has been tackled by applying the concept of cooperative coverage. The importance of a rail link was evaluated by factors influencing the operation and probability of accident involving specific type of rolling stock on a rail section. The importance was calculated by assigning weights to the factors by use of AHP (Analytical Hierarchical Process) and then evaluating their relative importance by use of the 'Technique for Order of Preference by Similarity to Ideal Solution' (TOPSIS) method. Further, the problem of location of relief facilities has been solved treating it as a multi-objective problem with following four objectives. The *first objective* is, maximizing the importance of all the links that can be covered. While the *second objective* function, attempts to maximize total coverage in the network. The *third objective* of the problem aims to maximize the assignment of all the nodes to the potential rescue facilities thereby increasing the desired redundancy in the system, whereas the fourth objective assigns the demand nodes to the potential relief facilities such that the overall first response time in the network is minimized. The multi-objective problem has been solved by application of Augmented ε-constraint Method (AUGMECON) proposed by Mavrotas[17] in an interactive fashion to solve the 'Accident Relief Facility Location Problem' named as ARELP.

However, the efficacy and validation of such optimization-based solutions in real-life conditions cannot be computed. In such a scenario, simulation techniques can offer a practical and easy solution for validating the existing solution's efficacy and help arrive at a completely new solution by applying the simulation technique to a real-life situation.

Simulation is a powerful tool used to model and analyze complex systems. It also has the potential to provide insight under different dynamic conditions and identify critical issues in implementing a theoretical concept by exploring various scenarios without being a costly and time-consuming real-world experiment.[18] In the area of simulation techniques, Jain *et al.*[19] have proposed a framework for integrating modeling, simulation, and visualization tools for emergency response, which is the basis for the methodology development. This paper presents a conceptual architecture that partitions the incident management simulation and gaming solution space into standard components. Recent literature is surveyed to identify related models and/or simulators wherever available for each defined component. The suggested components and the survey lay some preliminary groundwork in developing a holistic model of the incident response domain. Overall, disaster operations management focuses on the use of simulation methodology, which can be classified into Spatial Decision Support System (SDSS) and Discrete Event Simulation (DES) models (De Silva *et al.* 2000)[20] In this research, simulation modeling and spatial technologies are coupled to design a system that would combine powerful capabilities of both to aid disaster preparedness process. Spatial Decision Support System mainly focuses on the integration of forecasting early warning with Geographic Information System (GIS) applications. In the Discrete Event Simulation (DES), the system is modelled as a series of 'events' that occur over time. It assumes that there is no change in the system between the events. Numerous works have been done in DES including Homer *et al.*[21] which have proposed a flexible GIS-based network flow model for routing. In their study, scenario visualization is made possible by identifying the locations of the localized distribution centers and including multiple policies. Similarly, the "Disaster Digital Twin" platform consisting of a fusion of real-time hazard simulation to support disaster response teams in the anticipated disaster viz. tsunami is proposed in a study by Koshimura *et al.*[22] In this study they forecast tsunami inundation, social sensing to identify dynamic exposed population, and multi-agent simulation of disaster response activities to find optimal allocation or strategy of response and achieve the enhancement of disaster resilience. In another study Unluyurt *et al.*[23] have evaluated Emergency Medical Service by simulating a locational model. The authors have conducted simulation analysis to evaluate the performance of optimal location of ambulances and the estimation of 'real coverage' of population. Similarly, Basaglia *et al.*[24] have studied the sudden arrival of a high number of injured people to a hospital following a major disaster. Their work have analysed different emergency plans, interviews with healthcare professionals and an extensive literature review to derive two Discrete-Event Simulation models of a hospital digital twin, representing operations in routine and post-earthquake conditions. Similarly Ceferino *et al.*[25] have demonstrated how plans that leverage hospital-system coordination can address this demand-capacity mismatch, reducing waiting times of critically injured patients by a factor larger than two. In this study also, the authors have proposed a methodology to simulate the effective plans for patient transfer and allocation of the ambulances and mobile operating rooms.

From the review of these studies, it is pretty evident that simulation techniques have proven beneficial for performance analysis of various strategies of disaster management. In railway specific application of simulation, Godman *et al.*[26] traces the use of Simulators and different approaches and scales of simulation techniques. Ho *et al.*[27] discuss the difficulties and requirements of effective simulation models for this specialized industrial application and the development of a general-purpose multi-train simulator. In this work, the author attempts to study

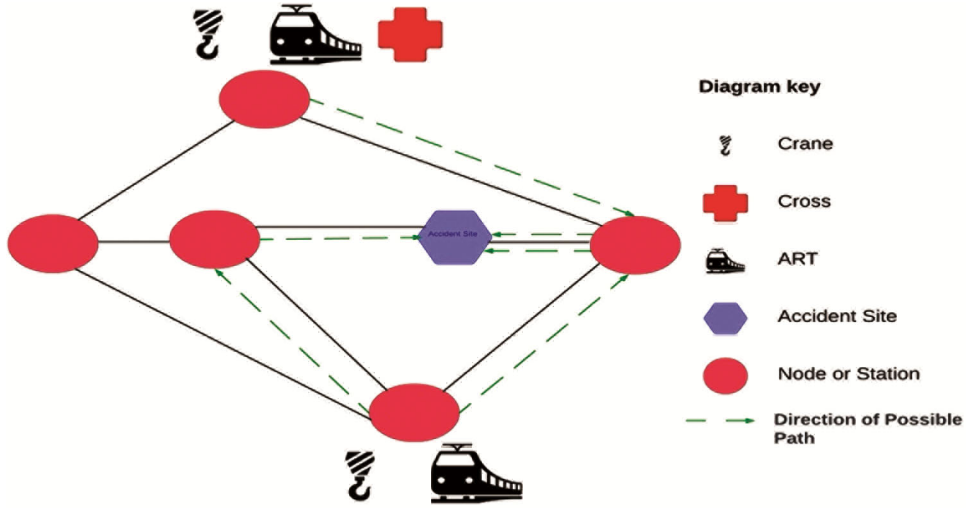

Fig. 1 — Schematic presentation of network [Nodes, Arcs], location of equipment and possible paths

integrated applications of various systems, from train movements to signaling and other allied systems. It includes the study of the performance of multiple machines installed on rolling stock through simulation of the functions of this equipment. In another application of simulation techniques in railways, the behavior of passengers is studied in order to design the safe space required for handling the projected passenger traffic at a railway installation forecasted with rapid economic growth and an increase in the speed of trains. The study is presented by Cao *et al.*[28] Similarly, the delay in train operation due to nodes and station congestion is studied by Kianinejadoshah *et al.*[29] In their work comparative application of analytical and simulation methods have been done for combined railway node-lines capacity assessment.

Simulation techniques have been proven to be a validation tool for abstract concepts in various critical applications, including simulation of various complex dimensions affecting operation and visualization and planning of various critical activities during an emergency. However, there is a need for research on the application of simulation to railway accident rescue operations, which involve complex operations and the location of rescue relief equipment. Accordingly, this work has proposed to simulate the random events of accidents over a railway network and generate the demand for the resources at the time of the accident by utilizing historical data. This work has attempted to address the gap in modelling of location of accident relief trains over a railway network. The mathematical concept of optimization through simulation has been applied to a practical problem to provide a ready-made tool to a decision maker for the validation of a decision based on mathematical fundamentals.

The Problem Description

The problem pertains to locating facilities over a network of Indian Railways, which consists of a series of continuous arcs connecting the two possible nodes in the set N and such a combination of arcs are termed as 'links' in this work. Each link represents a set of stations connected by continuous arcs, with unique characteristics such as track specifications, flow of passenger and freight traffic, and vulnerability. Any point on the network's links can potentially experience an accident and require accident relief facilities. There are certain locations on a network where an accident relief facility or a combination of these facilities can be located. Due to unpredictability of the location, frequency and intensity of the accident, the location of these relief equipment becomes critical in overall scheme of disaster management in Railways. The representative diagram in Fig. 1 depicts possibility of various location and representative combination of the possible paths for deployment of the equipment during emergency.

The railway network considered in this study can be represented as an undirected Graph: G = (N, A), where N represents the set of all nodes (i.e., stations) in the network and A represents the set of all arcs connecting the stations. Let N represent the set of stations that are normal stations or junctions in the network.

The relief facilities considered in this study include Accident Relief Train (ART), Accident Relief Medical Van (ARMV), and Crane, each providing specific services for accidents of varying magnitudes.

The locational decisions already obtained through three different studies have been considered for the purpose of comparison and evaluation of effectiveness of the results. The results obtained by these studies are presented in Table 1.

A comparative analysis is made between above three sets of solutions. First solution being the one explained in literature review section for multi-objective problem and second being the current practice of locating the accident relief equipment over NCR at present. The third solution for demonstration purposes has been taken as a set covering model solved for the coverage of the entire network. By this way the results of three use cases are evaluated and a comparative analysis is done through simulation study in this work. Following is the definition of concept of coverage used in the study.

Definition of Coverage

In this study, each equipment type, namely ART, ARMV, and Crane, possesses distinct capabilities, utility, and cost implications. Practical considerations, coupled with validation, lead us to presume that if a Crane reaches an accident site within 4 hours of ordering, all points/stations within that radius are considered covered. Correspondingly, the time frames for ART and ARMV are 3 hours and 2 hours, respectively. The demand generated through simulation at each node must be covered by at least one relief facility within predefined time or distance constraints else the node is considered uncovered. Multiple facilities can cover a single demand node. The equipment available at the nearest facility is used in order to reach to the site in quickest possible time. The uncovered node incurs a proportional penalty, thereby increasing the cost of accident response.

The Methodology of the Study

The primary objective of this study revolves around validating solutions for a facility location problem. This entails comparing solutions derived

Table 1 — Results of the facility locations obtained through different studies

		Existing			Solution from multi-objective study			Set covering problem		
Sr. No.	Station	ART	ARMV	Crane	ART	ARMV	Crane	ART	ARMV	Crane
1	PRYJ	✓	✓		✓	✓				
2	CNB	✓	✓	✓	✓	✓	✓	✓	✓	✓
3	BANDA	✓	✓		✓	✓	✓			
4	TDL	✓	✓		✓	✓		✓	✓	
5	GZB									
6	JHS	✓	✓	✓	✓	✓		✓	✓	
7	AGC	✓	✓	✓	✓	✓	✓	✓	✓	
8	MTJ	✓	✓		✓	✓				
9	GWL	✓	✓		✓	✓		✓		
10	KURJ									
11	MBA									
12	CAR									
13	NYN								✓	
14	MKP							✓		
15	LAR									
16	DHO							✓		
17	BHA							✓		✓
18	AH									
19	MHF									
20	AWR								✓	
21	PWL									
22	ALJN									
23	SKB									
24	MNQ									
25	ETW								✓	
26	UDMR									
27	BZM									
28	KID								✓	✓

from various scenario combinations within the problem. Historical data from a specific zone is harnessed for simulating scenarios, considering the distribution of demand across the network. The accident relief equipment's placement is pre-defined, and resource supply during crises is simulated, adhering to real-life constraints.

Scenario generation involves random selection of accident locations from the network's list of stations, with demand simulated using the Monte Carlo simulation method proposed by Mooney.[30] Demand for various scenarios are generated by randomly selecting locations across the entire network. The demand generated by the simulation method at every instance should be attended by at least one facility as already described above. The problem is formulated as a transportation optimization program to ensure coverage of demand with given constraints.

The unavailability may arise out of a strategic decision of not locating an equipment at that location or the equipment despite being located is not available at that instance due to either being down or engaged in other activity. In both the cases a suitable penalty is assumed to understand the cost repercussions of these situations and make a comparative assessment of the same. The process flow is elucidated through a flow chart in Fig. 2.

Algorithm for scenario simulation

Input:

1. Network parameters nodes and links (N, A) and distance d_{ij} between them. C_{ij} cost of transportation etc.
2. Set of locations (stations) for siting relief facilities indexed by j.
3. The historic data of past accidents and their demand for different accidents.

Step 1. Chose a random location i form the list I of nodes of the network (N, A)

Step 2. Monte Carlo Simulation for demand generation.

Step 3. Solve the transportation problem for supply of relief equipment from optimal locations to meet the demand generated through step 2 at a location in step 1.

Step 4. Impose the penalty on cost as applicable on the scenario stipulated.

Output. Print the results and compare

"Trans-Sim Optimization Program (TSOP)"

The optimization program as described above is named as 'Trans-Sim Optimization Program'. It is applied to simulate the scenarios based on the demand in the past accidents which have occurred over a rail network. The location of the relief equipment is

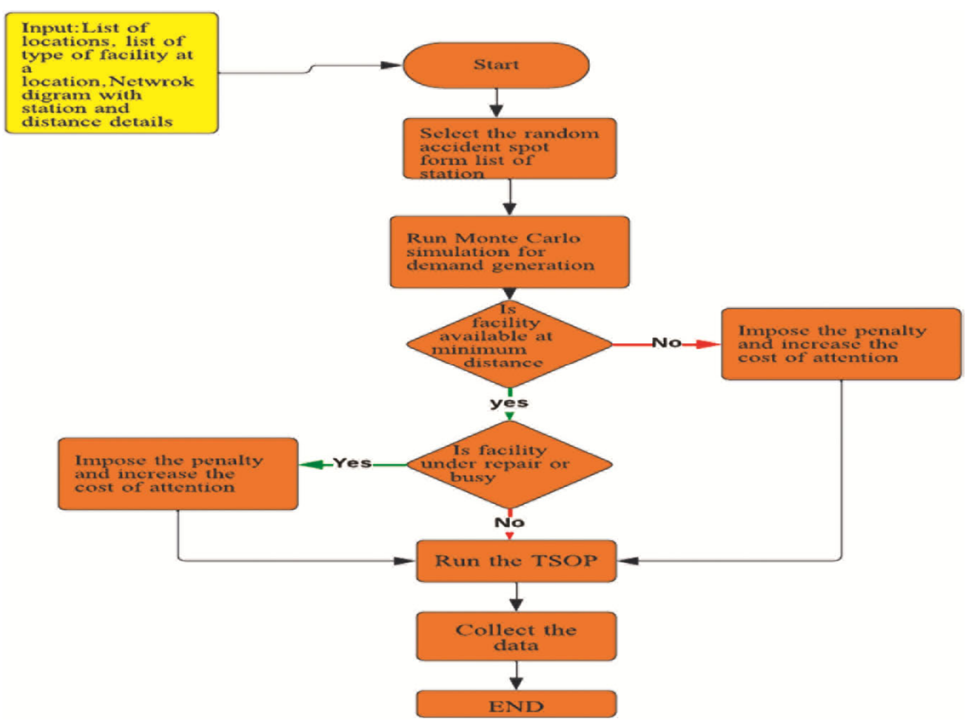

Fig. 2 — Steps in the simulation Algorithm

already known in terms of distance from the accident site and the capability of the site to address the scale of the accident i.e. the ability to supply the required number of equipment for a given instance of the accident. The model is formulated as follows.

Mathematical Model (TSOP)

List of notations

Category	Symbol	Description
Sets and indices	I	Set of demand nodes in the network indexed by i
	J	Set of locations (stations) for siting relief facilities indexed by j
	F	Set of relief facilities indexed by f, F = {ART, ARMV, Crane}
Parameters	C^f_{ij}	Travel cost of asset f from a node I to node j
	H_j	Cost of deployment of asset from a location J
	Δ^f_j	1 if asset f is available at location j,0 Otherwise
	β^f_i	1 if asset f in in demand at location I,0 Otherwise.
	D^f_i	Demand of asset f at location i
Decision variable:		
	x^f_{ij}	1 if an asset f is deployed from point j to a location I, 0 Otherwise.
	Y_j	{1 *if the asset is available at location* 0 *Otherwise*

Objective Function:

$$Min \sum_{f\in F} \sum_{j\in J} c^f_{ij} * x^f_{ij} + \sum_{j\in J} Y_j * H_j \quad \dots (1)$$

Constraints:

$$\sum_{j\in J} x^f_{ij} = D^f_i \quad \dots (2)$$

$$x^{CRANE}_{ij} \le x^{ART}_{ij} \quad \dots (3)$$

$$x^f_{ij} \le \Delta^f_j * \beta^f_i \quad \dots (4)$$

$$\sum_{j\in J} \sum_{f\in Demand} x^f_{ij} \le \sum_{j\in J} \sum_{f\in Demand} \Delta^f_j \quad \dots (5)$$

$$x^f_{ij} \in \{0,1\}, \forall (i,j,f) \in (I,J,F) \quad \dots (6)$$

$$Yj \in \{0,1\}, \forall j \in J \quad \dots (7)$$

The first equation represents the Objective Function of the problem (TSOP), which minimizes overall cost of transportation of assets from available location to the demand point. Constraint Eq. (2) ensures that complete demand at a point should be met by supplying assets from different locations. The additional condition of movement of CRANE always and with ART is satisfied with constraint Eq. (3). The constraint in Eq. (4) restricts supply of an asset from a location where it is available to a location of demand if it is actually in demand and is available at the location. The total numbers of assets to be supplied to a location should not never exceed the demand at that location is depicted through Eq. (5).

Table 2 — Input parameters for the case study

Parameter	Description	
Number of nodes (stations) in the network	105	
Number of links	132	
Type of accident relief facilities	ART, ARMV and CRANE	
The average speed of the relief facilities	75 kmph	
Maximum allowable time (hours)	ART	3 hrs
	ARMV	2 hrs
	Crane	4 hrs

Application of the Simulation "Trans-Sim Optimization Program (TSOP)"

The algorithm is applied to validate various results obtained through the studies mentioned above. The three cases are considered in this study and their effectiveness is compared on the parameters like total cost involved in attending 500 accidents at randomly chosen locations of a railway network. Comparative analysis of these three cases have been done in terms of utilization of equipment from various locations, cost of attending total cases generated during this simulation study.

The locations obtained through three cases mentioned above are summarized in Table 1. These locations of equipment are used as input parameters for simulation study. The input parameters of the case study are given in Table 2.

Equipment and Experiment

All experiments were carried out on a personal computer equipped with an Apple M2 chip, running with the Mac operating system. The computer boasts impressive hardware specifications, including an 8-core CPU, an 8-core GPU, a 16-core Neural Engine, 8GB of unified memory, and a 256 GB SSD storage drive. For the simulation model, Python was utilized in conjunction with the Gurobi Optimizer version 10.0.2 build, which represents the latest and most advanced mathematical programming solver available. This implementation was executed within the Jupyter Integrated Development Environment (IDE).

The results obtained from the computational experiments are discussed below.

Results and Discussion

The distribution of this demand is illustrated in Fig. 3, which was derived through 500 iterations for each case.

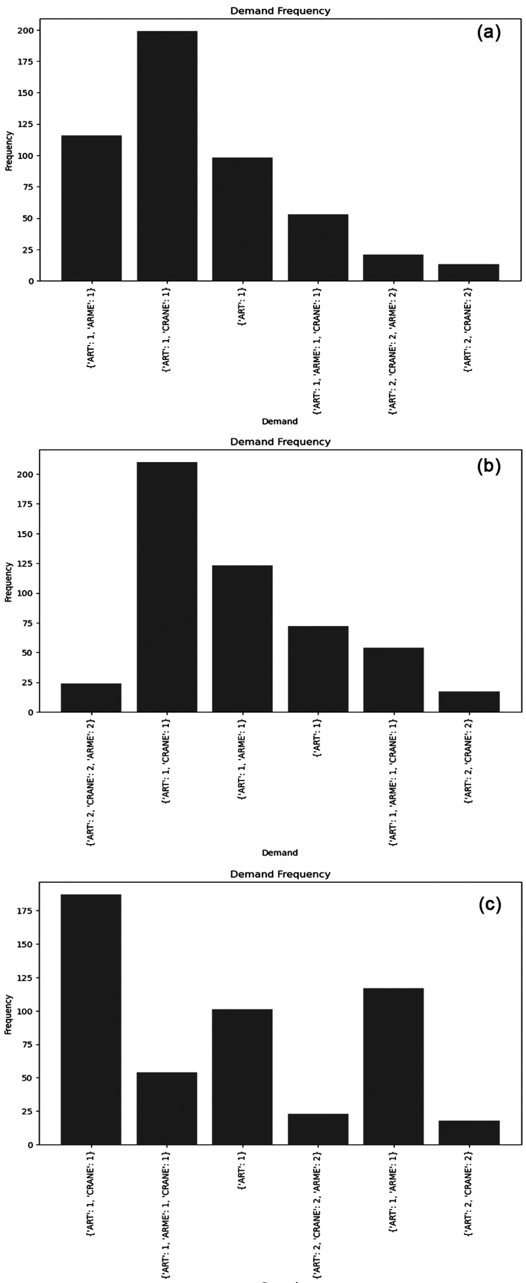

Fig. 3 — Demand pattern in different case of simulation: (a) multi objective, (b) current location, and (c) set covering

Remarkably, across all three cases, the highest demand is consistently observed for the combination of one ART and one CRANE, closely followed by the demand for one ART and one ARME, which matches the historical demand data available and considered for this study.

To fulfill these demands, equipment deployment is executed from various locations, subject to predefined movement conditions or combinations dictated by the demand. The most influential factor governing equipment movement is the condition that CRANE always moves in tandem with ART. The distribution of asset utilization is presented in Table 3.

Notably, in the current location of equipment and the location determination through multi-objective problem solving, the highest equipment utilization is observed from AGC. Conversely, in the case of the Set Covering model solution, CNB location yields the maximum utilization. It is noteworthy that the Set Covering model involves more equipment than the other two considered solutions. In some of the cases, the use of the equipment has been noted to be zero. It is because the equipment is not available at that location in the solutions or it is not located at the location in current scheme of locating the equipment.

The value of the objective function (i.e. the minimum cost involved in attending an accident) of the transportation problem revolves around minimizing the cost associated with responding to accident events. For a comparative assessment of the solutions obtained through three distinct use cases, we compare the total cost incurred in responding to 500 simulated accident cases. Intriguingly, the solution derived from solving a multi-objective problem result in the lowest cost for attending to accidents.

We define coverage in the study (as previously described) and impose penalties on the cost of attending an accident if it remains uncovered due to specific time limits and constraints already defined above.

The total number of penalties imposed for 500 iterations in each case is calculated and compared using the graph presented in Fig. 4. Notably, in the case of the multi-objective approach, the total number of penalties is the lowest when compared to the other two cases. Conversely, the set covering model incurs the highest penalties despite ensuring coverage of the entire network. The reason behind this intriguing result lies in the specific combinations of equipment movements for certain cases. In some instances, the demand necessitates the use of equipment combinations such as 'ART' and 'CRANE' or 'ART,' 'ARME,' and 'CRANE,' while the available equipment for the set covering solution consists of single units or combinations not suitable for the required movements. Consequently, even though specific equipment is available, a location may not be adequately served for the desired combination, resulting in the imposition of penalties. The detailed insight in multi-objective optimization considered in the study reveals that the solution obtained through multi objective optimization serves the best amongst all three solutions available as it provides best result meeting optimality of conflicting objectives.

Table 3 — The distribution of asset utilization for various scenario and demand profiles in different study

		Multi-objective	Current location	Set covering
ARME	AGC	70	63	26
	BANDA	26	6	0
	BINA	16	13	22
	CNB	19	34	45
	DDU	10	26	21
	GWL	7	5	0
	JHS	12	27	11
	JP	9	9	27
	NDLS	21	16	32
	PRYJ	10	14	14
	TDL	11	12	19
ART	AGC	174	172	45
	BANDA	66	18	0
	BHA	0	0	91
	BINA	43	20	44
	CNB	71	89	109
	CPU	2	1	0
	DDU	37	60	63
	DHO	0	0	5
	ETW	0	0	5
	GWL	13	8	6
	JHS	24	77	20
	JP	27	20	45
	MKP	0	0	4
	NDLS	41	33	48
	PRYJ	18	19	29
	TDL	18	24	27
CRANE	AGC	125	121	0
	BANDA	45	0	0
	BHA	0	0	89
	BINA	31	15	30
	CNB	48	68	87
	DDU	27	44	45
	JHS	0	59	0
	JP	17	16	34
	NDLS	27	23	38

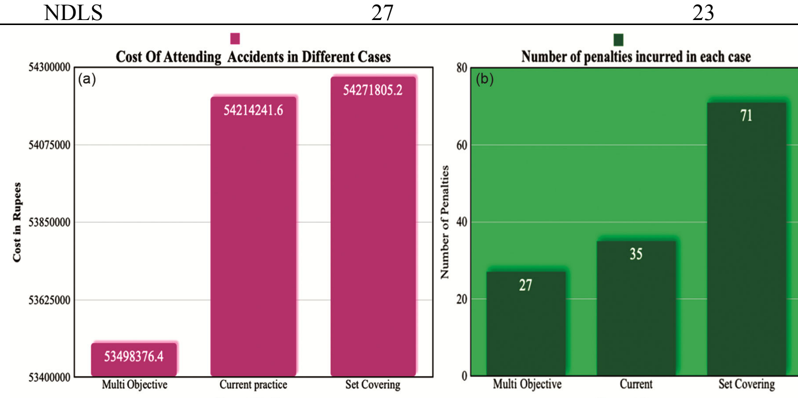

Fig. 4 — Comparison of the Cost of Attending the Accident and Number of Penalty Imposed in 500 Iterations

Conclusions

The paper explores the vital realm of accident relief simulation, shedding light on the complex dynamics and intricate decision-making processes involved in responding effectively to unexpected incidents across a vast network. The strategy of movement of one facility with another emerges as a single primary factor influencing the location decision of the equipment on the network. The study further revealed intriguing variations in asset utilization across different locations. The concept of penalty imposition for uncovered accident sites, as outlined in this study, serves as an important decisive factor in location decision. The operation constraint had played a major role on overall cost of the accident attention including the number of penalties and associated cost. The research proposed through this study is applicable over a vast network of railways with various operational characteristics. As we move forward, these findings can serve as a foundation for further research and practical applications in the field of accident relief and emergency response.

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