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ORIGINAL RESEARCH

Two phase algorithm for bi-objective relief distribution location problem

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Abstract
The location planning of relief distribution centres (DCs) is crucial in humanitarian logistics as it directly influences the disaster response and service to the affected victims. In light of the critical role of facility location in humanitarian logistics planning, the study proposes a two-stage relief distribution location problem. The first stage of the model determines the minimum number of relief DCs, and the second stage find the optimal location of these DCs to minimize the total cost. To address a more realistic situation, restrictions are imposed on the coverage area and capacity of each DCs. In addition, for optimally solving this complex NP-hard problem, a novel two-phase algorithm with exploration and exploitation phase is developed in the paper. The first phase of the algorithm i.e., exploration phase identifies a near-optimal solution while the second phase i.e. exploitation phase enhances the solution quality through a close circular proximity investigation. Furthermore, the comparative analysis of the proposed algorithm with other well-known algorithms such as genetic algorithm, pattern search, fmincon, multistart and hybrid heuristics is also reported and computationally tested from small to large data sets. The results reveal that the proposed two-phase algorithm is more efficient and effective when compared to the conventional metaheuristic methods.

Keywords Heuristic · Location problem · NP-hard problem · Relief distribution

1 Introduction

Disaster is an occurrence that affects human functioning, causes human suffering, environmental damage, and economic and human life loss on such a scale that renders coping up with the situation is beyond the ability of the affected community (Boonmee et al., 2017). For handling such a situation, the affected community requires help from external sources.

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Humanitarian logistics is one of the operations that play a significant role in managing disaster situations and serving the affected areas (Praneetpholkrang et al., 2021). It involves planning, procurement, and controlling the efficient, cost-effective flow and storage of goods and materials for alleviating the suffering of vulnerable people (Thomas and Kopczak, 2005; Elluru et al., 2019; Kaur and Singh, 2019). These aspects of humanitarian logistics are crucial in both pre-and post-disaster situations (Behl and Dutta, 2019).

Humanitarian logistics in the pre-disaster phase include pre-planning operations against possible future disaster situations, such as pre-positioning of facilities, allocation of inventory, capacity, planning for supply, relief distribution in disaster-prone areas (Abazari et al., 2021; Yáñez-Sandivari et al., 2020). In disaster situations, it involves performing immediate actions after the disaster occurs, such as evacuating affected people, providing emergency services, blood and medical supplies (Duhamel et al., 2016; Sharma et al., 2019). Moreover, post-disaster helps people to get back to normal life and enhance human and economic growth. In addition, the disaster also impacts the firm's layout and location decisions due to a surge in demand during and post-disaster.

Tayal and Singh (2019) studied layout issues for disaster relief. Very recently, Devi et al. (2021) studied the location-allocation problem of health care facility networks and developed a mixed-integer linear program. Recent research shows promising efficiency improvements through studies using advanced technologies such as big data, blockchain, artificial intelligence and predictive analytics to improve humanitarian operations (Dubey et al., 2019a, 2020; Gupta et al., 2021; Jha et al., 2021; Modgil et al., 2020).

The effects of natural disasters are usually instant and reflected through a single disruptive event. Advancements in disaster management areas have made it possible that disaster-prone regions can usually be prepared in advance with all possible options to quickly start the relief operations to provide maximum relief to the affected ones. However, exceptional challenges still remain a possibility, such as the case of pandemics. Contrary to natural disasters, it grew, evolved and continued with no certainty, thus making the relief operation more challenging (Ivanov, 2021a, 2021b). An example of such a disastrous situation is the pandemic resulting from the novel Coronavirus that has afflicted the entire world in the last two years. The virus also referred to as COVID-19, has spread globally in a short span of time and severely affected human life and economic growth (Chowdhury et al., 2021).

The impact of the ongoing pandemic has been global and unpredictable, and it involves multiple shocks and long term uncertain states creating panic situations, unavailability of resources, disruption in logistics and relief operations. The most distinctive feature of Covid-19 is that the virus spreads through contact, which makes the relief operation more challenging. The relief work, in this case, had to face additional restrictions in the form of the largest quarantine in human history (Kharroubi & Saleh, 2020), which included lockdown situations imposed by a number of countries. Restrictions during these lockdowns included movement restriction, social distancing and prohibition of mass gathering, which usually cause undesirable outcomes, including resource unavailability, movement restriction, labour shortage and logistics disruptions (Singh et al., 2021). To address these challenges, the paper considers a similar case where the movement is restricted, and the existing structures are unable to satisfy the demand due to limited resources and movement restrictions. To serve essential items to the unsatisfied demand points, the aid providing organization has to establish temporary relief distribution centres or service facilities.

The decision of location and allocation of service facilities plays a significant role in the humanitarian relief operation. In the case of the pre-disaster situation, the strategic planning of location decisions is critical for risk prevention against future disaster occurrence. Also, the disaster response cost can be reduced by disaster preparedness and preparation (Goldschmidt and Kumar, 2019). However, in a post-disaster situation, relief planning involves decision making regarding the location of the relief distribution centres, medical care centres, shelter locations, evacuation centres, and other critical facility centres (Liu et al., 2019; Li and Teo, 2019; Sun et al., 2021).

The planning of relief distribution centres includes two main issues viz. what is the minimum number of DCs needed to serve the entire demand? And where to locate DCs for cost-effective operations? To optimally answer these two challenging issues, the paper considers a two-stage relief distribution location problem, where the objective is to determine the minimum number of DCs required and to optimize the location of DCs to minimize the cost for serving the unmet demand points. Most of the past studies in relief location planning focus on the minimization of unmet demand, maximization of survivor, minimization of response time, and cost-effective operations (Burkart et al., 2017; Sharma et al., 2019; Oksuz and Satoglu, 2020; Farrokhizadeh et al., 2021; Praneetpholkrang et al., 2021). Most of the available research in relief distribution planning either consider coverage or capacity limitation (Paul et al., 2017; Zhang et al., 2017; Liu et al., 2019; Munyaka and Yadavalli, 2021), while in a real-life scenario, delivery distance and capacity are jointly restricted by resource limitations.

However, as mentioned above, the purpose of this study is to obtain the minimum number of DCs and their optimal location in planar decision space for cost-effective operation. In this paper, the capacity and the coverage area of each DC is assumed to be restricted within a certain range. In order to avoid mass gathering at the DCs in the light of pandemics such as Covid-19, the paper considers relief transportation at a demand location and employs a maximum delivery distance restriction for each DCs. The distribution involves delivery at the demand location as the movement of the individuals are restricted within a certain range. The DCs can only deliver the goods to the demand points within a certain distance as the affected area is large and one DC can not fulfil the demand of the entire affected area. Moreover, in disaster situations, DCs facing capacity restrictions is very common due to the size limitations and unavailability of resources, especially in the case of temporary DCs (Gutjahr and Dzubur, 2016; Zhong et al., 2020). Thus, to make the problem closer to the real scenario both capacity and coverage limitations is included in this study.

To address the above challenging issues, a two-stage model is formulated where, the first stage optimizes the minimum number of DCs, and the second stage optimize the optimal location of DCs to meet the unsatisfied demands. Figure 1 shows the two stages of the proposed model.

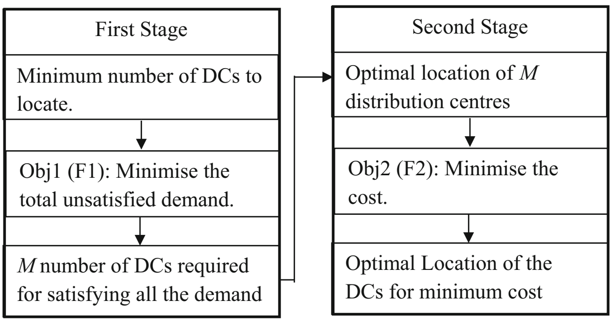

Fig. 1 Two stages of the proposed model

To optimally solve the two-stage relief distribution location problem, a novel two-phase algorithm is proposed. The first phase is the exploration phase based on obtaining an optimal or near-optimal solution. This phase investigates the entire search space thoroughly. The second phase is the exploitation phase that performs an intensive search in close circular proximity of the solution obtained from the exploration phase to further improve the solution quality. The two major contributions of the paper are (1) formulating a two-stage model for finding the number of relief distribution centres and their optimal location (2) developing an effective and efficient algorithm for solving this NP-hard problem.

The rest of the paper is organized as follows. Section 2 provides the literature review. Section 3 describes the mathematical modelling of the problem. Section 4 introduces the proposed algorithm. Section 5 presents numerical analysis and discussion of the result. Section 6 provides implications of the study. Section 7 is dedicated to the conclusion and future scope.

2 Literature review

Humanitarian logistics has three planning stages for the pre-and post-disaster situation. These stages are as follows—(1) Preparedness phase is a pre-disaster situation that includes risk prevention actions and preparation against future disaster possibility in disaster-prone areas; (2) Response phase includes actions taken immediately after disaster occurrence; and (3) Recovery phase involves road clearing, relief distribution, helping people in resuming normal life, and improving economic growth (Özdamar and Ertem, 2015).

Facility location planning is an important stage in both pre-and post-disaster situations and plays a significant role in the proper functioning of the humanitarian logistics system. In recent years due to the increasing severity of disasters across the globe, more attention is being paid to modelling a location problem, developing optimization approaches, and simulation processes in humanitarian logistics. These studies involve the location decision of facilities such as relief distribution centres, shelters, medical centres and waste disposal centres. Recent research includes the survey and review on humanitarian logistics (Özdamar and Ertem, 2015; Banomyong et al., 2019; Behl and Dutta, 2019), operations research (OR) models (Gösling & Geldermann, 2014; Ivanov and Dolgui 2021), mathematical models in humanitarian supply chain management (Habib et al., 2016; Sawik, 2020), and humanitarian operations for COVID-19 (Ghorbanzadeh et al., 2021; Queiroz et al., 2020; Singh et al., 2021).

Dönmez et al. (2021) reviewed the impacts of facility location uncertainties on humanitarian logistics. Dubey et al. (2019b) provide research questions and future research direction for disaster relief operations. Some other research studies involve disruption risk possibilities in the location decision to deal with future uncertainties (Cui et al., 2010; Wang and Ouyang, 2013; Ghavamifar et al., 2018). Wei et al. (2020) formulated a bi-objective optimization problem for location and routing for relief supply. Zhong et al. (2020) implement a risk-average approach for location and routing of relief distribution under stochastic demand in disaster-affected areas. Sanci and Daskin (2021) proposed an L shaped integrated algorithm to solve the location and network restoration problem. Manopiniwes and Irohara (2017) formulated a stochastic optimization model to prepare for disaster response in pre-and post-disaster operations.

Several studies in humanitarian relief planning have introduced single and multi-objective facility location models for improving both the effectiveness and efficiency of the humanitarian system (Abazari et al., 2021; Burkart et al., 2017; Duhamel et al., 2016; Vahdani et al., 2018). The current study considered a two-stage relief distribution location problem with both monetary and non-monetary objectives for the optimal planning of relief distribution centres. To deal with the more realistic scenario the study includes both delivery distance and capacity constraint. Related facility location literature addressing single and multi-objective problems with capacity and coverage limitations in humanitarian logistics are reviewed in Table 1.

Demand coverage is an important decision in relief distribution planning. As in disaster-affected areas, aid providing organizations aim to provide essential items including food, water, medical services, and hygiene items to all the affected people to reduce human suffering. Thus, a number of research studies emphasize locating DCs to maximize demand coverage. For instance, Jia et al. (2007) presented a problem of location decision for providing relief operation to maximum coverage area. Najafi et al. (2015) proposed a multi-objective logit model for relief centre location. Paul et al. (2017) demonstrate a new multi-objective approach for modifying the existing Chemical Response Enterprise structure for rapid response to maximize coverage by relocation and minimize the associated cost. Zhang et al. (2017) employed uncertainty theory to solve the problem of maximum demand coverage in an uncertain environment.

Also, in a disaster situation, the availability of resources is a huge challenge. Hence, several studies in disaster planning introduce capacity limitations in their studies (Gutjahr and Dzubur, 2016; Muggy and Stamm, 2017; Liu et al., 2019; Nagurney, 2021; Sun et al., 2021; Munyaka and Yadavalli, 2021). Gutjahr and Dzubur (2016) formulate a bi-objective bi-level problem for optimally locating capacitated relief distribution centres. Muggy and Stamm (2017) present a two-stage model for post-disaster health care locations. The study consists of nine cases for capturing uncertainties in the capacity of the facility and individual ability for travelling. Liu et al. (2019) presented a modelling framework for medical service location and causality allocation for the post-disaster situation to maximize the expected survival and minimize the total operational costs of the process. Nagurney (2021) construct a supply chain network model for multiple firms competing for profit maximization considering labour constraints.

We can observe from the preceding discussion and Table 1 that only a few studies consider both capacity and coverage limitations in the location of DCs (Najafi et al., 2015; Gutjahr and Dzubur 2016; Burkart et al., 2017; Farrokhizadeh et al., 2021). However, usually, relief centres face both capacity and coverage limitations. It is particularly true for pandemic situations like Covid-19. As countries imposed lockdowns to control the spread of the virus, which caused movement restriction and the unavailability of food, water, medicine, hygiene products and other essential items, especially for the poor labour class people (Berman, 2020). To address these challenges in the future, the current study included both maximum delivery distance and capacity limitation for each distribution centre. In this paper, it is considered that relief materials are to be transported at demand locations that lie within the coverage range of the distribution centre. Capacity restrictions are also employed for each DC to address the limitation in resource availability.

Facility location literature relating to humanitarian logistics is summarised in Table 1. It shows a comprehensive review of prior studies addressing facility location planning for pre-and post-disaster situations. The literature is grouped based on the objective function, modelling characteristics such as decision space, capacity, coverage, demand and other unique feature of the problem, solution approaches and area of implementation. The classification helps in identifying the modelling characteristics and solution approaches employed in the literature to solve various humanitarian logistics problems.

Table 1 Summary of paper and model for facility location in humanitarian logistics (Objective, variable, solution algorithm, facility location type)

Authors	Objective	Search space	Capacity	Coverage	Number of objectives	Demand	Others	Solution Algorithm	Facility location type
Jia et al. (2007)	Max covering	D	-	Co	S	UK	Quantity and quality of coverage requirement	Genetic algorithm Location-allocation heauristic Lagrangean relaxation	Large scale emergencies
Najafi et al. (2015)	Min response time Min cost	N	C	Co	M	–	Multi-objective logit model	Genetic algorithm approach	Disaster relief centre
Duhamel et al. (2016)	Max total population assisted	D	C	–	M	K	Multi-period location-allocation model	Blackbox coupling heuristics. Variable neighborhood Descent local search	Post-disaster relief operation
Gutjahr and Dzubur (2016)	Min cost Min uncovered demand	–	C	Co	M	K	User equilibrium model	Integrate adaptive epsilon-constraint method, Branch-and-bound procedure, Frank–Wolfe procedure	Post-disaster relief distribution centre
Burkart et al. (2017)	Min cost Min unmet demand	D	C	Co	M	K	Modelling beneficiaries choice	Adaptive epsilon constraint method	Disaster relief logistics
Muggy and Stamm (2017)	–	–	C	–	S	UK	Dynamic condition	–	Post Disaster health care

Table 1 (continued)

Authors	Objective	Search space	Capacity	Coverage	Number of objectives	Demand	Others	Solution Algorithm	Facility location type
Paul et al. (2017)	Demand coverage Min cost of unit relocations	N	–	Co	M	K	Relocations	ε-constraint method	Relocation of response facility
Zhang et al. (2017)	Min number of facility Max total demand coverage	N	–	Co	S	UK	Uncertain response time, disruption risk	Integer programming	Emergency Service facility
Hu and Dong (2019)	Min total cost	D	C	–	S	K	Two-stage model	Mixed-integer program	Pre-positioning of relief supply
Kinay et al., (2019)	Max minimum weight among open facilities Min overall distance travelled by customers	D	C	–	M	UK	Multi-criteria chance constraint	Victorial optimisation Goal programming	Preventive disaster management
Li and Teo (2019)	-	N	C	–	M	K	Multi-period bilevel model	Genetic algorithm	Post-disaster road repair

Table 1 (continued)

Authors	Objective	Search space	Capacity	Coverage	Number of objectives	Demand	Others	Solution Algorithm	Facility location type
Liu et al. (2019)	Max number of expected survival Min total cost	N	C	–	M		Temporary location	ε-constraint method	Post-disaster medical service
Mondal et al. (2019)	Evaluating optimal allocations considering the allocable and demand percentage of resource types	D	–	–	M	K	Resource allocation	Particle swarm method	Disaster response
Ramshani et al. (2019)	Min cost	D	–	–	S	K	Two-level distribution chain	Tabu search Problem specific heuristic	Disruption risk
Sharma et al. (2019)	Min response time	D	–	–	S	K	Determine the optimal number of distribution centre	Tabu search heuristic	Blood facility
Yahyaei and Bozorgi-Amiri (2019)	Min evacuation cost	N	C	–	S	UK	Robust optimization	Monte Carlo procedure	Pre-disaster, Shelter and relief supply network

Table 1 (continued)

Authors	Objective	Search space	Capacity	Coverage	Number of objectives	Demand	Others	Solution Algorithm	Facility location type
Maghfiroh and Hanaoka (2020)	Min delivery time Min response period	N	C	–	M	K	Multi-model	Mixed integer linear programming problem	Post-disaster relief distribution
Mohammadi et al. (2020)	Min logistics cost Min relief operation time Min variation in upper and lower bound of transportation cost	N	C	–	M	K	Multi-echelon humanitarian logistics network	AUGMECON2	Relief distribution and victim evacuation
Oksuz and Satoglu (2020)	Number of facilities Min cost	–	C	–	M	K	Two-stage stochastic model	–	Temporary emergency medical centre location
Wei et al. (2020)	Min time window violation Min operational cost	N	C	–	M	K	Time window constraint	Hybrid ACO algorithm	Post-disaster relief distribution

Table 1 (continued)

Authors	Objective	Search space	Capacity	Coverage	Number of objectives	Demand	Others	Solution Algorithm	Facility location type
Zhong et al. (2020)	Min waiting time Min cost	N	C	–	M	UK	Bi-objective CVaR-R model	Hybrid genetic algorithm	Relief centre location and vehicle routing
Abazari et al. (2021)	Min distance Min max travel time	D	–	–	M	UK	Relief planning with uncertain parameters	MINLP Grasshopper optimization algorithm	Pre-positioning of relief centres,
Farrokhizadeh et al. (2021)	Min unmet demand Min cost	D	C	Co	M	UK	Disaster under uncertainty	Augmented ε-constraint method Lagrangian relaxation	Blood supply planning in natural disaster
Munyaka and Yadavalli (2021)	Min cost	D	C	Co	S	K	Decision support framework	Analytic hierarchy process	Prepositioning of relief supply chain
Nagurney (2021)	Profit maxi-mization	N	C	–	S	K	Labour constraint Competition	Heuristic	Supply chain network model for Covid 19
Praneetpholkrang et al. (2021)	Min total cost Min victim evacuation time Min number of shelter	D	C	–	M	K	Multi-objective shelter location planning	Epsilon constraint method, Goal programming	Shelter location-allocation
Sanci and Daskin (2021)	Min cost	N	C	–	S	UK	Two-stage stochastic model	L shaped algorithm	Disaster relief centre

Table 1 (continued)

Authors	Objective	Search space	Capacity	Coverage	Number of objectives	Demand	Others	Solution Algorithm	Facility location type
Sun et al. (2021)	Min injury severity score Min cost	N	C	-	M	UK	Response planning under uncertainty	ε-constraint method	Post-disaster relief logistics
Proposed Model	Number of DCs and its location to meet demand with min total cost	P	C	Co	M	K	Two-stage model Relief transported at demand location Max delivery distance limitation	Novel exploration and exploitation-based algorithm	Relief location planning

Search space: Discrete (D), Network (N), Planar (P). Capacity: Capacitated (C). Coverage: Co. Objective: Single (S), Multi-objective (M). Demand: Known (K), Unknown (UK)

Table 1 also presents the distinguishing feature of the current study from past literature. Only a few studies consider both capacity and coverage constraints in relief location planning. However, the current study is performed on planar search space considering both capacity and coverage limitation for optimal location planning of relief distribution centres. Most of the models discussed in Table 1 are hard-to-solve optimization problems; thus, studies employed metaheuristics and hybrid heuristics solution approaches. The complexity of the model increases with the inclusion of capacity and coverage constraints; thus, a novel two-phase algorithm is developed in this study to provide the optimal solution.

Further, it can be observed from Table 1 that research studies in disaster cases are mainly focused on the pre-planning of the relief facilities (Munyaka and Yadavalli, 2021; Abazari et al., 2021), evacuation planning (Yahyaei and Bozorgi-Amiri, 2019; Praneetpholkrang et al., 2021), blood and medical supply (Farrokhizadeh et al., 2021; Sharma et al., 2019; Oksuz and Satoglu 2020), post-disaster recovery and planning (Duhamel et al., 2016; Gutjahr and Dzubur, 2016; Manopiniwes and Irohara, 2017; Li and Teo, 2019; Sun et al., 2021; Wei et al., 2020).

The number of facilities to be located and their optimal location is an important question in all these humanitarian logistics operations. Moreover, in relief distribution centre planning, to serve the affected people in minimum time, the location and proximity of the distribution centre become crucial. However, establishing a large number of DCs incur high costs and also becomes limited by resource availability (Oksuz and Satoglu, 2020; Praneetpholkrang et al., 2021).

The proposed two-stage relief distribution location problem discuss these challenging issues jointly to provide the minimum number of distribution centres to meet demand at minimum cost. Only limited studies considered both these objectives in relief centres location planning. Oksuz and Satoglu (2020) formulated a two-stage stochastic problem for finding the optimal location and number of medical centres to open and determining the optimal location of these facilities. Praneetpholkrang et al. (2021) formulated a multi-objective optimization model for minimizing the total cost required, minimization of victim evacuation time and minimization the number of shelters required to service the victims in shelter location-allocation problems. The distinguishing characteristics of the proposed model can be observed in Table 1. As shown in Table 1, rarely any study is available on determining the number of DCs and their optimal location to meet unsatisfied demand with consideration of relief transportation at demand location providing coverage and capacity constraints. Moreover, these characteristics of the model make the study adaptable in real-life scenarios and for dealing with situations like Covid-19.

The optimal locations of facilities are crucial for the effective and efficient functioning of humanitarian logistics. There are a substantial number of algorithms available in the literature for solving various location problems. Exact methods like branch-and-cut, branch-and-bound (Gutjahr and Dzubur (2016), Integer programming (Zhang et al., 2017), Multi integer linear programming, Lagrangian relaxation (Jia et al., 2007; Zhen et al., 2014) have been previously used in the literature. However, the location problems are mostly NP-hard and exact methods required excessive computational time even for small data set problems. Thus, meta-heuristic algorithms are used for complex location problems such as tabu search (Ramshani et al., 2019), genetic algorithm (Jia et al., 2007; Najafi et al., 2015; Li and Teo, 2019; Zhong et al., 2020), ant colony (Wei et al., 2020; Yegane et al., 2016), firefly algorithm (MirHassani et al., 2015), particle swarm optimization (Plastria and Vanhaverbeke, 2007).

The effectiveness of the algorithm is crucial for location decisions in disaster management as it has a direct impact on human life and human survival. In many cases, the results of these metaheuristic algorithms diverge significantly from the optimal solution. Thus, many research studies are devoted to developing model-based heuristics for providing the optimal result in a reasonable time (Jia et al., 2007; Nagurney, 2021; Ramshani et al., 2019). Considering the criticality of location decisions in disaster relief operations, this study also attempts to determine the optimal location of the proposed problem by developing a new heuristic approach in this paper.

3 Mathematical model

3.1 Problem Statement and assumptions

This study has two objectives, the first objective is to find the minimum number of distribution centres (DCs) required for satisfying demand in the disaster-affected area, and the second objective is to optimally locate these DCs to minimize the delivery cost. For a more realistic scenario, the coverage area and capacity of each distribution centre are assumed to be limited. The two-stage model formulated in the paper wherein the first stage of the model focuses on determining the minimum number of DCs while the second stage determine the optimal location of DCs identified from the first stage. The study includes two stages to meet all demands and to provide full relief at minimum cost. The first stage of the model determines the minimum number of DCs required to meet demands, which acts as an input to the second stage. The second stage provide optimal locations for the DCs to provide full relief at minimum cost. The two-stage process is shown in Fig. 2.

The assumptions considered in the problem to optimally solve the problem are: the Search space is assumed to be planar, the demand is satisfied by the nearest distribution centre, and each demand point is allocated to only one distribution centre, and the demand is assumed to be known and constant. In addition, each distribution centre has a capacity limitation and can provide relief to the demand points that lie within the coverage range. Also, the relief

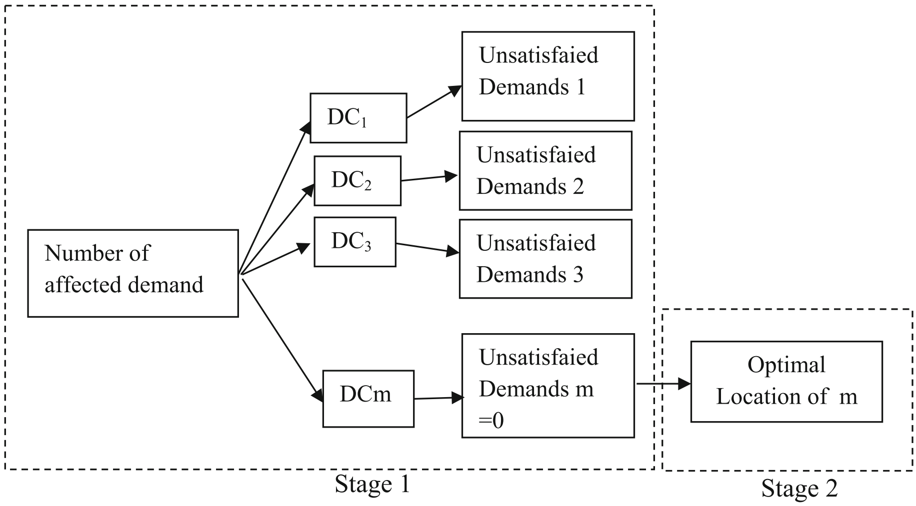

Fig. 2 A proposed two-stage model

Table 2 Notations used in modelling of the problem

Parameters	• i: Indices for demand point (i = 1, 2……….n) • j:Indices for DCs (j = 1, 2……….m) • f: Already existing firms • a_i: Location of demand points (x_i, y_i) (i = 1, 2……….n) • n: Number of demand points • d_i: Maximum possible demand at i • L_f: Search space for facility location of DC j X_j= (x_j, y_j), $X_j \subset L_j$ • C_j: Capaity of DC j • Λ: Penalty cost associated with unsatisfied demand
Variables	• m: Number of DC • X_j: DC location j, $X_j = (x_j, y_j)$, $X_j \subset L_j$ • t_i^j: Unit demand transportation cost from DC location X_j to demand point i • $d.^j$ (x_j, a_i): Distance between DCj and demand point i • $d.^f$ (X_f, a_i): Distance between already existing firm f and demand point i • D_i: Demand at the demand point • W: Total demand $\sum_{i=1}^{n} d_i$
Functions	• $f(d(X^j, a_i)$: Unit cost of transportation as a function of distance • M: Total available demand share • MD_f: Maximum possible delivery distance of the existing firm • MD_{dcj}: Maximum possible delivery distance of DC • M_f: Demand share of already existing firms • $M_{u:}$ Unsatisfied demand points • M_j: Market share attracted by DC j

material is transported at demand locations from relief distribution centres. The location and possible coverage range of already existing firms are known.

3.2 Parameters, variables and functions

The list of various notations used to define parameters variables and functions are presented in Table 2.

3.3 Problem formulation

In many disaster-affected areas, people suffer from the unavailability of essential items and health services. The existing firms face difficulties in serving these demands due to the impact of the disaster and resource unavailability. This study assumes that due to resource limitation, the existing firms limit their services to an optimal coverage area and satisfy only limited demand points. The focus of this paper is to locate temporary DCs to serve the people suffering from the unavailability of essential goods.

The demand points satisfied by the already existing facilities in the affected area are given by Eq. (1).

$$M_f = i \in (1.....n) : d^f(X_f, a_i) \le MD_f \forall f \tag{1}$$

It can be observed from Eq. (1) that the already existing firms restrict the delivery coverage. The unsatisfied demand points due to this limitation are given by Eq. (2).

$$M_u = M - M_f \tag{2}$$

The objective of this study is to first determine the number of distribution centres required to satisfy the unsatisfied demand points considering coverage and capacity limitations and then determine the optimal location of these DCs to minimize the cost required to satisfy these demand points. The two objective functions are given by Eqs. (3) and (4). The first objective is to minimize the number of unsatisfied demands. The second objective determines the optimal location of these DCs to minimize the cost of satisfying the demand points.

$$\text{Min } F1 = \left(W - \sum_{j \in m} \sum_{i \in M_{jc}} D_i \right) \tag{3}$$

$$\text{Min } F2 = \sum_{i \in M_{1c}} \left(t_i^1(X_1)\right) D_i + \sum_{i \in M_{2c}} \left(t_i^2(X_2)\right) D_i .... \sum_{i \in M_{mc}} \left(t_i^m(X_m)\right) D_i + \sum_{i \in (Mu-(M1c+M2c......Mmc)} \lambda \tag{4}$$

Subjected to:

$$M_{ja}(X^1, X^2, ., X^m) = \text{i} \in (1 \ldots M_u) : d^j(X_j, a_i) < MD_j \forall j \in (1 \ldots .\text{m}) \tag{5}$$

$$\left.\begin{array}{l} M_{1b}(X^1, X^2, ., X^m) = i \in (1 \ldots M_{1a}) : d^1(X_1, a_i) < \min(d^2(X_2, a_i), d^3(X_3, a_i), ..., d^m(X_m, a_i)) \\ M_{2b}(X^1, X^2, ., X^m) = i \in (1 \ldots M_{2a}) : d^2(X_2, a_i) < \min(d^1(X_1, a_i), d^3(X_3, a_i), ..., d^m(X_m, a_i)) \\ M_{mb}(X^1, X^2, ., X^m) = i \in (1 \ldots M_{ma}) : d^m(X_m, a_i) < \min(d^1(X_1, a_i), d^2(X_2, a_i), ., d^{m-1}(X_{m-1}, a_i)) \end{array}\right\} \tag{6}$$

$$M_{jc}(X^1, X^2, ., X^m) = \text{i} \in \left(1 \ldots M_{jb}\right) : \sum_i \text{D}i \le C_j \ldots \forall j \in (1 \ldots .\text{m}) \tag{7}$$

$$t_i^f\left(X_f\right) = f\left(d\left(X_f, a_i\right)\right) = \left[\sum_{k=1}^{2} (x_f^k - x_i^k)^2\right]^{1/2} \tag{8}$$

$$L_f \subseteq R^2 \tag{9}$$

$$W = \sum_{i=1}^{i=n} d_i \tag{10}$$

Equation (5) shows the restriction on coverage area at each distribution centre. Equation (6) states that the demand is satisfied by the nearest DCs. Equation (7) represents capacity limitation at each distribution centre. Equation (8) represents the function used for measuring transportation cost. Equation (9) restrict the search to planar search space. Equation (10) represents the amount of maximum possible demand.

4 Proposed algorithm

The proposed algorithm integrates two phases for optimal search. These phases are termed as *Exploration* and *Exploitation* phases. The first phase focuses on identifying near-optimal solutions, while the second phase investigates the solution of the first phase for improvement of solution quality. The Exploration phase examines the search space for a near-optimal solution. On the other hand, the Exploitation phase concentrates the search concentrically on the circular proximity of the first phase solution.

The proposed algorithm implements the relationship of leader and follower in the search process for an optimal solution. The leader motivates the follower to achieve a higher objective, and the follower follows this lead for improvement of the performance and proceeds towards the new leadership position. In this context, the *leader points* are decision variables with the best solutions, and *follower points* are a fraction of good points selected from the population. The complete discussion of these two phases is explained in the following section.

4.1 Phase 1: exploration phase

The steps involved in the Exploration phase are discussed below.

Step1: Initial Population Generation: This step initiates the search by randomly generating the initial population. In an optimization problem of N variables, the solution point is represented by an array of size 1xN. The randomly generated initial population with N variables and M size is given below.

$$\begin{aligned} Q_1 &= [q_{11}, q_{12}, q_{13} \cdots q_{1n}] \\ Q_2 &= [q_{21}, q_{22}, q_{23} \cdots q_{2n}] \\ &. \\ &. \\ Q_M &= [q_{n1}, q_{n2}, q_{n3} \cdots q_{nm}] \end{aligned}$$

Q represent the solution points of the optimization problem.

Step 2: Selection of Initial Active Population: In this step, a portion of the initial population from step 1 is selected as an active population. The active population takes part in the next step as the leader and follower points. The objective function value is evaluated for the population points generated in Step 1 and arranged on the basis of their attractiveness. A portion of these attractive solution points (P_{ib}) is selected as an active population for the next step.

Step 3: Selection of Leader and follower points: The leader and follower points are selected in this step for the next population generation. The decision variables with the best solutions are selected as leaders, while followers are a combination of good and worst points. The follower points with good solutions have more tendency toward advancement while the worst solution points add divergence in the search process. The search starts from all the leader points simultaneously. For the first iteration, a portion of the active population acts as the leader points, while the other points act as followers.

Step 4: Interaction process (New Population Generation): In this step, the next population is generated by the interaction between leaders and followers. The leader points guide the follower points toward improvement. The search process is a *multi-point search,* which is guided by different leader points at different locations of the search space.

This interaction between leader and follower points is performed by a *rectangular corner* and *diagonal mean* movement. In each iteration, the follower point moves towards the leader point in search of a possible optimal solution. The new population generated by the interacting leader and follower points are shown in Fig. 3a. ((X_l, Y_l), ($X_l^{'}$,$Y_l^{'}$)) are leader points and ((X_f, Y_f), ($X_f^{'}$,$Y_f^{'}$)) are follower points and ((X_m, Y_m), ($X_m^{'}$,$Y_m^{'}$)) is obtained by mean diagonal movement.

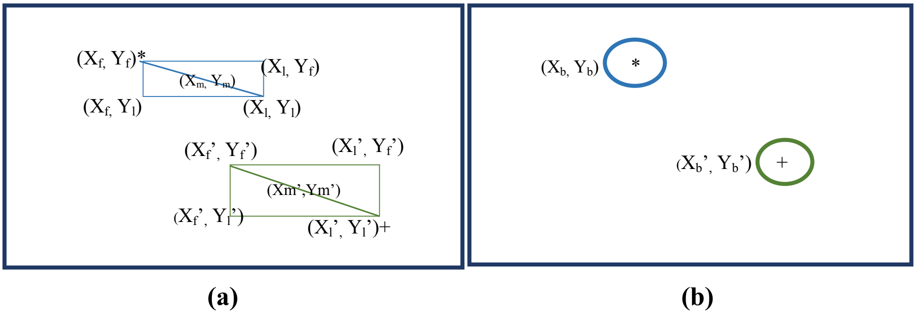

Fig. 3 **a** Interaction process of exploration phase. **b** Interaction process of the exploitation phase

The combinations of leader and follower for *m* variable points are shown in Fig. 4. The total $5^{(number\ of\ firms)}$ x *number of leaders* x *number of followers,* number of new population points are generated by the interaction of each leader and follower point. The objective function is calculated for the new population points and arranged in ascending order based on attractiveness. A portion of the good and worst population are selected as good solution points (P_b) and as weak solution points (P_w) for the new active population.

Step 5: Diversification: In each iteration, some new random populations (P_d) are added to avoid the possibility of trapping the solution at the local minima.

Step 6: New active Population: In this step new active population is selected. It is a combination of good (P_b), weak (P_w) and diversification population (P_d). The good population points help to focus the search on the proximal region of the optimal solution. The weak population increases the range of the search, and the addition of the diversification population avoids trapping at local minima.

	Possible Combinations of new population		
		Firm 1	**Firm 2**
1	*Best location*	(X_{L1}, Y_{L1})	(X_{L2}, Y_{L2})
2	*Next best location*	(X_{F1}, Y_{F1})	(X_{F2}, Y_{F2})
3	*Fixing Firm 2 and changing Firm 1*	(X_{F1}, Y_{L1})	(X_{L2}, Y_{L2})
4		(X_{F1}, Y_{L1})	(X_{F2}, Y_{F2})
5		(X_{L1}, Y_{F1})	(X_{L2}, Y_{L2})
6		(X_{L1}, Y_{F1})	(X_{F2}, Y_{F2})
7		$((X_{F1}+X_{L1})/2, (Y_{F1}+Y_{L1})/2)$	(X_{L2}, Y_{L2})
8		$((X_{F1}+X_{L1})/2, (Y_{F1}+Y_{L1})/2)$	(X_{F2}, Y_{F2})
9	*Fixing Firm 1 and changing Firm 2*	(X_{L1}, Y_{L1})	(X_{L2}, Y_{F2})
10		(X_{F1}, Y_{F1})	(X_{F2}, Y_{L2})
11		(X_{L1}, Y_{L1})	(X_{L2}, Y_{F2})
12		(X_{F1}, Y_{F1})	(X_{F2}, Y_{L2})
13		(X_{L1}, Y_{L1})	$((X_{F2}+X_{L2})/2, (Y_{F2}+Y_{L2})/2)$
14		(X_{F1}, Y_{F1})	$((X_{F2}+X_{L2})/2, (Y_{F2}+Y_{L2})/2)$
15	*Changing position of both Firm 1 and Firm 2*	(X_{L1}, Y_{F1})	(X_{F2}, Y_{L2})
16		(X_{L1}, Y_{F1})	(X_{L2}, Y_{F2})
17		(X_{L1}, Y_{F1})	$((X_{F2}+X_{L2})/2, (Y_{F2}+Y_{L2})/2)$
18		(X_{F1}, Y_{L1})	(X_{F2}, Y_{L2})
19		(X_{F1}, Y_{L1})	(X_{L2}, Y_{F2})
20		(X_{F1}, Y_{L1})	$((X_{F2}+X_{L2})/2, (Y_{F2}+Y_{L2})/2)$
21		$((X_{F1}+X_{L1})/2, (Y_{F1}+Y_{L1})/2)$	(X_{F2}, Y_{L2})
22		$((X_{F1}+X_{L1})/2, (Y_{F1}+Y_{L1})/2)$	(X_{L2}, Y_{F2})
23		$((X_{F1}+X_{L1})/2, (Y_{F1}+Y_{L1})/2)$	$((X_{F2}+X_{L2})/2, (Y_{F2}+Y_{L2})/2)$
24	*Best with next best*	(X_{L1}, Y_{L1})	(X_{F2}, Y_{F2})
25		$(X_{F1} Y_{F1})$	(X_{L2}, Y_{L2})

5^2 combinations

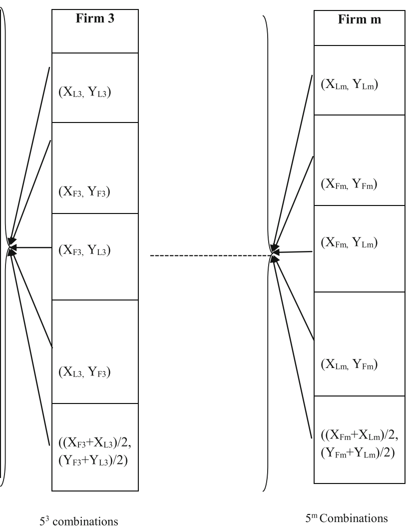

Fig. 4 Possible combinations of new population

Step 7: Termination Criterion 1: Calculate the difference between the best F_B and the previous best solution F_{Bprev} for determining the error. The process between step 3 to step 7 will be continued till termination criteria are met, i.e. the error is less than 10^{-6}.

Step 8: Report optimal solution: Report the best solution P_{Best} and corresponding decision variable. This decision variable will act as an initial start point for the exploitation phase.

4.2 Phase 2: exploitation phase

In the exploitation phase, the search is concentrated on the near-optimal solution point obtained from phase 1. In this phase, the search converges toward an optimal global solution with each iteration. The steps involved in the second phase are mentioned below.

Step 1: Initial start point and search region: The decision variables corresponding to the best solution from phase 1 will act as an initial start point in this phase. The Exploitation phase aims to closely examine the neighbourhood region of the best solution obtained by the exploration phase. The initial search process is performed in the circular region with the start point as centre and radius r.

Step 2: Random population generation: In this step, the random populations are generated in the close circular proximity of the start point. The search process employed in the exploitation phase is shown in Fig. 3b.

Step 3: Selection of leader and follower: In this step, the objective function value is calculated for each population points generated in step 2 (Exploitation phase). The objective function value is arranged in ascending order. The decision variables with the best solution act as leader points. However, the combinations of good (P_{b2}) and worst points (P_{w2}) are selected as followers.

Step 4: Interaction process: In this step, the new population is generated by interacting leaders and followers points. The interaction between leader and follower points is performed by a *rectangular corner* and *diagonal mean* movement, as explained in the exploitation phase. For the interaction process, refer to step 4 of phase 1.

Step 5: New start point: In this step, the objective function value is calculated for each population points generated in step 4 and the decision variable with the best solution is selected as the new start point. The previous start point is substituted by the new start point, which acts as a new leader point.

Step 6: New search region: This step converges the search towards the best result. The coverage radius decreases by half after each iteration. and concentrate the new population towards the centre. In this step, the circular region of radius ($R/2^{numberofiteration}$) are explored. The new search region is explored and steps 2 to step 6 are repeated till termination criteria are met.

Step 7: Termination Criteria: The exploitation phase terminates after 20 iterations (I) and reports the optimal result.

The flow diagram and the pseudo-code of the proposed algorithm are presented in Figs. 5 and 6. The flow diagram follows the steps as explained in the exploration and exploitation phase. The first seven steps of the exploration phase are performed till termination criteria are met. The decision variable with the best solution is reported in step 8, which will act as an initial start point of the exploitation phase. Furthermore, step 2 to step 7 of the exploitation phase is performed till the termination criteria are met. The best solution and corresponding decision variable are reported as the final optimal solution of the exploitation phase.

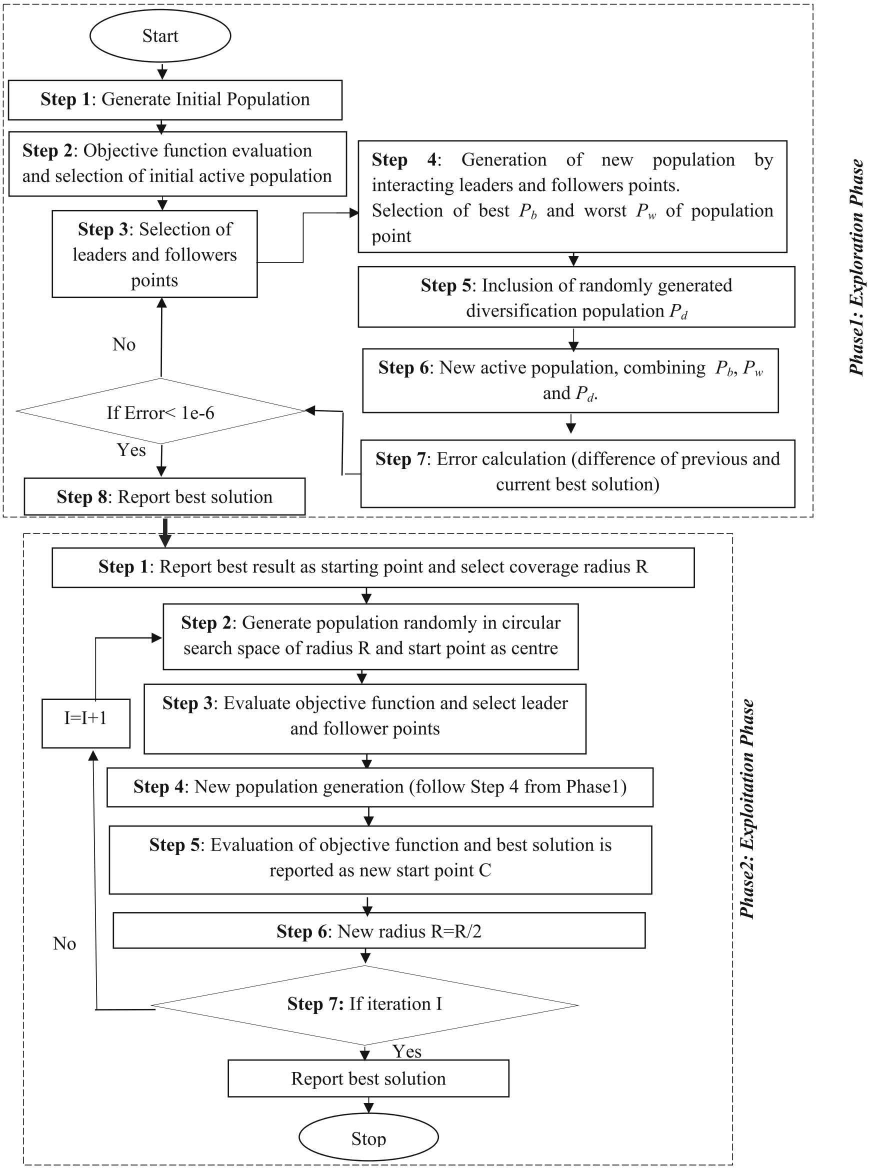

Fig. 5 Flow chart of the proposed algorithm

5 Computational analysis

Fifteen data sets are generated randomly to examine the proposed algorithm and compare it with other well-known heuristics. The proposed algorithm and all other heuristics are coded in MATLAB 2017a (Appendix A for MATLAB code for 4 variables). It is executed in a machine having intel-i3 processor 2.0 GHz with 4 GB RAM.

Algorithm 1: Proposed Algorithm

begin

Phase1: Exploration phase

Step 1. Generation of initial random population points (P).

Step 2. Evaluation of objective function for determining initial population points.

Arranging objective function values and corresponding decision variables in ascending order. select 15% of the decision variable with the best objective function value as initial active population points (P_{ib}).

While ($\varepsilon < 10^{-6}$)

Step 3. Select best solution points as leaders (best, second and fourth-best solution points in this case). Other active populations will behave as followers.

Step 4. New population generated by interacting leaders and followers points. Possible steps in population generation are as follows:

4.1 For Firm m

4.1(a) Best location point (X_{Lm}, Y_{Lm}).

4.1(b) Next location point (X_{Fm}, Y_{Fm}).

4.1(c) Keeping Y_F fixed and shifting X_{Fm} to X_{Lm}.

4.1 (d) Keeping X_F fixed and shifting Y_{Fm} to Y_{Lm}.

4.1(e) Shifting both (X_{Fm}, Y_{Fm}) to (($X_{Fm}+X_{Lm}$)/2, ($Y_{Fm}+Y_{Lm}$)/2)

The objective function is evaluated at each new population point and arranged on the basis of attractiveness. Select follower points as a combination of good (P_b) and worst (P_w) points.

Step 5. Add (P_d) random for diversification.

Step 6. The combination of P_b, P_w and P_d will act as a new active population.

Step 7. Check termination criterion.

Step 8. Report near-optimal solution $P_{Best.}$

Phase 2: Exploitation phase

Step 1. The near-optimal solution from Step 8 will act as an initial point in the exploitation phase.

For (20 iterations)

Step 2. The population are generated randomly in the circular search space of radius 0.2 with the previous best solution as the centre point.

Step 3. Calculate the objective function value for the population points generated in step 2 and arrange it on the basis of attractiveness. Select the best, 4th and 5th best solution points as leaders and the combinations of good (P_{b2}) and worst (P_{w2}) points as followers.

Step 4. New possible solutions are generated in this step by interaction the leader and follower points as mentioned in Step 4 of the exploration phase.

Step 5. Calculate the objective function for the population generated in step 4 and select the best solution as a decision variable.

Step 6. In the next iteration, the best solution point of Step 5 (phase 2) will act as a centre and the new radius will be half of the previous radius.

Step 7. Check termination criterion and report the optimal solution

Stop

Fig. 6 Pseudo-code for the proposed algorithm

5.1 Experimental setup

The performance of the proposed algorithm is evaluated for 15 cases. The problem is performed for 15 data sets randomly generated in a planar search space with ([0 10], [0 10]). The problem is conducted for demand points that varies between $n = [10, 5000]$. It is assumed that demand points are uniformly randomly distributed in the range of (0, 10], and the maximum possible demand (d_i) at any demand point lies between (1, 100]. The penalty cost constant is taken as 50. The delivery range for any distribution centre is given between (0, 3.5], and the capacity of each distribution centre is assumed to be one-third of the total demand. However, the location that already existed in the market is (2, 2), and the maximum delivery range is (0, 3].

In the first stage of the problem, the performance of the proposed algorithm is compared with two metaheuristic methods genetic algorithm and pattern search algorithm. However, in the second stage for objective two, the comparison is provided with six different methods viz. Genetic Algorithm (GA), Fmincon, Genetic Algorithm-Fmincon (GA-Fmincon), Pattern Search (PS), Genetic Algorithm-Pattern Search (GA-PS), and Multistart (MS). The parameters of these algorithms are briefly discussed below.

***Genetic Algorithm*:** In this paper, the traditional GA (Deb, 1999) is employed. The combination of the parameters is referred from Lai et al. (2010). Population size (P): 50, Selection process: Tournament selection, Crossover probability (P_c): 0.75% and mutation probability (P_m) 1%.

***Pattern Search*:** For pattern search operation initial mesh size of 1 and maximum mesh size of infinite is employed. The other parameters, such as mesh expansion factor and contraction factor, are 2 and 0.5 respectively, while the start point of the search is random.

***Genetic-Pattern Search algorithm*:** The two heuristics approach GA and PS, are integrated into this method. The best result of the genetic algorithm is selected as a start point for pattern search optimization (Guo et al., 2018). The pseudo-code for GA-PS is mentioned below.

Pseudo code: GA-PS

GA_{opt} $(\text{T}_{\text{Best}}) \rightarrow (X_g, Y_g, X_g', Y_g')$ optimal solution of GA.

$(X_g, Y_g, X_g, Y_g') \subset L_f$.

$L_f \epsilon$ R.^{2}

PS $\rightarrow$ F_{start} (X_g, Y_g, X_g', Y_g').

Report PS_{opt}.

***Fmincon*:** This heuristic approach is used for solving constrained nonlinear multivariable functions. An interior-point algorithm is employed in this method. The start point selected in this problem is random.

***Genetic-Fmincon*:** This hybrid heuristic is an integration of genetic algorithm and Fmincon. The optimal result of the genetic algorithm is selected as a start point for Fmincon. The pseudo-code for GA-Fmincon is mentioned below.

Pseudo code: GA-Fmincon

GA_{opt} $(\text{T}_{\text{Best}}) \rightarrow (X_g, Y_g, X_g', Y_g')$ optimal solution of GA.

$(X_g, Y_g, X_g', Y_g') \subset L_f$.

$L_f \epsilon$ R.^{2}

Fmincon $\rightarrow$ F_{start} (X_g, Y_g, X_g', Y_g').

Report $\text{Fmincon}_{\text{opt}}$.

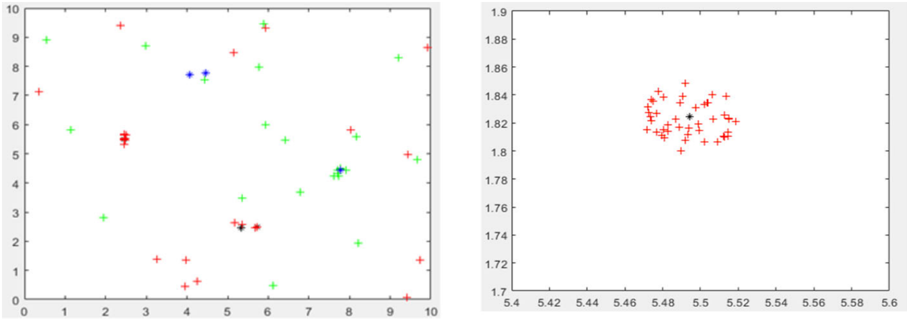

Fig. 7 **a** Exploration phase. **b** Exploitation phase

Multistart**:** In MultiStart (MS) heuristic, the search starts from multiple start points. In this method, multiple local solutions to a problem are obtained. The start point is selected randomly in this problem with 100 start points.

Proposed Algorithm**:** The process of the proposed algorithm is described in Sect. 4. The search process in the decision space of the two phases of the proposed algorithm is shown in Fig. 7. The process is performed using MATLAB 2017a software. Figure 7a represent the search process of the exploration phase. The stars are leader points, while the positive sign represents follower points. Figure 7b shows the exploitation phase process. The star represents the near-optimal solution or leader point obtained by phase 1, and the positive sign is the population of follower points generated in the close circular proximity of the solution. Figure 7a shows that the search process is performed in the entire decision space to obtain a near-optimal solution.

Figure 7a represents output obtained from the first phase, i.e. exploration phase. However, in Fig. 7b, the search is concentrated on the proximity of the solution obtained from the exploration phase. Figure 7b represents output obtained from the second phase, i.e. exploitation phase.

5.2 Result and discussion

The results obtained by the proposed algorithm for both stages are discussed in this section. The comparative analysis of the proposed algorithm is also provided for fifteen cases.

5.2.1 Stage level 1: minimum number of distribution centre

The first stage of the proposed model is focused on finding the minimum number of distribution centres to cover all unsatisfied demand points. The experiment is conducted for 15 random data sets with the smallest data set of 10 to the largest data set of 5000. The comparison of the proposed algorithm with well-known metaheuristic GA and PS are conducted for evaluation of performance analysis. The algorithms are executed five times for each data set, and the best result is reported in Table 3. The heuristics are compared for accuracy of Ɛ $= 10^{-6}$. The best solution comparing all three heuristics are reported in the $\mathrm{Obj}_{\mathrm{Best1}}$ column. The unsatisfied demands considering the various number of distribution centres for each data set are also reported. The minimum number of distribution centres required to serve the unsatisfied demand points are given in Obj_{Best1} column.

Table 3 Unsatisfied demand points and minimum number of DCs

S. no	Test problem	Unsatisfied demands				Minimum number of DCs			
		Number of DCs	GA	PS	Proposed Algorithm	GA	PS	Proposed Algorithm	Obj_{Best1}
1	10 demand points	1	160	160	160	3	3	3	3
		2	40	40	40				
		3	0	0	0				
2	100 demand points	1	2480	2482	2479	3	3	3	3
		2	813	796	785				
		3	0	0	0				
3	200 demand points	1	4474	4474	4474	3	3	3	3
		2	1292	1292	1287				
		3	0	0	0				
4	300 demand points	1	6848	6848	6842	3	4	3	3
		2	1971	2070	1963				
		3	0	55	0				
		4	–	0	–				
5	400 demand points	1	8103	8108	8102	3	4	3	3
		2	3188	2879	2768				
		3	0	1	0				
		4	–	0	-				
6	500 demand points	1	11,974	11,976	11,974	3	3	3	3
		2	3762	3754	3753				
		3	0	0	0				

Table 3 (continued)

S. no	Test problem	Unsatisfied demands				Minimum number of DCs			
		Number of DCs	GA	PS	Proposed Algorithm	GA	PS	Proposed Algorithm	Obj_{Best1}
7	1000 demand points	1	23,327	23,326	23,326	4	4	4	4
		2	7366	7383	7340				
		3	86	93	7				
		4	0	0	0				
8	1500 demand points	1	31,697	31,697	31,697	4	4	4	4
		2	1002	9454	9422				
		3	58	23	37				
		4	0	0	0				
9	2000 demand points	1	44,867	44,867	44,867	4	4	4	4
		2	12,058	12,199	12,371				
		3	76	86	66				
		4	0	0	0				
10	2500 demand points	1	57,691	57,691	57,691	4	4	4	4
		2	17,377	16,989	16,803				
		3	101	143	139				
		4	0	0	0				
11	3000 demand point	1	69,807	69,808	69,807	4	4	4	4
		2	22,066	21,802	21,825				
		3	447	388	253				
		4	0	0	0				
12	3500 demand point	1	80,236	80,236	80,236	4	4	4	4
		2	26,778	22,869	22,775				
		3	639	445	299				

Table 3 (continued)

S. no	Test problem	Unsatisfied demands				Minimum number of DCs			
		Number of DCs	GA	PS	Proposed Algorithm	GA	PS	Proposed Algorithm	Obj_{Best1}
		4	0	0	0				
13	4000 demand points	1	89,004	89,008	89,004	4	4	4	4
		2	27,530	27,300	27,343				
		3	104	222	104				
		4	0	0	0				
14	4500 demand points	1	100,327	100,327	100,327	5	4	4	4
		2	32,117	32,039	31,771				
		3	272	283	187				
		4	114	0	0				
		5	0	–	–				
15	5000 demand points	1	114,564	114,564	114,562	5	4	4	4
		2	35,186	34,725	34,558				
		3	408	503	408				
		4	51	0	0				
		5	0	–	–				

It can be observed from Table 3 that for five test problems (1,2,3,4,5), the proposed algorithm recommends locating three DCs, while for other test problems (6,7,8,9,10,11,12,13,14,15) minimum of four DCs are recommended to serve the unsatisfied demand points. However, the result of the genetic algorithm deviated from the best result for two test problems (14,15). The algorithm suggests locating five firms for test problems 14 and 15. Same as, the result of pattern search differs from the best result for instances 4 and 5 and proposes to locate four firms instead of 3. It can be observed from the result that the performance of the proposed algorithm is better than the genetic algorithm and pattern search methods for both the unsatisfied demand points and the minimum number of DCs. In the second stage of the proposed model, the best result of stage one is employed for obtaining the optimal location of the DCs.

5.2.2 Stage level 2: optimal location of distribution centres

In the second stage of the proposed model, the minimum number of DCs recommended by the first stage is employed for obtaining the optimal location of DCs. The performance of the proposed algorithm is compared with six well-known meta-heuristic methods, GA, FMINCON, GA-FMINCON, PS, GA-PS and MS. The performance is for the same data sets employed in stage one. The algorithms are executed 5 times for each data set and the best result is reported in Table 4 for comparison. The algorithms are compared for the accuracy of $\mathcal{E} = 10^{-6}$. The optimal result comparing all seven algorithms for each instance is reported under the column $\text{Obj}_{\text{Best2}}$.

It can be observed from Table 4 that algorithms GA, Fmincon, GA-Fmincon deviate from the best result for all the fifteen datasets and MS, PS, GA-PS deviate for fourteen instances out of fifteen. However, the proposed algorithm only deviates for three instances (7,8,10) with a deviation of less than 1%. The proposed algorithm performs better than PS, GA-PS, MS for 14 test problems and from GA, Fmincon, GA-Fmincon for all 15 test problems. The performance of the proposed algorithm is significantly better than all six algorithms.

The percentage deviation of all seven algorithms from the best result ($\text{Obj}_{\text{Best2}}$) are reported in Table 5. The maximum deviation is highlighted for each heuristic. The maximum deviation reported for MS, GA, PS, GA-PS, Fmincon and GA-Fmincon is 1.7612, 2.8823, 6.1499, 2.7782, 2141.9437 and 950.9738, respectively. However, the maximum percentage deviation for the proposed algorithm is less than 1% (0.9906). It can be concluded from Tables 4 and 5 that the performance of the proposed algorithm is much better than all the six algorithms, MS GA, PS, GA-PS, Fmincon, GA-Fmincon in terms of solution quality.

Figure 8a and b shows the percentage deviation of all seven algorithms for each data set. As shown in Fig. 8a, MS, GA, PS, and GA-PS deviate continuously and significantly from the best solution. However, the proposed algorithm varies from the best value for only three instances with a deviation of less than 1%. However, Fmincon and GA-Fmincon highly deviate from the optimal value with the maximum deviation of 2141.9437 and 950.9738 respectively.

It is important to highlight that even a small % deviation in many cases can lead to a significant difference in location. The execution time of all seven algorithms is reported in Table 6. It can be observed that the proposed algorithm requires more time than GA, PS, GA-PS, Fmincon, GA-Fmincon for almost all the instances and the MS algorithm less time than the proposed algorithm. Although, it is important to mention here that the effectiveness of the algorithm is more important than efficiency in the location decision. The proposed algorithm provides a significantly better result than all the six algorithms in a reasonable time.

Table 4 Objective function value by Fmincon-GA, PS-GA, Heuristic and best optimal solution

S. NO	Demand	Obj_{Best1}	GA	MS	PS	GA-PS	Fmincon	GA- Fmincon	Obj_{Best2}	Proposed Algorithm
1	10	3	397.709468	397.705451	422.161948	397.707839	8916.290410	397.708330	397.703588	**397.703588**
2	100	3	8227.575120	8363.052116	8302.458113	8227.574895	17,253.165059	86,372.275568	8218.309365	**8218.309365**
3	200	3	15,494.881383	15,483.607546	15,472.088130	15,472.088130	15,769.564416	15,472.088130	15,471.738015	**15,471.738015**
4	300	3	23,184.051265	23,212.565567	23,226.427775	23,184.034852	29,930.192579	23,184.039710	23,183.662377	**23,183.662377**
5	400	3	29,925.219081	29,925.797598	29,926.599462	29,925.216416	33,193.037494	29,925.203604	29,924.924638	**29,924.924638**
6	500	3	39,731.748430	39,758.462871	39,747.891657	39,731.747291	64,672.589767	39,731.746038	39,731.729258	**39,731.729258**
7	1000	4	67,274.196238	67,613.861424	69,509.749652	**67,274.099728**	70,445.597775	67,274.178934	67,274.099728	67,572.300795
8	1500	4	102,578.812764	**99,705.003526**	99,989.080849	102,578.716445	104,320.474491	102,578.719442	99,705.003526	99,962.321578
9	2000	4	134,802.193396	131,728.058672	134,840.924649	134,802.145400	139,569.450938	134,802.187235	131,711.720458	**131,711.720458**
10	2500	4	174,916.869432	173,400.329395	**173,213.286445**	174,916.775641	195,916.708218	174,916.794084	173,213.286445	174,929.221197
11	3000	4	210,983.508087	214,522.993174	217,702.646493	210,983.227038	242,640.788476	210,983.401734	210,971.001734	**210,971.001734**
12	3500	4	248,647.573174	242,131.432610	249,327.603075	248,647.463109	242,978.787016	248,647.502291	242,124.021753	**242,124.021753**
13	4000	4	282,581.321193	275,579.273966	279,193.383492	282,581.309290	277,723.056053	282,581.321051	274,942.973055	**274,942.973055**
14	4500	4	311,457.665828	306,196.560028	305,360.447628	311,457.137550	312,234.069790	311,457.581439	305,336.894688	**305,336.894688**
15	5000	4	350,498.349089	349,625.092817	353,495.121867	350,498.273945	360,596.415796	350,498.276959	349,120.591796	**349,120.591796**

Table 5 Comparison of percentage deviation

S. no	Demand	% Deviation						
		MS	GA	PS	GA-PS	Fmincon	GA-Fmincon	Proposed Algorithm
1	10	0.0005	0.0015	6.1499	0.0011	2141.9437	0.0012	0.0000
2	100	1.7612	0.1127	1.0239	0.1127	109.9357	950.9738	0.0000
3	200	0.0767	0.1496	0.0023	0.0023	1.9250	0.0023	0.0000
4	300	0.1247	0.0017	0.1845	0.0016	29.1004	0.0016	0.0000
5	400	0.0029	0.0010	0.0056	0.0010	10.9210	0.0009	0.0000
6	500	0.0673	0.0000	0.0407	0.0000	62.7732	0.0000	0.0000
7	1000	0.5050	0.0001	3.3232	0.0000	4.7143	0.0001	0.4837
8	1500	0.0000	2.8823	0.2849	2.8822	4.6291	2.8822	0.2581
9	2000	0.0124	2.3464	2.3758	2.3464	5.9659	2.3464	0.0000
10	2500	0.1080	0.9835	0.0000	0.9835	13.1072	0.9835	0.9906
11	3000	1.6836	0.0059	3.1908	0.0058	15.0114	0.0059	0.0000
12	3500	0.0031	2.6943	2.9752	2.6943	0.3530	2.6943	0.0000
13	4000	0.2314	2.7782	1.5459	2.7782	1.0111	2.7782	0.0000
14	4500	0.2815	2.0046	0.0077	2.0044	2.2589	2.0046	0.0000
15	5000	0.1445	0.3946	1.2530	0.3946	3.2871	0.3946	0.0000

5.2.3 Cost comparison between stage level one and stage level two

This section shows the deviation in the total operational cost by locating DCs with the objective of demand coverage (Objective 1) and by locating with the objective of the total cost minimization (Objective 2). It can be observed from Table 7 that there is a significant difference in the operational cost by adding stage two. The maximum percentage deviation in cost is 32.9835. Mostly the studies either consider locating the minimum number of DCs for maximum demand coverage or locate a fixed number of DCs with the objective of cost minimization. It can be observed that the proposed two-stage model not only recommend the minimum number of DCs and cover all unsatisfied demand points but also minimize the operational cost significantly by locating each DCs at the optimal location.

It can be observed from Fig. 9 that the percentage deviation in operational cost is significant for each data set. It implies that the addition of the second stage enhanced the location decision significantly.

The two-stage selection process employed in this paper is shown in Fig. 10. It is executed using the software MATLAB 2017a. The location selection process for demand data set 100 are presented.

Figure 10a shows the location of one DCs, already existing firm and positive points represent unsatisfied demand points. Figure 10b shows two DCs, an already existing firm and unsatisfied demand points. Figure 10c shows three DCs and an already existing firm. Figure 10d shows the optimal location of DCs. The magenta-coloured star represents the demand covered by an already existing firm. The other coloured star signifies demand satisfied

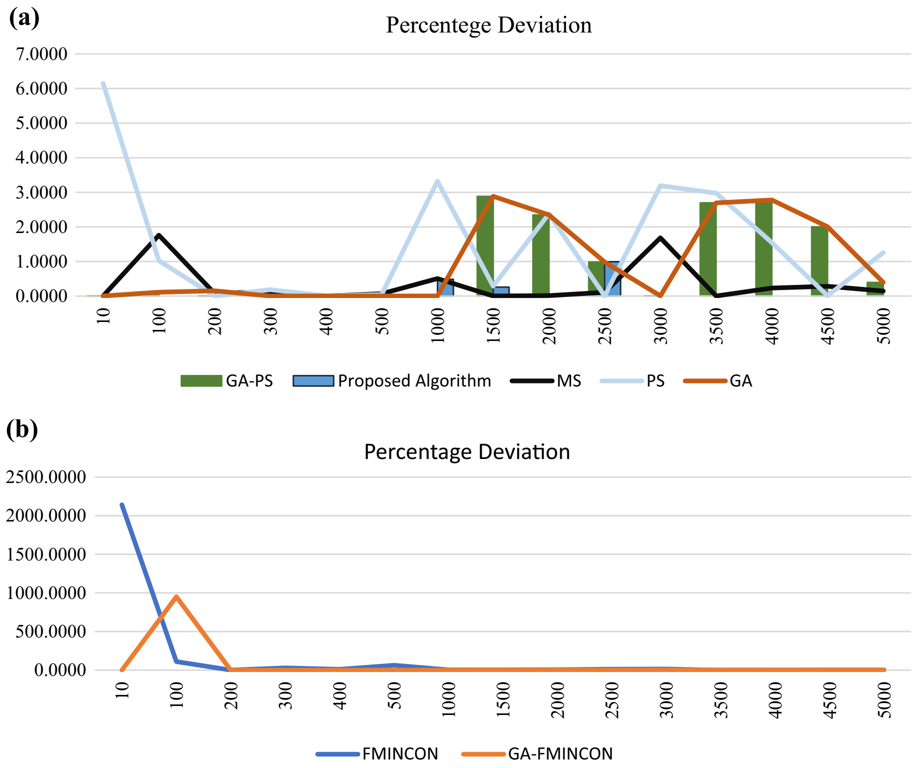

Fig. 8 **a** Comparison of percentage deviation of MS, GA, PS, GA-PS and proposed algorithm with the best solution. **b** Comparison of percentage deviation of Fmincon- GA-Fmincon with the best solution

by DCs, the circle represents coverage area, the dot represents the location of the DCs, and the positive sign represents unsatisfied demand point.

6 Implications of the study

(a) ***Theoretical and methodological implications***
The current study contributes to literature both theoretically and methodologically. The paper presents a mathematical model for relief planning operations in disaster situations. A novel two-stage model developed in the paper presents a methodological perspective through which both monetary and non-monetary kind of objectives can be fulfilled while achieving better optimal outputs compared to a single-stage method. Most of the past work consider minimization of unmet demand or maximization of survival (Burkart et al., 2017; Duhamel et al., 2016; Liu et al., 2019). However, the focus on monetary aspects often compromises the focus towards demand satisfaction. This proposed mathematical model is an improvement above those studies since it takes care of monetary and non-monetary kind of objectives i.e., satisfying the full demand and provide full relief. Meeting all demand with full relief are the few crucial things that should be considered while practicing and modelling relief distribution problem. The proposed model

Table 6 Computational time for different data sets

S.no		Time						
		MS	PS	GA	Fmincon	Fmincon-GA	PS-GA	Proposed algorithm
1	10	313.1	10.4	15	1.7	17.1	18.1	73.2
2	100	201.4	8.1	44	2.2	45.9	50.7	86.1.1
3	200	234.5	12.8	52	2.4	66	56.8	94.9
4	300	214.2	8.1	96	2.3	98.9	100.6	99.6
5	400	240.9	11.7	86.2	2	94.9	91.6	128.3
6	500	215.4	8.3	92	2.1	95.1	99.1	187.2
7	1000	340.3	15.9	180	3.6	184.9	188.2	1920.5
8	1500	362.1	10.2	220	4.9	223.1	226.9	2440.9
9	2000	430.5	22.1	261	4.8	263.4	268.8	3100.6
10	2500	434.2	20.6	309	5.4	314.1	318.6	3256.1
11	3000	473.5	19.3	312	5.8	315.2	323.8	3612.9
12	3500	408.2	19.5	380	6.9	384.7	390.5	4679.3
13	4000	417.1	24.9	386.5	5.6	391.3	399.4	3804.9
14	4500	467.1	24.6	240	6.1	243.8	251	4652.7
15	5000	512.7	29.2	261	5.7	265.7	269.1	4791.5

Table 7 Operational cost by stage one and stage two

S.NO	Demand	Operational cost by Objective 1 (Demand coverage)	Operational cost by Objective 2 (Cost minimization)	Percentage Deviation
1	10	5.288800278037078e + 02	3.977035878839719e + 02	32.9835
2	100	8.326407354612082e + 03	8.218309365295794e + 03	1.3153
3	200	1.578197724020343e + 04	1.549765074543557e + 04	1.8346
4	300	2.339432558053250e + 04	2.318366237673021e + 04	0.9087
5	400	3.010575251252444e + 04	2.992492463787193e + 04	0.6043
6	500	4.139556791218394e + 04	3.973172925839003e + 04	4.1877
7	1000	7.554535152713383e + 04	6.759948662687567e + 04	11.7543
8	1500	1.025602820410913e + 05	9.996232157794613e + 04	2.5989
9	2000	1.451258493746368e + 05	1.317117204582614e + 05	10.1845
10	2500	1.813412753088776e + 05	1.749292211970448e + 05	3.6655
11	3000	2.185053265287638e + 05	2.109710017339862e + 05	3.5713
12	3500	2.613202905274121e + 05	2.421240217530740e + 05	7.9283
13	4000	2.864574731500480e + 05	2.749429730551978e + 05	4.1880
14	4500	3.211757299250345e + 05	3.053368946882575e + 05	5.1873
15	5000	3.567360290223259e + 05	3.491205917955199e + 05	2.1813

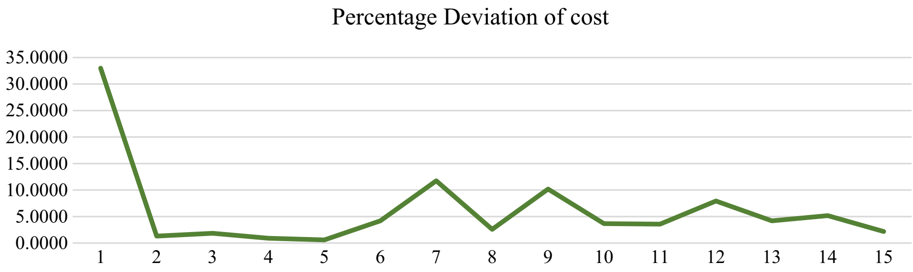

Fig. 9 percentage deviation of operational cost of objective 1

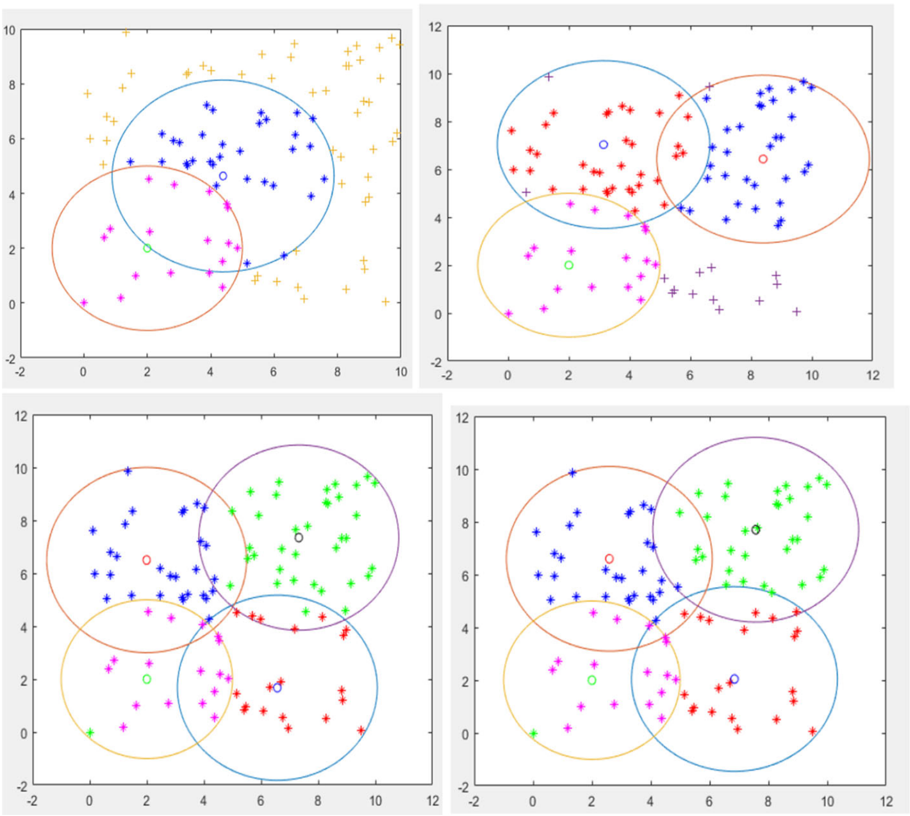

Fig. 10 **a** One DC and an already existing firm. **b** Two DCs and an already existing firm. **c** Three DCs and already existing firm. **d** Optimal location of DCs

captures these two vital aspects of the relief distribution problem and brings uniqueness in the proposed model. Moreover, the proposed model also demonstrates significant cost savings as compared to the single-stage coverage based model (Jia et al., 2007; Zhang et al., 2017). The cost comparison is shown in Table 7. Thus, the proposed work provides a significant improvement over earlier methods.

The model provided in the study also covers location planning of relief centres in disaster situations, especially Covid-19 like crises, where human movement is restricted, and relief needs to be delivered at demand points. The model thus can guide further work in the direction of relief location planning for disaster situations where pre-positioned sites and preparedness are unavailable. Further, the optimality of the result is crucial in disaster planning as it affects the humanitarian operations and service for the affected people. The novel two-phase algorithm developed in the study thoroughly search the decision space to ensure optimal results. Due to this unique exploration and exploitation search processes, the proposed algorithm performed extremely well for location problems and can be implemented for solving relief centres and other location-related problems.

(b) ***Managerial Implications***

The proposed model will help relief planning managers in the effective planning of DCs in both pre-and post-disaster cases. Human life is the primary concern in the disaster situation; thus, the DCs need to be located in close proximity to the demand, but too many DCs can cause a waste of resources and money. However, insufficient DCs can cause the demand unsatisfaction. The proposed work assists the relief planning manager in determining the optimal number of DCs to satisfy the demand of affected people while at the same time minimizing the wastage of money and resources arising from too many DCs.

During the Covid-19 situation, the main challenges that the decision-makers faced included avoiding mass gathering at DCs, movement restriction due to lockdown, resources unavailability, decisions on relief distribution planning, and locations. The present work helps the decision-maker to plan relief operations in the presence of these challenges. Covid-19 caused multiple shocks, and due to lack of proper planning, second waves hit human life and the economy more severely. The proposed work can assist decision-makers and relief planning agencies in pre-planning the relief centre location against such disasters impact in the future.

7 Conclusion, limitations and future scope of the study

In this paper, a two-stage model is proposed for locating relief distribution centres in disaster-affected areas. The first stage of the model is focused on finding the minimum number of DCs while the second stage determines the optimal location of these DCs to minimize the total cost. The coverage area and capacity of each relief distribution centre are limited by resource availability. To optimally solve this model, a two-phase algorithm is proposed in this paper. The first phase of the algorithm, i.e., *exploration phase* identifies a near-optimal solution while the second phase, i.e. *exploitation phase* improve the solution quality through investigating the *close circular proximity* of the best solution obtained in phase 1.

The performance of the proposed algorithm is tested on 15 data sets. In the first stage, a comparison is provided between the proposed algorithm and GA, PS algorithm. However, in the second stage, the comparative analysis is performed with MS, GA, PS, GA-PS, Fmincon and GA-Fmincon algorithms. The experimental analysis shows that in the first stage, the proposed algorithm provides the optimal result for all the test problems in a reasonable time. In the second stage, the algorithm deviates for three instances with a maximum deviation of less than 1%. However, the performance of the proposed algorithm is significantly better than the other well-known heuristics such as MS, GA, PS, GA-PS, Fmincon, and GA-Fmincon in solution quality. These heuristics deviate from the best solution continuously and significantly for almost all the test problems. The paper also indicates that the proposed two-stage model provides optimal location as compared to the demand coverage model. The major contributions of this study are (a) proposing a two-stage model for the relief distribution centre, (b) introducing both capacity and coverage constraint (c) proposing a novel two-phase algorithm to optimally locate the DCs.

The work proposed in the paper is an effort to model a real scenario of relief distribution problem. However, the proposed study has also few limitations like any other study. Some of these limitations are related to the modelling assumptions considered in Sect. 3. The demand data is considered to be known and fixed for the study. However, in a real-life scenario, the demand can fluctuate because of multiple uncontrollable factors resulting in altered outcomes. Furthermore, the scope of this study does not include the possibility of delivery disruptions in the model and unavailability of resources. These limitations can be addressed in the future as well to further improve the proposed model.

In future, refinement of the model can be done by additional survey. The uncertainties in demand and disruption in delivery can be introduced in the future by considering the probability distribution function of the demand and delivery. In addition, the competitive factor between already existing firms can be performed.

Appendix A (MATLAB Code)

See Table 8.

Table 8 Optimal location of DCs

S. no.	Demand	Optimal Location
1	10	(6.478670, 8.111774) (8.147237, 1.576131) (1.269868, 9.571670)
2	100	(7.367749, 2.241030), (1.777632, 7.575504), (6.398254, 7.759252)
3	200	(7.482605, 2.0581779), (6.597941, 7.484263), (2.169083, 7.696552)
4	300	(7.632851, 7.428594), (7.33987, 2.406851), (2.670916, 7.336997)
5	400	(7.198386, 7.518608), (7.332037, 2.399892), (2.172289, 7.002603)
6	500	(8.124467, 7.776386), (7.642779, 2.117346), (3.233149, 7.104526)
7	1000	(8.378268, 7.362111) (7.574775, 2.349993) (1.712344, 7.416179) (5.040473, 6.557472)
8	1500	(7.349475, 2.327294), (4.505742, 6.521729), (1.461435, 7.659459)), (7.860669, 7.723567)
9	2000	(8.414071, 7.206314) (7.230204, 2.380852) (1.638024, 7.473028) (4.984683, 7.124113)
10	2500	(7.249521, 2.108470), (8.313077, 7.552475), (4.999358, 6.612372), (1.869906, 7.498676)
11	3000	(7.316564, 2.166229), (4.990984, 6.797730), (1.619450, 7.450014), (8.389143, 7.55238)
12	3500	(7.33968, 2.150158), (1.505828, 7.162321), (4.833992, 7.378361), (8.278271, 7.055343)
13	4000	(7.452032, 8.38707), (6.759058, 4.976557), (2.164873, 7.17172), (7.561801, 1.715282)
14	4500	(7.225931, 2.199880), (1.622073, 7.181577), (4.861103, 7.583102), (8.29659, 7.154021)
15	5000	(7.745488, 8.28223), (6.514195, 5.012629), (2.173873, 7.285376), (7.571205, 1.657550)

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