Decision Analytics Journal 5 (2022) 100128

Contents lists available at ScienceDirect

Decision Analytics Journal

journal homepage: www.elsevier.com/locate/dajour

A multi-objective evolutionary optimisation model for heterogeneous vehicles routing and relief items scheduling in humanitarian crises

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ARTICLE INFO

Keywords:
Multi-objective scheduling
Disaster
Evolutionary algorithm
Optimisation
Relief items distribution
Heterogeneous vehicles
Humanitarian Crisis

ABSTRACT

In a disaster scenario, relief items distribution is required as early as possible for the disaster victims to reduce the associated risks. For the distribution tasks, an effective and efficient relief items distribution model is essential to generate relief items distribution schedules to minimise the impact of disaster to the disaster victims. However, developing efficient distribution schedules is challenging as the relief items distribution problem has multiple objectives to look after where the objectives are mostly contradictorily creating a barrier to simultaneous optimisation of each objective. Also, the relief items distribution model has added complexity with the consideration of multiple supply points having heterogeneous and limited vehicles with varying capacity, cost and time. In this paper, multi-objective evolutionary optimisation with the greedy heuristic search has been applied for the generation of relief items distribution schedules under heterogeneous vehicles condition at supply points. The evolutionary algorithm generates the disaster region distribution sequence by applying a global greedy heuristic search along with a local search that finds the efficient assignment of heterogeneous vehicles for the distribution. This multi-objective evolutionary approach provides Pareto optimal solutions that decision-makers can apply to generate effective distribution schedules to optimise the distribution time and vehicles' operational cost. In addition, this optimisation process also incorporated the minimisation of unmet relief items demand at the disaster regions. The optimised distribution schedules with the proposed approach are compared with the single-objective optimisation, weighted single-objective optimisation and greedy multi-objective optimisation approaches. The comparative results showed that the proposed multi-objective evolutionary approach is an efficient alternative for finding the distribution schedules with optimisation of distribution time and operational cost for the relief items distribution with heterogeneous vehicles in humanitarian crisis.

1. Introduction

Relief items distribution is a type of resource constraint scheduling problem which is similar to many other resource constraints scheduling problems such as workforce scheduling and job scheduling [1]. However, in a disaster scenario, relief items supply is one of the crucial decision-making problems where relief items are supplied from multiple supply points to affected disaster regions. In the relief process, the distribution schedules are aimed to plan relief items supply as early as possible to minimise the disaster impact on the victims, save lives and improve the victim's lifestyle [2,3]. At large, relief items distribution scheduling requires identifying optimal distribution strategies that are mainly intended to minimise disaster victims' suffering [4,5]. In general, under disaster scenarios, the decision-making strategy defines the effectiveness of the relief items distribution [6,7].

In a disaster scenario with multiple supply points and disaster regions, two aspects: deciding the effective sequences of relief items distribution schedules from supply points to the disaster regions and selection of vehicles, are among the key challenges. The distribution schedules directly affect the distribution time and operational cost [8,9], however, the appropriate vehicle selection is crucial too in optimising the distribution task. Considering the vehicle selection, some of the distribution approaches are designed with single-type vehicles for transportation [8,10]. Though, in most disaster scenarios, there appears a heterogeneous vehicle fleet. Therefore, the vehicle selection strategy needs to be based on heterogeneous vehicles where the heterogeneous vehicles have their constraints regarding capacity, cost and speed, which make the vehicle selection task complex. Taking account of these complexities, the appropriate selection of vehicle type is crucial for the optimisation of the distribution tasks [11,12]. The

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https://doi.org/10.1016/j.dajour.2022.100128
Received 29 June 2022; Received in revised form 6 September 2022; Accepted 11 September 2022
Available online 15 September 2022

vehicle selection becomes even more challenging when the supply points have a limited number of each kind of heterogeneous fleet vehicle. Furthermore, effective path selection from supply points to the disaster regions with feasible shortest path has been another challenge for the distribution schedule as in a disaster scenario, more often, many connecting roads get obstructed or permanently damaged [13,14]. These multiple aspects bring the scope of use of multi-criteria decision making as the integrated multi-criteria increase the effectiveness for the decision making process when there appears multi-objective scenario [15]. For the effective humanitarian crisis management, multiple objectives need to be considered together due to the nature of uncertainty and complexity associated with multi-criteria problems [16]. In other words, the decision-makers need to consider multiple criteria while planning effective distribution schedules with a heterogeneous vehicle for relief items distribution in humanitarian crisis [17,18]. With the integrated multi-criteria, decision-makers can plan the effective relief items distribution schedule to minimise the disaster impact.

The scheduling problem that has been considered in this paper is the **Relief Items Scheduling Problem (RISP)** in disaster scenarios. The RISP is a complex problem where the resource is constrained with the distribution of relief items from multiple supply points to multiple disaster regions satisfying the relief demands and available resources. In general, key challenges for RISP are uncertainties on information, limited vehicle availability, efficient resource utilisation and efficient distribution schedule [19,20]. The RISP model presented in this paper is a multi-objective problem in terms of minimisation of distribution time and operational cost on generating relief items distribution schedule from multi-supply points to the multi-demand regions under the heterogeneous vehicles' scenario. The RISP has been broken down into sub-problems in terms of distribution sequence selection, vehicle selection, transportation path selection, and minimisation of unmet relief item demand as shown in Fig. 1. The distribution sequence selection sub-problem covers the selection of optimised disaster regions sequence for the relief items distribution. For this, finding the right sequence is set as the main objective for this sub-problem so that this sub-problem congregates towards minimisation in the travel distance and hence optimising the travel time and vehicles' operational cost. The vehicle selection sub-problem set to optimise the selection of correct vehicles based on the vehicles' capacity and relief demands. The transportation path selection sub-problem covers the selection of shortest travel path from the supply points to the disaster regions whereas the minimisation of the unmet demand subproblem is set to cover the objective that minimises the gap between supplied and need of relief items at all the disaster regions. These sub-problems need to be solved individually as each of these sub-problems has its objectives and constraints.

In this RISP distribution model, the generalised evolutionary algorithm framework is used for the generation of distribution sequences that evolved over generations. For a given distribution sequence, a greedy heuristic search is used to find the best possible choice of selection of supply point for the selected disaster region in the sequence as the heuristic algorithms minimise the time, effort, and errors in comparison to the conventional searching approaches [21]. As a sub-problem, the best fit vehicle selection approach has been applied depending upon the demand request from a disaster region. The best fit selection optimises the vehicles' constraints in terms of capacity, cost and speed. Besides, for effective transportation path selection, a competent search strategy has been applied that covers the global search domain as well as the local search domain to find the best feasible shortest path. The global search explored to obtain the optimum distribution sequence among the number of disaster regions whereas the local search domain selects the nearest supply point for relief items distribution to the particular disaster region in the sequence. All these sub-problems are optimised individually and hence, in the combination, the solution gives the optimised relief items distribution schedules.

The major contributions of the paper are summarised as (i) optimisation of multi-objective distribution in terms of distribution time and operational cost with heterogeneous vehicles (ii) A generalised evolutionary framework with greedy search, in the combination of both global and local search domain, to obtain the distribution sequences and (iii) a best fit based approach for the appropriate vehicle selections that maximises the vehicle selection constraints. For the evaluation of the presented model, single-objective distribution, weighted single-objective distribution and greedy-based evolutionary distribution approaches are compared with simulated results. The comparative study showed that the presented approach has improved results in terms of distribution time and operational cost in comparison to other presented approaches.

The rest of the paper is structured as follows: in Section 2, literature related to the RISP problem is presented. In Section 3, the problem model with the solution method is presented. The subsequent sections present computational experiments and compared findings of the performance of the presented approach and compared it with other approaches. Finally, conclusions and directions are presented for future work.

2. Related work

Over the years, different distribution strategies have been implemented where the objective functions play a crucial part in comparing the results of distribution schedules. In doing so, some of the distribution models only considered one objective at a time, mostly either minimisation of travel time or minimisation of cost, as can be seen in the distribution model used by Safaei et al. [22]. However, optimisation of one objective does not give effective distribution; therefore, multi-objective models are defined for the distribution task [23–26]. In the multi-objective models, objective functions are often optimised by guiding the search technique in its exploration of the search space. Studies on disaster relief items distribution showed that traditional cost optimisation is not the central focus in disaster scenarios. Other parameters such as response time and effective vehicle routes are also among the objective functions [27]. In a multi-objective problem, generally, the objectives are conflicting in nature which prevents simultaneous optimisation of each objective at the same time. Our previous study [28] shows that different methods have been used to resolve multi-objective scheduling problems. Studies around relief items distribution have shown that multi-objective models are mostly categorised as either generalised mathematical approaches or soft computing approaches [29–34].

In the mathematical approach, one of the common approaches is to convert the multi-objective problem into a single objective problem using weighting coefficients [35]. The weighted-sum aggregation approach has been a representative instance of the utility function approach that changes the multi-objective problem into a single-objective problem by assigning weight factor to the objectives [35]. Setting the numerical weights to the objectives as of their relative importance mostly relies upon the decision maker's knowledge. The conventional weighted aggregation-based approach has main weakness in terms of applying only one Pareto solution from one run of optimisation. Kima and Weck [36] proposed an adaptive weighted sum method to solve multi-objective optimisation problems that emphasised unvisited sections by altering the weights rather than applying a predefined weight choice and also specified added inequality constraints. The adaptive weighted sum method produced Pareto optimal solutions within non-convex regions and rejected non-Pareto optimal solutions. The adaptive weighted-sum method approximated a Pareto front by regularly increasing feasible solutions on the front. Defining appropriate weight is always challenging since there is not a fixed rule for the selection of weight factor. Evolutionary dynamic weighted aggregation used [37] to deal with the multi-objective optimisation problem with a concave Pareto front in one run. The optimiser moved from one stable optimum point to another optimum point covering the whole Pareto front. The varying weights force the optimiser to move on the Pareto fronts for the convex points

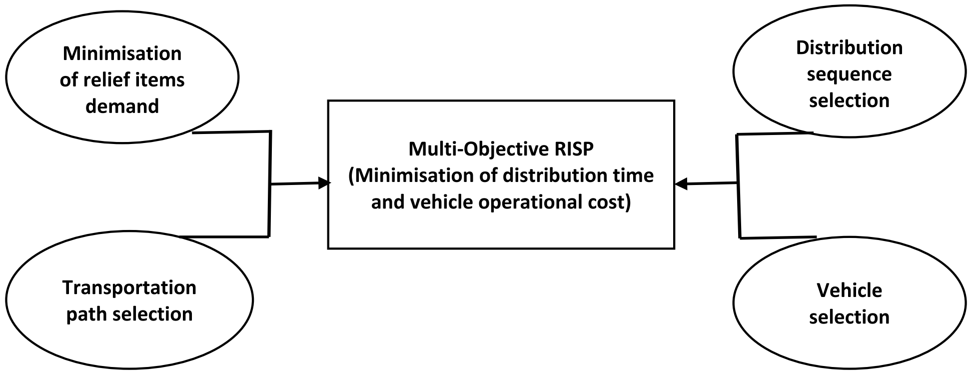

Fig. 1. Relief Items Scheduling Problem and its associated sub-problems.

In soft computing, the general strategy is to identify a complete Pareto optimal solution set or a descriptive subset [23,38–40]. A Pareto optimal set gives a set of solutions that are non-dominated to each other. Selecting one Pareto solution over another Pareto solution, there is always some amount of trade-off among objectives. Pareto optimal solution sets are often chosen over single optimised solutions because they reflect the real-scenario with multi-objectives optimisation. Soft computational techniques have been used to find the direct optimum solution set using a population-based problem-solving metaheuristic algorithm. Pareto approaches [41–44] have been used for multi-objective optimisation under soft computational techniques. Also, identifying the feasible Pareto frontier with the optimisation of all the objectives individually is among one of the approaches for solving the multi-objective problem by applying Pareto ranking [45,46]. These methods are useful for complex problems, mainly those that required scheduling. Chiang and Lin [47] applied an evolutionary algorithm for multi-objective flexible scheduling to get a set of Pareto optimal solutions with diverse populations. Deliktaş et al. [48] applied evolutionary algorithm along with hill climbing approach for job scheduling. In their model, the objective function was guided weighted sum while searching for the optimum solution. Abbas et al. [43] applied Pareto-frontier Differential Evolution (PDE) algorithm to solve multi-objective optimisation with step by step mutation. Those steps were randomly generated from Gaussian distribution. Deb et al. [49] suggested non-dominated sorting based multi-objective evolutionary algorithm called non-dominated sorting genetic algorithm II (NSGA-II), with a fast non-dominated sorting approach. The algorithm used a selection operator that produced a mating pool by combining the parent and offspring populations and selecting the best solutions based on fitness. The modified method found a Pareto-optimal solution set near a reference set points in the neighbourhood of the corresponding Pareto-optimal solution [50]. Solutions close to the reference point helped the decision-maker to get solution close to the preferred region of their priority.

In disaster scenarios, it is often required to determine the optimal combination of vehicles that will generate efficient ways to distribute relief items. Simultaneous optimisation with the vehicle composition and routing is required in heterogeneous vehicle routing (HVR) [51,52]. Choi and Tcha [53] used a column generation based approach for HVR to optimise the routing under given objectives and constraints. The model selected vehicles from different supply points by optimising the travel time and cost. Dondo and Cerda [54] applied a cluster-based optimised for HVR. The model first generated cost-effective feasible clusters and assigned vehicles for distribution within the cluster. The distribution had been based on the "cluster first-route second" principle. The principle applied in such a way that the demand points were clustered considering the given clustering criteria and then vehicle routing had been applied for the distribution within the cluster of demand regions. A constructive heuristic approach with local search [55] was applied for HVR where a demand sequence was generated by constructing a distribution schedule one by one such that the highest priority demand appears first. A scenario-based method has been applied that look after the road condition with heterogeneous vehicles fleet [56]. However, this model did not address the vehicle selection criteria, which is an important aspect of efficient distribution scheduling. Zarouk et al. [57] applied heterogeneous network with variable demand and supply with maximum allowed driving time to generate optimised schedules. A scenario-based results are analysed for investigating the effectiveness of the transportation network. In these all studies, heterogeneous vehicles are considered for the enhancement in the effectiveness in the scheduling task. However, the selection of the vehicles remain challenging in any scenarios.

Over the years, the greedy heuristic search has been among the many approaches that have been used in scheduling problem solving [8,58–60]. Greedy heuristic search generates good-quality, approximate solutions quickly. It applies the heuristic search locally to obtain optimal choice at each stage with the scope of finding a globally optimum solution. Greedy heuristic search is modified in the appropriate ways to address the problem's objectives and constraints that lead to developing a relatively simple system to develop and implement. The RISP also contains vehicle routing problem (VRP) with their constraints as sub-problem. The relief items distribution tasks occur in many geographically dispersed locations, and resources have to travel between supply points and disaster regions [61]. Shadlou et al. [33] applied greedy heuristic search for integrated crew routing and drone scheduling for relief items distribution to the disaster regions. Similarly, Mehtab et al. [32] also applied greedy heuristic approach for the relief items distribution with the multi-objectives. In their work, they consider the uncertainty related with demand and disaster regions' reachability. The greedy search finds the optimum schedule for the relief items distribution under the given scenarios.

Analysing different models for distribution task in the disaster scenarios reveals that most of these optimisation approaches are concentrated on minimisation of time and cost under one kind of vehicle assumptions. However, more often supply points have heterogeneous vehicles. Therefore, effective vehicle routing for the heterogeneous fleet of vehicles is crucial for relief items distribution schedule to operate with flexible demand and transportation circumstances. Considering this, an optimum model is essential to generate the relief items distribution schedules under heterogeneous vehicle scenario to support the victims in any humanitarian crisis.

3. Problem model

The RISP problem can be solved in different ways. One of the approaches can be a weighted single-objective approach which requires some assumptions and prior information from the decision-makers. Different weight ranges are applied to generate a distribution schedule. Because of the assumptions and the priority setting among the objectives, there is a trade-off in the solutions. One way to overcome the problem of defining weights is to use multi-objective optimisation that

Table 1
Variables and description used in the model.

Variables	Description
DR	Disaster Region.
SP	Supply Point.
Dc	Total demand for relief items at disaster regions.
V_t	Vehicle journey from a supply point to multiple demand regions.
r_{ij}	Assigned *DRs* for V_t with the jth journey of to the ith vehicle.
$f\delta d(r_{ij})$	A function that gives the partial relief items at r_{ij} demand regions.
$fdx,\ dy(r_{ij})$	A function that returns the location of r_{ij} demand region.
N_v	Number vehicles assigned in relief items scheduling.
kmax	Maximum number of vehicles journey planned in resource scheduling.
jxi	Executable missions of the assigned ith vehicle.
Φ_i	The velocity of the ith vehicle.
Ψ_i	Cost of the ith vehicle.
T_{ij}	Time spent between demand regions r_{ij-1} and r_{ij} of the ith vehicle.
T_{offset}	Offset time for the vehicle before starting the next journey.
DS	Distribution Schedule.
RI	Relief Items.

does not rely on a single weighted sum value rather compare all the individual objective values against those of other solutions. The multi-objective approach is capable of generating a solution close to the best possible solution without having information on user description and priorities [25]. In this paper, the RISP is modelled as a multi-objective problem covering its sub-problem's issues as discussed earlier. Generation of Pareto fronts with a multi-objective evolutionary algorithm with the greedy heuristic search is considered as a solution approach to find the optimised distribution schedule under the availability of the heterogeneous vehicle at supply points.

3.1. Objective function

Two objective functions and subjected constraints are set for the dynamic relief item distribution (RID) model. The minimisation of total distribution time and minimisation of the total vehicle's operational cost, are the objectives defined for this model incorporating minimisation of unmet demand for relief items at all demand regions. The delay factor (service time) is also applied in cases when any vehicle distributes relief items to more than one demand regions. In this model, a duration of 30 min is applied as delay time at each intermediate demand region in the distribution schedule route. A set of variables, as listed in Table 1, are formulated to define the RISP problem as follows:

i. **Minimisation of distribution time (f1)**

$$\text{Min } f1\ (DS) = \sum_{i=1}^{Nv}\sum_{j=1}^{jxi} \mathrm{T_{ij}} + 30*\mathrm{nV_t} + \mathrm{T_{offset}}, \qquad 1 \le \mathrm{jxi} \le \mathrm{kmax} \quad (1)$$

Where n is the total number of vehicle tours with multiple demand regions.
Subject to:

$$\mathrm{f\ (x)} = \begin{cases} \frac{\sum_{\alpha=1}^{j} \mathrm{D(fdx,dy(ri,j-1),fdx,dy(rij))}}{\Phi \mathrm{i}}, & \text{if } r_{\mathrm{i,j-1}} \text{ and } r_{\mathrm{i,j}} \notin \Phi \\ 0, \quad \text{Others} \end{cases} \quad (2)$$

ii. **Minimisation of total vehicles' operational cost (f2)**

$$Min\ f2\ (DS) = \sum_{i=1}^{Nv} \Psi i \quad (3)$$

Objective 1 and objective 2 are contradictory to each other in the RISP as minimisation of distribution time required the vehicles with higher speed leading to higher cost and vice-versa. In this model, the distribution time is calculated based on the distance travel by the vehicles from a supply point to the disaster regions with their corresponding speed whereas operational cost is calculated based on the vehicles operational cost per hour as listed in Table 3. These two objectives are primarily focused to satisfy unmet relief items demand at each disaster region by minimising the demand with each distribution schedule, mathematically represented as:

$$\text{Min}(DS) = Dc - \left(\sum_{i=1}^{Nv}\sum_{j=1}^{jxi} f\delta d(r_{ij}) \right), \quad 1 \le jxi \le kmax \quad (4)$$

Defining these objectives, five main constraints have been applied: *Supply point constraints*: A SP_i can supply relief items to one or more DR_i only if *RI* and V_I is available at that $SP_{i.}$ *Also,* SP_i can supply *RI* to one or more DR_i. *Demand regions constraint:* A DR_i can receive *RI* only if it has *RI* demand and can receive *RI* from one or more SP_i. *Relief items constraints: RI* are supplied from SP_i to DR_i using assigned $V_{I.,}$ *Vehicle constraints:* The vehicle must start its travel route from an SP_i and ends to assigned DR_i *and can carry RI* up to its maximum capacity. *Location and transportation constraints:* DR_i must be connected with one or more SP_i by available transportation routes directly or indirectly. Apart from these constraints, the following five assumptions are also postulated in this model.

1. The geographical location of supply points and disaster regions are known.
2. The total disaster victims' population of the disaster regions are known.
3. Relief items demand at any disaster regions is proportional to the victims' population at the corresponding disaster regions.
4. Relief items are bounded in a single bundle and can be loaded into any vehicle.
5. Transportation routes between disaster regions and supply points along with corresponding distance are known.

4. Multi-objective optimisation: Solution approaches

In this section, two approaches: Aggregated weight single objective optimisation and Multi-objective evolutionary optimisation are presented.

4.1. Aggregated weight single objective optimisation

Combining different objectives into a single objective is one of the approach for the aggregate multiple objectives into a single objective [62]. Two objectives, minimisation of distribution time and minimisation of vehicle's operational cost, of the RISP, are combined to form a single objective problem with weight factor. In this aggregated weight single objective optimisation, individual objective functions are normalised in their respective objective space then multi-objective optimisation is performed applying the usual weighted-sum approach. Selection of the right weight for individual objectives is always challenging as it depends on the decision makers' priority [63]. Finding

Table 2
A sample chromosome.

D1	*D6*	*D3*	*D8*	*D2*	*D5*	*D7*	*D4*	*D9*	*D10*

the right weight and hence the corresponding single objective function is challenging as there has been no standard guidelines for the weight selection. To overcome this limitation, different weights values are as used in functions *w1* to *w9* in the range 0.30 to 0.70. An interval of 0.05 is set to increase or decrease of the weight factor in the function w1 to w9. With these different weights, the optimised results are used to check the response of the weight factors to the single-objective optimisation. The use of different weight values gives a wider sense of comparative results so that the optimum result can be chosen. For the aggregation, the time and cost value are used as a normalised value since they have different unit. In normalisation, the maximum value is set to one and all other values are divided by the maximum value hence the normalisation process set the values in the interval [0,1].

w1 = 0.30 * time (f1) + 0.70 * cost (f2)
w2 = 0.35 * time (f1) + 0.65 * cost (f2)
w3 = 0.40 * time (f1) + 0.60 * cost (f2)
w4 = 0.45 * time (f1) + 0.55 * cost (f2)
w5 = 0.50 * time (f1) + 0.50 * cost (f2)
w6 = 0.55 * time (f1) + 0.45 * cost (f2)
w7 = 0.60 * time (f1) + 0.40 * cost (f2)
w8 = 0.65 * time (f1) + 0.35 * cost (f2)
w9 = 0.70 * time (f1) + 0.30 * cost (f2)

4.2. Multi-objective evolutionary optimisation

The multi-objective evolutionary approach has been applied as another solution strategy for RISP. A multi-objective approach can generate solutions without knowing the decision maker's preferences. The major concern of the multi-objective optimisation evolutionary optimisation is to explore a set of acceptable relief items distribution schedule as solutions that can be used by the decision makers. The decision-makers can choose the feasible distribution schedules from the population of solutions.

4.2.1. Evolutionary algorithm design

i. **Coding and Decoding**

In this work, a disaster region-based sequence coding–decoding has been applied to represent a chromosome. In the coding–decoding process, each disaster region is considered as a unique gene in the chromosome structure. The genes of the chromosomes, as shown in Table 2, is a sample example of the disaster regions sequence that needs relief item from the supply points. In this table, the symbol *D1* to *D10* represents demand regions in the form of a gene of the coded chromosome. Random order of all demand regions is used for chromosome coding while generating the initial population. In the population set, each chromosome represents a solution to derive distribution schedules from the supply points using a greedy-search-based strategy. The greedy search applies to find the supply points for the relief items distribution to the corresponding disaster region, encoded as a gene. This greedy search strategy starts from the first gene of the chromosome and then second and so on till the searching strategy finds the supply points for all the genes of the chromosome. The search strategy considers the demand for relief items of the corresponding disaster region and finds the nearest supply point for the supply relief items. When any vehicle tour is planned with extra relief items, the demand of the individual demand region is updated accordingly in the sequence.

ii. **Selection Operator**

The selection operation chooses the individuals based on their fitness for reproduction considering both the objectives of the RISP problem. For the population diversity at each generation, mixed populations with ranking and tournament selections approach are applied. Elitism is applied to increase the performance of the evolutionary algorithm. Solutions based on minimisation of distribution time and minimisations of operational cost are sorted as of their objective function individually. Best 10% individuals of objectives: minimisation of distribution time, minimisation of operational cost and 10% of non-domination ranks Pareto front solutions are preserved at each generation. The remaining population domain is selected based on tournament selection. For the tournament selection, 30 tournaments are run among randomly selected individuals from the population. The winner of each tournament is selected as a representative population. Altogether, 60 individuals are chosen as population density at each generation.

iii. **Crossover Operator**

Crossover expects to carry the features of two selected parent solutions to next-generation offspring solutions. Two cut points are randomly selected and the swapping of genes between the cut points of the chromosomes is applied in the crossover process. After the crossover, the offspring may have contradictory genes because of the gene swapping. To avoid such cases, a repair process has been applied to avoid contradictions in the proposed algorithm. In the repairing process, any duplicated gene occurring in the gene sequence is replaced with the missing gene (disaster region). While repairing the chromosome, all the disaster regions representation in the chromosome sequence is guaranteed.

iv. **Mutation Operators**

The mutation is applied to execute the swapping of genes. Two random numbers are generated to find mutation genes and hence swapping of genes is applied as mutation function. The process is continuously applied for many iterations. 0.05 mutation rate is fixed in this evolutionary approach after several experimentations with different mutation rate ranging from 0.01–0.5 with a gap of 0.05. With each mutation rate, the corresponding model has been evaluated. With this evaluation, the mutation rate 0.15 has found to be the best among the other mutation rates.

4.2.2. Distribution model: The proposed approach

The process for the evolutionary algorithm is applied as shown in Fig. 2. First of all, evaluation is applied to the solutions of the first-generation population according to the non-dominated method, and hence, Pareto level sorting is generated. At first, all the information, related to a disaster such as disaster regions, supply point, available vehicles and their types, connecting travel routes and available relief items are gathered. Based on this information, the initial population is developed with a set of randomly generated chromosomes representing the sequence of demand regions being served. A greedy heuristic search is applied to find the nearest supply point for each disaster region in the sequence. The greedy algorithm also includes a local search to assign the vehicles from the heterogeneous vehicles fleet for the relief items distribution. The distance matrix is used for the nearest supply point finding.

Greedy heuristic search is applied to each gene of the chromosome where the demand regions search for the nearest supply point first for the relief items. The greedy search finds the nearest supply point based on the shortest distance between the supply point and the corresponding demand region and resource availability at the supply point. The search look to assign the nearest supply point to allocate relief item distribution with the selection of appropriate vehicles to the corresponding demand region. If the nearest supply point does not have the required relief items or the vehicles availability, the greedy-search looks for the next nearest supply point that have enough relief items and vehicles. With the greedy-search, each demand region gets its corresponding supply points based on the relief items and vehicles availability. The greedy search also implements the vehicle's free space check to each assigned vehicle for each transportation tour. If the

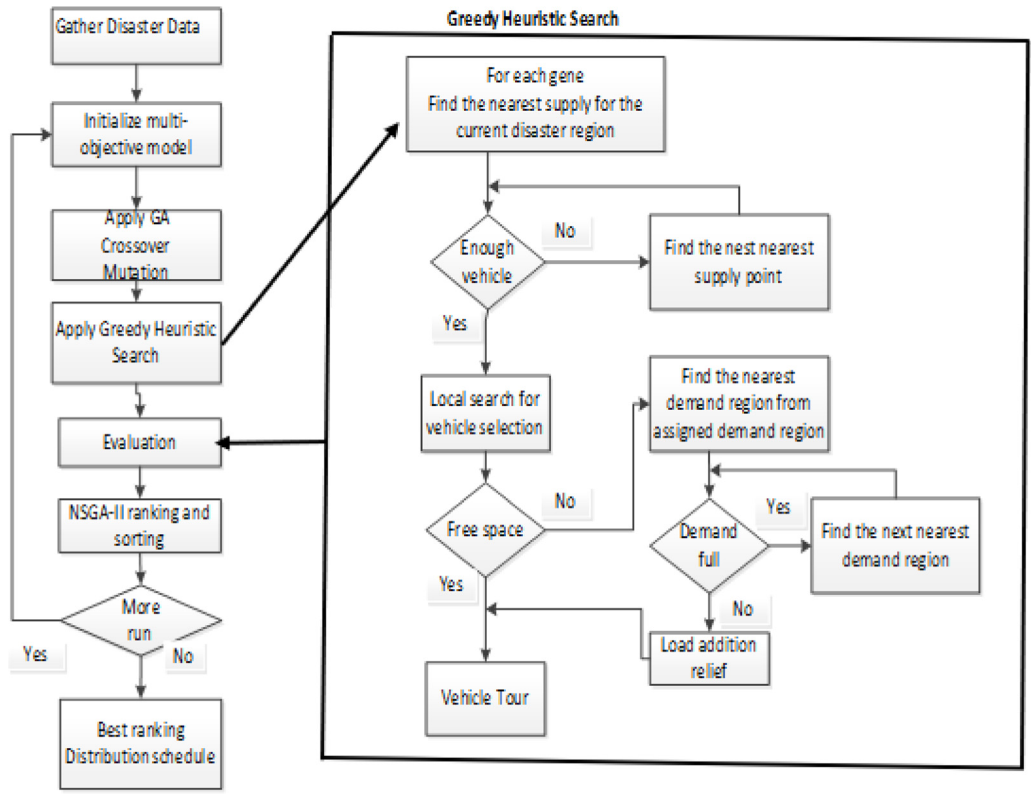

Fig. 2. General flow of RISP solving using evolutionary approach.

relief load of the assigned vehicle is more than 90% of the loading capacity, the vehicle carries relief items to the assigned demand regions only. In case if the assigned vehicle has more than 10% space to carry extra relief logistic then a greedy heuristic search is applied to explore the best nearest feasible demand regions from the currently assigned demand regions to deliver the extra relief items. The additional vehicle is assigned as per the demand need with the free space check on each vehicle trip. Once the demand of the nearest demand regions is met, the algorithm generates a transportation tour for the next nearest neighbour in the chromosome gene sequence. The genetic algorithm (GA) is applied to optimise the sequence of disaster regions being served such that it optimises relief items distribution schedule.

The distribution schedule is planned for all the disaster region of the chromosome and hence evaluated the solution strength of each solution in the set. An evolutionary algorithm is used to find the Pareto fronts of the solution set. GA is applied to generate a new set of chromosomes with 100 iterations. 100 iterations have been applied as a limiting number to get the optimum solution as the simulation with higher number of iterations has not shown any further convergence. Elitist non-dominated sorting GA (NSGA-II) applied where Parent and offspring populations are selected together and hence, non-dominated sorting is applied to generate the combined population into multiple levels of non-domination. Solutions from the best non-domination levels are selected front-wise as a subset of solutions.

5. Computational experiment and result analysis

The performance measure is applied to analyse the effectiveness of the proposed multi-objective RISP model with a heterogeneous vehicle fleet with the case study formulated analogously of the Chi-Chi earthquake in Taiwan [8]. In this case study, disaster information in terms of the suffered population had been collected from the disaster regions. Relief items had been distributed to twenty-nine disaster regions from four supply points. The simulation had been performed with R-programming.

Table 3
Vehicle parameters of each type at supply points.

Parameter	Type-1	Type-2	Type-3	Type-4
Cost/Hour (£)	1000	1500	2200	3500
Capacity (kg)	4000	3000	2500	2000
Speed (kmph)	40	50	60	80

Table 4
Vehicle count of each type at supply points (S1: S4).

Supply point	Vehicle-type 1	Vehicle-type 2	Vehicle-type 3	Vehicle-type 4
S1	4	2	3	3
S2	3	4	5	3
S3	4	6	2	5
S4	5	5	7	5

5.1. Heterogeneous vehicles routing (HVR)

The objective of HVR is to select the vehicle sets and routes from the supply points by optimising the selection criteria. For the HVRP in this model, vehicles are considered from four categories based on their cost, capacity and speed. A fixed synthesised value on vehicle cost, capacity and speed are considered for each vehicle types as presented in Table 3. The number of vehicles available of each type at each supply point assumed in this work is listed in Table 4.

The best-fit algorithm is applied as a sub-problem domain for the selection of vehicle at any supply point for the transportation of relief items from that supply point to the assigned disaster region. In this algorithm, best fit vehicles in terms of vehicle capacity are compared with the relief items demand of the disaster regions. The optimisation is applied based on the best-matched vehicle in term of demand and capacity. The sub-problem optimises and generate different vehicle selection which directly affects the global distribution sequence optimisation and disaster region demand minimisation.

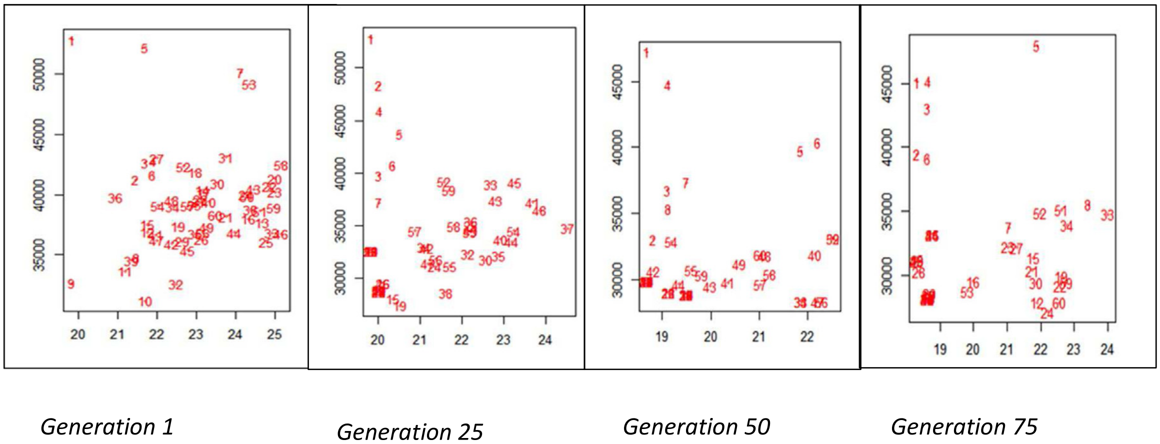

Fig. 3. Generation of Pareto fronts with intermediate stages.

5.2. Evolutionary algorithm design analysis

To optimise the multi-objective using an evolutionary approach (NSGA-II), Pareto fronts are generated to find the best distribution schedule. At first, the evolutionary algorithm design is evaluated regarding selection, cross-over and mutation rate responses on Pareto fronts convergence. Simulations results have been conducted to identify the suitable operators and parameters of the evolutionary algorithm. In the evolutionay process, an individual chromosome has been generated by randomly assigning each disaster regions as a gene in the chromosome structure. The population size is set as 60 with random chromosomes generation. A combination of rank and tournament selection methods has been applied to form the mating pool. Elitism is used by selecting the best 30% solutions based on ranking (minimum distribution time, minimum cost and Pareto fronts) from the current generation to the next generation. The remaining individuals are decided based on tournament selection. Two-point crossover with the repair is applied to avoid any possible conflict in genes exchange during the crossover. This allows removing chromosomes with the faulty gene in terms of repetition of the same gene or missing any gene in the chromosome.

Fig. 3 shows the generation of the Pareto fronts with intermediate stages in an evolutionary approach. Four plots show how the evolution algorithms converge into Pareto fronts with each generation. It also shows how the solutions with the assigned selection, cross-over and mutation parameters values converged into better Pareto fronts at a faster rate.

5.3. Performance analysis

In the computation experiment, the RISP has been solved with three different approaches and results are compared to validate the efficiency of the proposed scheduling approach for relief items distribution. In the first approach, the problem is evaluated independently based on individual objective functions: minimisation of distribution time and minimisation of operational cost. In the second approach, these two objectives are evaluated as a single objective function by applying different weight functions (w1–w9) to the objectives. Since the outputs range of these objectives is different, so normalisation has been applied to both objective values. In the third approach, the problem is solved using the evolutionary approach NSGA-II. The distribution time and operational cost for each solution are compared with single-objective methods, weighted single objective method and GSMOGA (Greedy-Search-based Multi-Objective Genetic Algorithm) to compare the effectiveness of our approach for RISP distribution schedules in a disaster scenario.

In the first approach (single-objective optimisation), for the analysis, 15 simulation runs have been applied and the average values of these best solution of the 15 runs are set for result analysis. The performance measure showed that applying the minimisation of time can achieve lower distribution time but it also has been noticed that there has been a higher range of operational cost as minimisation of distribution time selected the vehicles with higher speed requiring higher operational cost and vice-versa for the minimisation of cost the first and the second bar in Figs. 4 and 5. This shows that individual objective optimisation is not a feasible option as it leads to giving a contradictory higher value of other objective function. In the second approach, aggregated weighted single objective has been applied. In this second approach, defining the appropriate weight is challenging to combine two objective functions into a weighted single objective. To overcome this, a different range of weight factors (w1–w9), as described in Section 4.1, have been applied to combine two objectives. With the normalised values distribution time and operation cost of the best solution is noted for each weight combination. From the plot, as shown in Figs. 4 and 5, it has been observed that with higher the weight factor of distribution time the better is the solution and vice-versa for the operational cost. This signifies that there is a trade-off between distribution time and operational cost while applying the right weight factor. Defining the right weight factor is a challenge for the decision-makers to find an efficient distribution schedule. Analysis of the results from these two approaches justifies that there is the need for multi-objective optimisation that can give a solution with minimisation of both distribution time and operational cost simultaneously.

With the defined set-up, the evolutionary algorithm (NSGA-II), has been applied for multi-objective optimisation. The evolutionary algorithm optimises both the objective simultaneously. After all these experimental results, the performance plots of the best solutions regarding the best minimum distribution time and operational cost among the solution approach four approaches have been compared as presented in Figs. 4 and 5. Comparing the results, it has been observed that the evolutionary algorithm has a better result in comparison to the other three approaches as it gives a simultaneously optimised solution with two objectives. While comparing the best result from the NSGA-II, it has been noted that the NSGA-II solution takes 0.1 more hours as distribution time than the best solution when the only minimisation of time has been optimised but that has the highest operational cost among all the plotted solutions. In terms of operational cost, NSGA-II has as best as the solution found by minimisation of operational cost only. Analysing all the results, it can be observed that the NSGA-II approach for relief items distribution schedule with the heterogeneous vehicle also shows efficient results in terms of both distribution time and operational cost than other presented methods.

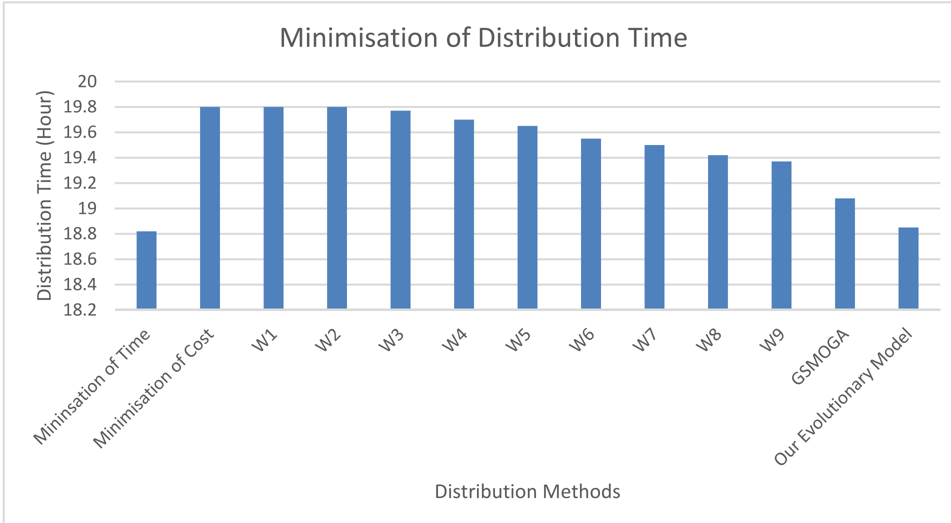

Fig. 4. Comparison plot of delivery time (f1) taken by the best solutions for different approaches.

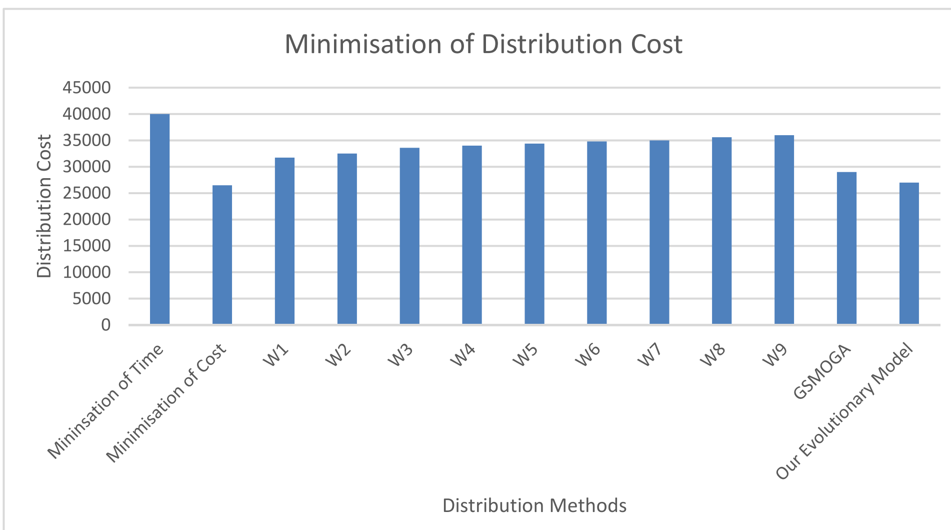

Fig. 5. Comparison plot of delivery cost (f2) taken by the best solutions for different approaches.

6. Conclusion

An effective relief items distribution schedule is the main concern for any post-disaster relief management in humanitarian crisis. Minimisation of distribution time and operational cost are the two major objectives for RISP. In this paper, RISP with heterogeneous vehicles with varied speed, cost and capacity has been considered. A greedy heuristic search is applied to find a suitable assignment of vehicles for relief items distribution from a supply point to disaster regions. Finding the effective relief items distribution strategy is the key priority to the decision-makers after any disaster. The effective relief items distribution helps to minimise the disaster impact and help in early recovery. Considering this, four different approaches have been applied to find a solution with a comparative analysis to generate the optimum distribution schedule using a case study of the Chi-Chi earthquake scenario. In the first two approaches, minimisation of distribution time and operational cost is generated with corresponding vehicles' cost and travel time respectively. It is found that minimising one objective gives a higher value of another objective. In the third approach, weighted single-objective optimisation is applied to find the feasible optimum solution in terms of both time and cost. Multiple weight ranges have been used to realise the impact of weight factors in the selection of the optimum solution set. Because of the different scale normalisation is required to apply weighted single-objective optimisation. The evolution algorithm is applied as a fourth approach for the multi-objective optimisation that generated Pareto fronts. These Pareto fronts defined a set of feasible solution that can be used by decision-makers for efficient schedule generations. Having a set of alternatives gives a wider range of operational flexibility while implementing the distribution task. This evolutionary approach is also compared with the GSMOGA. The presented evolutionary approach has been the better option for RISP with the multi-objective optimisation under heterogeneous vehicles to generate distribution schedules in disaster scenarios. In the presented work, in the absence of real data availability, simulated data for heterogeneous vehicles are used to generate distribution schedules, which appears as the limitation of this presented work. This presented approach can be further enhanced with the use of other factors such as priority, response time, GIS mapping. Inclusion of these additional components can further enhance the effectiveness of the distribution task.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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