Optimization models and solving approaches in relief distribution concerning victims' satisfaction: A review

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Optimization Models and Solving Approaches in Relief Distribution Concerning Victims' Satisfaction: A Review

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Abstract: Relief distribution is one of the most popular topics within the field of emergency logistics. Optimization models and solving approaches have become one of the most powerful tools for tackling relief distribution problems. In this context, victims' satisfaction should be considered as one significant indicator to evaluate relief distribution operations. Therefore, this survey addressed some of the most representative publications working with optimization models and solving approaches in relief distribution concerning victims' satisfaction. Firstly, collected models were discussed from the commonly used objectives for describing victims' satisfaction: the shortest travel time, the lowest unsatisfied demand, and the maximum fairness. Second, gathered solving approaches are analyzed from exact algorithms, heuristic algorithms, and machine learning algorithms respectively. Heuristic algorithms are further studied into four groups: genetic algorithm, ant colony optimization, particle swarm optimization, and others. Finally, three development trends of models and approaches in relief distribution concerning victims' satisfaction are showcased.

Keywords: Relief distribution, Victims' satisfaction, Optimization models, Heuristic algorithms, Survey

1 Introduction

Emergency events have often negative impacts on human life and social development. Natural disasters, public health incidents, major accidents, and other emergencies may all be considered as emergency events. Every year, more than 500 emergency events kill around 75,000 people and impact more than 200 million others [1]. Emergency logistics seeks to make optimal schemes to deliver relief supplies to save lives and reduce victims' further suffering. It is about planning, executing, and controlling the efficient and effective flow and storage of relief materials from the supply depots to the demand depots [2]. Compared with commercial logistics, the cost and time of emergency logistics activities are opposed to each other, and time is more dominant in the goal [3]. Moreover, challenges such as additional uncertainties, complex coordination, limited resources, and harder-to-achieve timely delivery [4] need to be frequently considered to ensure the sustainability of emergency supplies.

Emergency logistics refers mainly to relief distribution, facility location, mass evacuation, and casualty [5] while relief distribution is the one concerned mostly in extant literature. Optimization models and solving approaches have become one of the most powerful tools for tackling relief distribution problems. A lot of research considers relief distribution as a special kind of vehicle routing problem (VRP) to meet victims' needs where limited vehicles have to be scheduled to accomplish delivery tasks in a rigidly limited time. Due to the large number and various types of supplies to be delivered, multiple depots, trips, and heterogeneous vehicles are typically involved [6]. Some works even integrate it with facility location and mass evacuation. VRP is a class of fundamental NP-hard problems [7]. Therefore, relief distribution in emergency logistics is a complex optimization problem that is much more difficult than VRP and its variants in common supply chains.

Unlike commercial logistics where profit ultimately decides whether to visit a customer or not, emergency logistics deals with human lives and has to attend to affected victims as much as possible. Relief distribution is supposed to ensure that the required reliefs are distributed to all demand victims. Thus, victims' satisfaction should be considered as a significant indicator to evaluate relief distribution operations. Many previous works have proposed literature reviews on emergency logistics for particular problems, methodologies, and applications in the last decade [3-9]. However, none of them has concentrated on relief distribution concerning victims' satisfaction, as far as our knowledge is concerned. Therefore, this paper will survey the most representative publications about optimization models and solving approaches in this field to identify some literature gaps and research opportunities.

The remaining sections of this paper are organized as follows. Section 2 discusses relief distribution optimization models concerning victims' satisfaction in three aspects. Section 3 analyzes solving approaches used to solve this group of problems, particularly heuristic algorithms. Section 4 presents discussions and future trends. Finally, conclusions are stated in section 5.

2 Optimization Models

2.1 Relief Distribution Optimization Models

Different from traditional VRP models where goods are distributed by a set of vehicles on routes beginning and ending at a single depot, the network structure of relief distribution optimization models is more flexible. Li et al. [11] proposed a multi-objective integer programming model concerning multi-items, multi-vehicles, multi-periods, soft time windows, and a split delivery strategy scenario where all vehicles began their tours from the same depot to visit one or multiple nodes, and finally returned to the original depot. Vieira et al. [12] formulated large-scale disaster relief in drought scenarios as multi-depot vehicle routing problems where each vehicle started its travel from one depot, upon completion of service to customers, and so it had to return to the depot. Viswanath et al. [13] designed a multicommodity maximal covering network for seeking routes that minimize the total travel time and maximize the total covered population where vehicles were not required to return to the starting depots.

As static models cannot well match real-world applications, dynamic factors and uncertain features are always discussed in relief distribution optimization models. Fikar et. al [14] presented an agent-based simulation optimization framework to model the impact of transport disruptions and disaster relief distribution considering both uncertainties in transport conditions and various actions from victims. Rivera-Royero et al. [15] proposed a rolling horizon methodology that considered dynamic parameters for relief distribution problems after the occurrence of a natural disaster while the assembly process of the relief kits was also concerned. Liu [16] et. al studied a robust model predictive control approach to obtain robust relief distribution plans and adjust them in accordance with updated real-time information in post-disaster relief distribution. Zhou et al. [17] designed a multi-objective optimization model for multi-period dynamic emergency resource scheduling problems where the roadway was a dynamic variable network at different scheduling periods and uncertainty might bring all kinds of risks.

Emergency logistics is a complex system and relief distribution always has an interdependent relationship with other emergency operations. Therefore, a lot of researchers integrated it with facility location and/or mass evacuation as a whole system. Zhang et. al [18] constructed a multi-objective location-routing programming model for emergency response considering carbon dioxide emissions with uncertain information. Vahdani et al. [19] addressed a mathematical integer nonlinear model to locate the distribution centers for, timely distribution of vital relief to the damaged areas, vehicle routing, and emergency roadway repair operations. Vahdani et al. [20] rendered a bi-objective optimization model to plan for relief distribution, victim evacuation, redistricting, and service sharing under uncertainty. Ghasemi et al. [21] studied a stochastic multi-objective optimization model where the pre-disaster phase focused on relief distribution centers allocation and the second phase paid attention to establishing temporary care centers to treat the injured people and distribute commodities to affected areas.

To sum it up, optimization models are widely used for relief distribution problems and they are efficient for most of the variants. The above analysis classified collected publications into three groups from the views of distribution structure, dynamic features, and hybrid systems. It is easy to observe there is no absolute rule to conduct the classification and some papers address attributes from more than one catalog. To better formulate specific applications in real-life environments, the complexity of mathematical models for relief distribution problems is increasing. As most research in this field covers at least one attribute of the three groups, these features will also be considered when discussing relief distribution optimization models concerning victims' satisfaction.

2.2 Relief Distribution Optimization Models Concerning Victims' Satisfaction

Table 1 Comparison of optimization models in relief distribution concerning victims' satisfaction

	Objectives	Constraints		
		Distribution structure (Returning to the starting depot)	Dynamic features	Hybrid systems
Fikar et al. (2016)	Minimize average lead time	Many to many (No)	Traffic conditions	Facility locations
Lu et al. (2016)	Minimize total time	Many to many (-)	Relief demands, and delivery time	-
Wang et al. (2014)	Minimize the maximum traveling time, minimize cost, and maximize the minimize route reliability	Many to many (No)	Route reliability	Facility locations
Wohlgemuth et al. (2012)	Minimize total travel time, minimize the number of vehicles	One to many (Yes)	Travel time, and unknown customers	-
Sabouhi et al. (2019)	Minimize the sum of arrival times of vehicles at affected areas, shelters, and distribution centers	Many to many (No)	-	Mass evacuation
Wei et al. (2020)	Minimize penalty for time window violation, and minimize total operational cost	Many to many (Yes)	-	Facility locations
Ozdamar et al. (2004)	Minimize unsatisfied demand	Many to many (No)	New requests, new supplies, and transportation means that become available	-

Shen et al. (2009)	Minimize unmet demand	One to many (Yes)	Uncertain demands, and travel time	-
Cao et al. (2021)	Minimize unmet demand rate, minimize potential environmental risks, and minimize emergency costs	Many to many (-)	Insufficient and uncertain supplies	-
Ahmadi et al. (2015)	Minimize total distribution time, minimize penalty costs of unsatisfied demand, and minimize fixed costs of opening local depots	Many to many (Yes)	Road destruction	Facility locations
Nayeem et al. (2021)	Minimize commodity shortage, minimize transportation costs, and minimize relief distribution centers' costs	Many to many (Yes)	Uncertain capacity of initial relief distribution centers and relief demands	Facility locations
Sheu et al. (2015)	Minimize relief undersupply impact and minimize relief oversupply impact and	One to many (-)	Uncertain distributing relief resources	-
Bozorgi-Amiri et al. (2016)	Minimize the maximum amount of shortages, minimize total travel time, and minimize total cost	Many to many (Yes)	Affected areas' demands, travel time, and cost	Facility locations
Cao et al. (2018)	Maximize the lowest victims' satisfaction and minimize the largest deviation on	Many to many (-)	Periodical demands and supplies under insufficient	-

	victims' satisfaction for all demand points and sub-phases		supply	
Huang et al. (2019)	Minimize the variance among fulfillment rates and minimize the variance among deprivation times	One to many (Yes)	Periodical demands and supplies	-
Zhu et al. (2019)	Minimize transportation cost, minimize absolute deprivation cost and, minimize relative deprivation cost	One to many (Yes)	-	Mass evacuation
Angelis et al. (2007)	Maximize total satisfied demand	Many to many (No)	Periodical demands	-
Clark et al. (2013)	Minimize unmet need, minimize transportation cost, and minimize inventory cost	Many to many (No)	Periodical demands	-

The shortest travel time is basically the primary factor to be considered in relief distribution optimization models, as loss can be minimized only when the emergency materials are delivered to the demand depots in time and accurately [8]. Moreover, it is important to pay attention to victims' unsatisfied demands if the demand cannot be fully satisfied by a single delivery. Besides, priority to the most seriously affected areas and equity among all depots must be concerned if there are multiple demand nodes. Accordingly, the shortest travel time, the lowest unsatisfied demand, and the maximum fairness are commonly used objectives for relief distribution optimization models concerning victims' satisfaction. All publications involved in this section are listed in Table 1 and the corresponding optimization models are specified by objective functions, distribution structure, dynamic features, and hybrid systems.

2.2.1 Travel Time

Fikar et al. [22] proposed presented a simulation and optimization-based decision-support system to facilitate disaster relief coordination between private and relief organizations with the objective to minimize the average lead time. To achieve the lowest value of total distribution time, Lu et al. [23] proposed a rolling horizon-based framework for real-time relief distribution which consisted of one state estimation and prediction module, and one relief distribution module. Wang et al. [24] constructed a nonlinear integer open location-routing model for relief distribution problems considering travel time, total cost, and reliability with split delivery. With the goal to avoid delays and increase equipment utilization, Wohlgemuth et al. [25] established a multi-stage mixed-integer model considering pickup and delivery problems for forwarding agencies handling less-than-truckload freight in disasters. Sabouhi et al. [26] proposed an integrated logistic system to simultaneously route and schedule vehicles for evacuating people and delivering necessary relief resources where the sum of total arrival times was minimized. Wei et al. [27] discussed an integrated location-routing problem where each affected area was associated with a soft time window for receiving relief supplies while the penalty for time window violation was considered as one objective function.

Travel time minimization is usually the primary objective of relief distribution problems. It is generally counted as the time required since the victims send out demands until the relief is delivered. Although most research does not emphasize it as an objective for evaluating victims' satisfaction, travel time is one that cannot be neglected. Some publications may not discuss travel time directly while lead time, arrival time, time delay, and so on should be considered as the variants. Moreover, travel time minimization is not only widely studied in single-objective optimization problems, but also coordinates with other objectives in multi-objective optimization problems. However, only cooperation between travel time minimization and general objectives such as total cost minimization is considered in this sub-section. Cooperation between travel time minimization and other victims' satisfaction objectives are analyzed in the following two sub-sections.

2.2.2 Unsatisfied Demand

Ozdamar et al. [28] formulated a hybrid model integrating the multi-commodity network flow problem and the VRP to minimize the amount of unsatisfied demand over time. Shen et al. [29] established a deterministic model for stochastic vehicle routing problems to minimize both the unmet demand and the total visit time with a chance-constrained programming technique. Cao et al. [30] studied the relief distribution problem as a bi-level integer programming model where the upper level considered the minimization of unmet demand rate, potential environmental risks, and emergency costs while the lower level focused on the maximization of victims' satisfaction. Ahmadi et al. [31] proposed a multi-depot location-routing model considering network failure, multiple uses of vehicles, and standard relief time where the penalty cost of unsatisfied demand was minimized with another two objective functions. Nayeem et al. [32] set up a robust optimization model to hedge against uncertainties in relief distribution centers' capacity and relief demand with the objective to minimize the weighted sum of commodity shortage and other costs. Sheu et al. [33] addressed a collaboration approach for maintaining supply-demand balance in post-disaster relief by two levels of recursive functions where both relief oversupply impact and relief undersupply impact was required to be minimized in the objective function.

Victims' unsatisfied demands are usually calculated as the difference between victims' expected amounts of relief and actual amounts of relief distributed to victims. A few papers considered victims' unsatisfied demands as the single objective in relief distribution optimization models while it is mainly integrated with other objectives in the multi-objective optimization models. Moreover, unsatisfied demands caused by uncertain demands have received increasing attention. The unmet demand rate and the penalty cost of unmet demands are also widely used to measure victims' unsatisfied demands while commodities shortage and supply-demand imbalance could be counted as the derived forms.

2.2.3 Fairness

Bozorgi-Amiri et al. [34] designed a dynamic stochastic programming model for a humanitarian relief logistics problem. There were three objectives and the one used to minimize the maximum amount of shortages among the affected areas in all periods was for ensuring relief commodity delivery to all demand points. Cao et al. [35] formulated the sustainable disaster supply chain by a mixed-integer nonlinear programming model to maximize the lowest victims' satisfaction, and minimize respectively the largest deviation in victims' satisfaction for all demand points and sub-phases. Huang et al. [36] studied a multi-period relief distribution network with time window and split delivery where three objectives were proposed to minimize the variances of delivery quantities, arrival times, and deprivation times in different locations. Zhu et al. [37] built two emergency relief routing models for injured victims considering equity and priority. The fairness issue was presented by the relative deprivation cost objective and measured by minimizing the absolute value of deviations between the absolute deprivation costs in any two disaster nodes. De Angelis et al. [38] established a vehicle routing variable depot full load model for emergency food aid deliveries by air in Angola. Although the objective function is for maximizing the total satisfied demand, fairness was formulated by a constraint that the lower bound on the demand must be satisfied for each client. Clark et al. [39] developed a network transshipment model for planning humanitarian relief operations in a similar way where fairness was ensured by a constraint that allowed planners to set minimum delivery levels for each recipient.

Commodity shortages, delivery time, and economic valuation are widely used measures to describe fairness in relief distribution problems. Minimizing their maximal values and minimizing their absolute values of deviations or variances in any two disaster nodes are frequently used techniques to formulate fairness. As unsatisfied demand, relief distribution problems concerning fairness are usually studied as multi-objective optimization problems. It can be considered as an extended discussion for travel time and/or unsatisfied demand. However, unlike travel time and unsatisfied demand which are mostly formulated as objective functions, fairness is formulated as constraints in some cases.

3 Solving Approaches

Two specific types of algorithms: exact and heuristic, are widely used to solve difficult combinatorial problems. Exact algorithms use sophisticated mathematical optimization methods to find the optimal solution. Heuristic algorithms search the solution space to find an area in which the solution might be located and then search for a solution in this area. Moreover, machine learning algorithms have emerged as a powerful tool in this field that requires an agent to learn for optimal or sub-optimal decisions based on supervised, unsupervised, or reinforcement learning. Because of their difference, discussions on solving approaches used to generate solutions for relief distribution models concerning victims' satisfaction are organized into three subsections. Moreover, all publications involved in this section are listed in Table 2 for readers' convenience.

Table 2 Comparison of solving approaches used to generate solutions for relief distribution problems concerning victims' satisfaction

	No. of objectives	Algorithms	Solution types
Rivera et al. (2016)	1	Extended bellman-ford algorithm	Optimal
Briskorn et al. (2020)	1	Branch and bound algorithm	Optimal
Safaei et al. (2020)	2	Goal programming	Optimal
Liu et al. (2021)	1	Multiple dynamic programming algorithm	Optimal
Aliakbari et al. (2022)	1	GA	Feasible
Li et al. (2019)	2	Steady-state parallel GA	Feasible
Chang et al. (2014)	3	Greedy-search-based multi-objective GA	Pareto
Ransikarbum et al. (2021)	2	Hybrid NSGA II	Pareto
Huo et al. (2022)	2	Improved NSGA-II	Pareto
Zhou et al. (2017)	2	MOEA/D	Pareto
Ferrer et al. (2020)	6	ACO	Feasible
Wang et al. (2016)	1	Hybrid ACO	Feasible
Zhang et al. (2018)	3	Immune ACO	Pareto
Ding et al. (2011)	1	Fish-swarm ACO	Feasible
Mohammadi et al. (2016)	3	Multi-objective PSO	Pareto

He et al. (2015)	1	PSO	Feasible
Mondal et al. (2019)	2	PSO	Feasible
Ejlaly et al. (2019)	3	Ultra-initiative PSO	Pareto
Li et al. (2014)	1	Improved simulated annealing algorithm	Feasible
Onoda et al. (2020)	2	Reactive tabu search	Feasible
Chen et al. (2020)	2	Improved differential evolution algorithm	Feasible
Ferrer et al. (2016)	6	GRASP	Feasible
Victoria et al. (2015)	1	Multi-start iterated local search	Feasible
Davoodi et al. (2019)	1	Hybrid benders decomposition and variable neighborhood search	Feasible
Alem et al. (2016)	1	Two-phase heuristic	Feasible
Lei et al. (2016)	1	Linear programming relaxation-based heuristic	Feasible
Yu et al. (2021)	3	Q-learning algorithm	Optimal
Fan et al. (2022)	3	Deep Q-Network-based approach	Feasible
Yang et al. (2020)	1	Heuristic multi-agent reinforcement learning scheduling algorithm	Feasible

3.1 Exact algorithms

Rivera et al. [40] designed an extended bellman-ford algorithm to minimize the sum of arrival times for a single-vehicle routing problem raised by disaster logistics where dominance rules, and lower and upper bounds were added to speed up the algorithm. Briskorn et al. [41] developed a method based on a branch and bound approach for solving the problem considering disaster road clearance and relief distribution simultaneously where every demand had to be fulfilled up to its individual deadline. Safaei et al. [42] presented a bi-objective bi-level optimization model to design an integrated framework for relief logistics operations. The goal programming approach was employed for the upper-level decision to minimize deviations of total operational cost and total unsatisfied demand. Liu et al. [43] addressed a multiple dynamic programming algorithm to minimize transportation time for medical supplies in major public health emergencies where the algorithm was a combination of some separated dynamic programming operations.

It is guaranteed that the exact algorithm generates the optimal solution if an optimization problem can be solved. Owing to the calculation accuracy, some researchers improve classic exact algorithms to solve relief distribution problems concerning victims' satisfaction and these algorithms could obtain better performance than commercial solvers such as CPLEX, Gorubi, and LINGO. However, exact algorithms are not able to propose solutions for all problems. Particularly, it is hard for them to generate feasible solutions for large instances in a reasonable time. Thus, the number of publications using exact algorithms to solve relief distribution problems concerning victims' satisfaction is relatively small since these problems are usually considered as large-scale optimization problems in real-life applications.

3.2 Heuristic algorithms

A heuristic algorithm usually consists of 4 components: (1) initial solutions initialization, (2) random operations to get new solutions, (3) objective function and fitness function calculation, and (4) elite strategy to filter good solutions. It iterates continuously from (2)-(4) until the termination conditions are reached. There is no general framework behind the design of a heuristic algorithm that is guaranteed to find the optimal solution. However, the development of heuristic algorithms has received a lot of attention in this field because of the computational complexity of relief distribution problems concerning victims' satisfaction.

3.2.1 Genetic algorithm (GA)

Aliakbari et al. [44] used a GA to solve a multi-echelon, multi-period, and multi-commodity VRP considering the fair distribution of goods and services in a way that social costs were minimized. Li et al. [45] developed a model for the post-disaster road network repair work scheduling and relief logistics problem while a maximum relative satisfaction degree-based steady-state parallel GA was designed to solve this model. Chang et al. [46] addressed a greedy-search-based GA that dynamically adjusted distribution schedules from various supply points according to the requirements to minimize unsatisfied demand, time to delivery, and transportation costs. With a focus on conflicting objectives between fairness and cost, Ransikarbum et al. [47] proposed a hybrid approach based on the non-dominated sorting genetic algorithm-II (NSGA II) to solve the relief distribution and short-term network restoration problem. Huo et al. [48] studied a postdisaster material scheduling and distribution model, and an improved NAGA II where overall dispatch time minimization and maximum waiting time minimization were taken as objectives. Zhou et al. [49] used the framework of multi-objective evolutionary algorithm based on decomposition (MOEA/D) to generate solutions for multi-period dynamic emergency resource scheduling problems considering affected areas' satisfaction and delayed delivery.

Inspired by the theory of biological evolution, GAs simulate the problem to be solved as a process of biological evolution while generating the next-generation solution through selection, crossover, mutation, and other operations [8]. It is probably the most well-known algorithm for solving relief distribution problems concerning victims' satisfaction. Some search uses the basic version directly while most of them modify certain genetic operations according to specific problems to increase overall performance. The NSGA II is inherited from the classic version but has developed as the most widely used method in this field if multiple objectives are considered. Moreover, the ranking and crowding mechanism of NSGA II is the base for many other multi-objective heuristic algorithms.

3.2.2 Ant colony optimization (ACO)

Ferrer et al. [50] developed an elaborated methodology based on ACO to address the last mile distribution problem in humanitarian logistics concerning cost, time, equity, reliability, security, and priority. By combining both saving algorithms and a simple two-step 2-opt algorithm, Wang et al. [51] proposed a hybrid ACO-based algorithm for emergency transportation problems during post-disaster scenarios where fairness and effectiveness were considered. Zhang et al. [52] combined ACO with artificial immune and used it to solve the routing optimization problem of grain emergency vehicle scheduling with needs satisfaction maximization, total cost minimization, and distribution time minimization. Ding et al. [53] designed a fish-swarm ACO to solve an emergency logistics distribution routing optimization model while seeking the shortest delivery time as the ultimate goal.

ACO is a probabilistic algorithm inspired by the ants' foraging behavior. It emulates the way that the ants manage to find the shortest path from their nest to food sources. The positive feedback is kept through the pheromone trails deposited by the ants when they move. Instead of using the basic version, most works develop it as a hybrid algorithm by combining its main idea with other methods. Moreover, a few researchers have tried to use ACO-based algorithms to generate Pareto-fronts for relief distribution problems concerning victims' satisfaction while it remains open to further research.

3.2.3 Particle swarm optimization (PSO)

Mohammadi et al. [54] designed a multi-objective PSO algorithm to solve a stochastic programming model that attempts to maximize demand coverage, minimize cost and minimize satisfaction difference for emergency supplies. He et al. [55] used K-means clustering to set up local distribution centers and PSO to design local optimal allocation routings for emergency relief VRP with the goal to achieve the shortest transport time. Mondal et al. [56] observed that PSO achieved the best results when it was utilized to minimize unsatisfied demand and resource non-allocable percentages for the resource allocation problem in a disaster response situation. Ejlaly et al. [57] found that the ultra-initiative PSO was efficient to produce good responses for the three-level relief cycle logistics under uncertain conditions and on a periodic basis where unfulfilled demand, fairness, and total cost were concerned.

PSO is a population-based stochastic optimization technique that simulates the social behavior of fish schooling or bird flocking. It optimizes a problem by iteratively updating each particle's velocity and position based on the cognition part and the social part. Owing to its high convergence speed, certain research just adopts the basic PSO to solve relief distribution problems concerning victims' satisfaction. However, techniques to avoid the algorithm stuck at local optima should receive more attention. Moreover, some literature has discussed the efficiency when using PSOs to solve multiple objectives optimization problems while there is still a lack of well-known multi-objective PSOs.

3.2.4 Others

Li et al. [58] adopted the improved simulated annealing algorithm to improve the calculation efficiency when solving an emergency resource dispatching model with the objective to minimize total travel time and constraints to decide the routes that need to be repaired first. Onoda et al. [59] proposed a reactive tabu search-based optimal vehicle routing method in the distribution area when a natural disaster occurred where the total distribution time and the maximum time of one distribution were both considered. Chen et al. [60] designed an improved differential evolution algorithm to solve a bi-level programming model for natural disaster relief concerning distribution time minimization and allocation fairness maximization. Ferrer et al. [61] addressed a humanitarian aid distribution model taking into account the cost and time of operation, the security and reliability of the routes, the equity and priority of aid handed out, and solved it by a GRASP-based metaheuristic. Victoria et al. [62] presented a mixed-integer linear program and a two-phase heuristic method based on multi-start iterated local search for solving the VRP with time-dependent demand in humanitarian logistics and total arrival time minimization. Davoodi et al. [63] developed an integrated model to minimize the late arrival of relief vehicles that cross points en route to disaster locations and solved this issue through hybrid benders decomposition and variable neighborhood search. Attempting to improve demand fulfillment policy, Alem et al. [64] established a two-stage stochastic network flow model for logistics planning in disaster relief and proposed a simple two-phase heuristic to solve it within a reasonable computing time. Lei et al. [65] studied a heuristic algorithm based on mixed-integer programming to find an inventory allocation and production plan with a shipping schedule for emergency operations scheduling so that total tardiness is minimized.

Simulated annealing, tabu search, GRASP, iterated local search, and variable neighborhood search are widely used heuristic algorithms for solving optimization problems. All of them can be adapted to generate feasible solutions for relief distribution problems concerning victims' satisfaction although the number of work that we have found in this field is limited. Instead of being used independently, most of them are cooperative with other methods, particularly variable neighborhood search. In addition to existing heuristic algorithms, some researchers have also tried to construct customized heuristic algorithms for specific applications. Computational experiments have verified their efficiency against commercial solvers while a further discussion between the proposed heuristics and existing heuristics is deserved.

3.3 Machine learning algorithms

Yu et al. [66] developed a Q-learning algorithm, a type of reinforcement learning method, to address resource allocation in humanitarian logistics using three critical performance indicators: efficiency, effectiveness, and equity. Several small-scale instances were tested in numerical experiments and showed that the execution time of the Q-learning algorithm was faster than that of an exact algorithm and the accuracy was higher than that of a heuristic algorithm. Keeping the same objective functions as [66], Fan et al. [67] applied Markov decision process to establish the formulation of the emergency supply distribution problem and designed a Deep Q-Network-based approach to tackle this issue. Computational results verified that the proposed algorithm could be a good compromise choice of the exact algorithm and the heuristic algorithm if solving speed and solving accuracy were both considered. Yang et al. [68] studied a heuristic multi-agent Q-learning scheduling algorithm, ResQ, to schedule a rapid deployment of volunteers to rescue victims in dynamic settings with the objective to minimize total distance. Compared with five classical search methods, ResQ had the best overall performance.

Using machine learning algorithms to solve optimization problems is an emerging technological topic. To the best of our knowledge, only three articles have tried to adopt machine learning algorithms to solve relief distribution optimization models while only [66, 67] care about victims' satisfaction. Moreover, all of these studies focus on Q-learning-based algorithms while supervised, unsupervised, and other reinforcement learning methods are overlooked. Q-learning has been proven to converge toward the optimal solution. However, it is hard to guarantee that its variants converge to the optimal solution while some of them even do not guarantee convergence. Although the aforementioned results display that Q-learning-based algorithms obtain better solution quality than heuristic algorithms and save more execution time than exact algorithms, it fails to overcome any of them from all metrics. Therefore, it is still hard for machine learning algorithms to replace exact or heuristic algorithms in this field.

4 Discussions and Future Trends

Relief distribution problems concerning victims' satisfaction has received a lot of attention in recent years. It is widely studied as a single-objective or multi-objective optimization problem where victims' satisfaction is usually formulated as the shortest travel time, the lowest unsatisfied demand, and the maximum fairness. However, few works have integrated psychological factors into victims' satisfaction with relief distribution problems. Different from general satisfaction, satisfaction concerning psychological factors is decided based on the potential value of losses and gains rather than the final outcome. Some researchers have discussed the importance of psychological factors in emergency situations while only decision makers' psychological factors are concerned [69, 70]. Victims' and decision makers' psychological factors are different and need to be formulated separately. Thus, establishing multi-objective relief distribution models where at least one objective deals with victims' satisfaction considering psychological factors deserve further discussion.

Most aforementioned works have discussed victims' satisfaction in relief distribution scenarios through theoretical knowledge and past experience. Rare studies have tried to integrate victims' satisfaction identification with optimization models and solving approaches in relief distribution concerning victims' satisfaction. Traditional methods such as case-based reasoning [71] and time series modeling [72] can be used to forecast victims' unsatisfaction relying on historical data while it is hard for them to work well for in-progress disaster areas. Social media platforms enable victims to keep in touch with outside and share real-time local information. Previous research has used social media data to predict disasters and issue early warnings [73, 74]. However, none of them have focused on mining victims' satisfaction as far as our knowledge is concerned. Therefore, how identifying new objectives and constraints for relief distribution models concerning victims' satisfaction through social media data remains a challenge and needs to be further elaborated.

Exact algorithms are only applicable for small-scale problems while machine learning algorithms are staying at the starting point for solving relief distribution problems concerning victims' satisfaction. Moreover, the computational time of exact algorithms and machine learning algorithms is much longer than heuristic algorithms when solving complex and large problems. Therefore, most studies use heuristic algorithms in this field. However, the execution time of heuristic algorithms is still long for emergency circumstances where decisions have to be made in a very short time. Graphics Processing Units (GPUs) parallelization can generally achieve promising speed-ups for time-sensitive issues. Certain works have tried to propose GPU-based parallel heuristic algorithms for optimization problems [75] while showing the difficulties to execute them completely on GPUs [76, 77]. It is even more challenging to develop GPU-based fully parallel multi-objective heuristic algorithms. However, it is interesting to utilize GPU computing techniques to enhance heuristic algorithms and study how to use them to generate fair solutions for relief distribution problems concerning victims' satisfaction within a short response time.

5 Conclusions

This paper presented a survey for some of the most representative publications working with optimization models and solving approaches in relief distribution concerning victims' satisfaction. Firstly, collected models were classified into three categories by the commonly used objectives and specified by objective functions, distribution structure, dynamic features, and hybrid systems. Meanwhile, the most frequently used formulation for describing victims' satisfaction: the shortest travel time, the lowest unsatisfied demand, and the maximum fairness were summarized. Second, gathered solving approaches were analyzed from exact algorithms, heuristic algorithms, and machine learning algorithms respectively. As the development of heuristic algorithms received more attention in this field, they were further studied by genetic algorithms, ant colony optimization, particle swarm optimization, and others. It concluded that most works combined the main idea of one algorithm with other methods rather than keeping the verbatim port of the original design. Finally, establishing multi-objective models considering victims' psychological factors, identifying new objectives and constraints through social media data, and developing GPU-based heuristic algorithms to solve large-size real-world applications were indicated as the future trends.

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