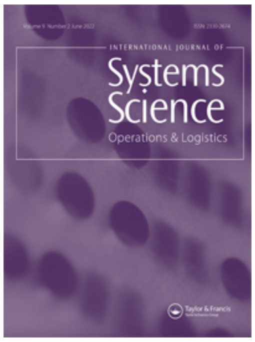


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# Multi-objective robust-stochastic optimisation of relief goods distribution under uncertainty: a real-life case study

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**ABSTRACT**
This paper proposes a multi-objective robust-stochastic humanitarian logistics model to assist disaster management officials in making optimal pre- and post-disaster decisions. This model identifies the location of temporary facilities, determines the amount of commodity to be pre-positioned, and provides a detailed schedule for the distribution of commodities and the dispatch of vehicles. Uncertainties in demand, node reachability by a particular mode of transportation, and condition of pre-positioned supplies after a disaster are considered. Another supposition of this paper is the equity in the distribution of commodities. This paper contributes to the existing literature by adding vehicle flow and multi-periodicity into a robust-stochastic optimisation model. A real-life case study of a flood in Bangladesh shows the applicability of our model. Finally, the findings show that the proposed model can aid decision-makers in allocating resources optimally.

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Humanitarian logistics; robust-stochastic optimisation; multi-objective optimisation; location selection; supply pre-positioning

## 1. Introduction

To reduce human suffering and economic loss caused by natural and human-made disasters, an effective and efficient framework for disaster management is mandatory (Altay & Green, 2006; Duhamel et al., 2016; Galindo & Batta, 2013; Holguín-Veras et al., 2013; Nezhadroshan et al., 2020; Ozdamar, 2011; Özdamar & Ertem, 2015). The term disaster management is defined by Altay and Green (2006) as all the activities, functions, and programmes carried out before, during, or after a disaster to reduce its impact. Disaster management activities can be categorised into four phases – namely, mitigation, preparedness, response, and recovery (Galindo & Batta, 2013; Mcloughlin 1985). *Mitigation* refers to all the activities performed before a disaster to reduce the long-term damage. *Preparedness* refers to the activities performed just before a disaster so that a more efficient response is possible (Abdi et al., 2019). *Response* refers to the disaster management activities performed immediately after a disaster. Finally, *recovery* refers to both short- and long-term activities to restore the normal functioning of the affected community after a disaster (Galindo & Batta, 2013).

Two of the key activities in the preparedness phase are location selection and pre-positioning of supplies (Fathollahi-Fard & Hajiaghaei-Keshteli, 2018). Optimum selection of a temporary facility can substantially reduce transportation costs and minimise response time (Balcik & Beamon, 2008). Pre-positioning of supplies is another key decision in the preparedness phase. Immediately after a disaster, the demand for relief supplies spikes (Rawls & Turnquist, 2011). Procuring massive amounts of supplies within a short time may prove difficult. Pre-positioning of supplies, therefore, can circumvent the problem (Paul & Hariharan, 2012). The response activities include the evacuation of the affected people, setting up temporary shelters for the injured, distributing relief supplies, and transporting injured people to medical facilities (Yi & Özdamar, 2007). Timely distribution is key to reducing human suffering (Bozorgi-Amiri et al., 2013; Yazdani et al., 2020). This study focuses on the preparedness and response phases.

Several papers have called for more in-depth research into the preparedness and response phases of disaster management (Altay & Green, 2006; Galindo & Batta, 2013; Özdamar & Ertem, 2015; Sahebjamnia et al., 2017). Holguín-Veras et al. (2012) pointed out the potential areas where current humanitarian logistics studies are lacking. Vehicle routing, inventory allocation, and optimal distribution of relief are three of them. To the

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authors' knowledge, few studies have so far incorporated all three considerations. In another study, Holguín-Veras et al. (2013) argued that social cost, which is the summation of logistics cost and deprivation cost, is the most appropriate objective function for the humanitarian logistics model. Except for a study by Haghani and Oh (1996), no studies have used summation of logistics and deprivation cost as objective functions. Uncertainty is inherent in a relief operation (Holguín-Veras et al., 2012). Uncertainty arises due to a lack of knowledge of the severity of the disaster immediately after the occurrence. Uncertainty in demand is the most important to consider (Davis, 2013). A disaster can damage the pre-positioned supply in the facilities (Bozorgi-Amiri et al., 2013; Haghi et al., 2017). Thus, the uncertainty of the condition of inventory must also be taken into account. At the onset of a disaster, parts of the facility may become unreachable by some transportation modes (Ahmadi et al., 2015; Rashid, 2000; Rezaei-Malek et al., 2016). This uncertainty should also be incorporated.

Many humanitarian models have been developed using deterministic and stochastic optimisation (Nezhadroshan et al., 2020). However, the relatively new robust optimisation field is comparatively unexplored. Only a handful of works have been done on robust optimisation (Bozorgi-Amiri et al., 2012, 2013; Haghi et al., 2017; Rezaei-Malek et al., 2016; Zokaee et al., 2016). To the authors' knowledge, only commodity flow has been considered in these robust-stochastic optimisation studies. Dispatching and routing of vehicles have not yet been studied. And except for a study by Rezaei-Malek et al. (2016), no study has considered a multi-period model. Equity in the distribution of relief supplies is a critical issue (Afshar & Haghani, 2012; Huang et al., 2012), yet few models have incorporated equity measures.

To cope with our contributions, a multi-objective, multi-period, robust-stochastic model optimising logistics and deprivation cost and considering vehicle flow and equity in distribution is an open problem and is the scope of this study. This study aims to develop a mixed-integer linear robust-stochastic optimisation model that incorporates facility location, inventory pre-positioning, distribution of commodity, dispatch of vehicles, and fairness in distribution. The model is a two-stage model where the first stage determines the location of temporary facilities and the amount of commodity to be pre-positioned and the second stage determines a detailed distribution schedule for commodities and a dispatch schedule for vehicles. The twofold objective of this model is to minimise logistics and deprivation costs. A lexicographic Tchebycheff method is used to generate the Pareto front and allow the decision-maker to tradeoff between the objective functions. A case study on the relief goods distribution in Bangladesh is presented to show the effectiveness of the model. Comparison between robust stochastic models and the deterministic model in terms of costs is performed to show the relative advantage of the robust-stochastic optimisation model over the deterministic one.

Generally speaking, this paper contributes to the existing humanitarian logistics literature by including the following factors in the robust-stochastic optimisation model.

(1) Vehicle flows with multiple periods, which give a detailed schedule of relief distribution and vehicle dispatch.
(2) A real-life case study on the relief goods distribution in Bangladesh is studied to examine the applicability of our robust-stochastic optimisation framework.

The rest of the paper is organised as follows: Section 2 gives a review of the relevant literature. Section 3 provides a brief overview of robust-stochastic optimisation. Section 4 describes the proposed research problem. Section 5 establishes the mathematical model. Section 6 presents a summary of the lexicographic Tchebycheff method. Section 7 describes a real-life case study. Section 8 discusses the results. Section 9 gives a discussion on the practical and managerial insights. Finally, Section 10 provides the conclusion and recommendations for future research.

## 2. Literature review

Since the 1980s numerous researchers have contributed to the enrichment of humanitarian logistics and the number of studies in this field is showing an increasing trend (Zhou et al., 2018). In this regard, many extensive reviews and surveys can be found in Altay and Green (2006), Galindo and Batta (2013), Habib et al. (2016), Özdamar and Ertem (2015), Safeer et al. (2014), Zheng et al. (2015), Bealt and Mansouri (2018) and Nezhadroshan et al. (2020).

In this section, the literature in the related fields is reviewed in three different but related scopes with regards to types of optimisation models. The review encompasses three major areas: deterministic logistics, stochastic logistics, and robust-stochastic logistics.

### 2.1. Deterministic logistics model

As far as we know, Knott (1987) presented one of the earliest research studies on disaster relief logistics. The objective of his model was to maximise food supply to relief camps. Haghani and Oh (1996) developed a multi-modal, multi-commodity, time–space network model for relief distribution. Their model formulates response time as demand and supply carryover cost because cost is much easier to quantify. Their objective function minimises transportation, transhipment, and carryover cost. They proposed two algorithms for the solution of the complex model: Lagrangian relaxation and iterative fix-and-run.

Özdamar et al. (2004) developed a multi-commodity model for relief distribution among disaster-affected victims. Their model is a dynamic planning model that allows re-planning after supply and demand information is updated. The Lagrangian relaxation method, as well as a greedy heuristic, is proposed as solution algorithms. Yi and Özdamar (2007) developed a location-distribution model that determined the location of temporary emergency centres and a detailed distribution and rescue plan. They considered vehicles as an integer commodity rather than a binary variable because this allowed for a more compact formulation, and the output of the model could be extracted to develop a detailed distribution schedule.

Tzeng et al. (2007) developed a relief distribution system with three objective functions: minimise cost, minimise transportation time, and maximise satisfaction. Fuzzy multiobjective linear programming was the method of choice as the weight relationships of the three objective functions cannot be defined clearly. Yi and Kumar (2007) used an ant colony optimisation to develop a model that considered both distributions of relief and rescue of injured people. Balcik et al. (2008) presented a last-mile distribution model in relief logistics. They developed a mixed-integer programming model that determines delivery schedules for vehicles and equitably allocates resources based on supply, vehicle capacity, and delivery-time restrictions. The objectives are to minimise transportation costs and maximise benefits to aid recipients. Abounacer et al. (2014) developed a location-transportation model that has three conflicting objectives. The location problem determines the location, number, and size of relief distribution centres, and the transportation problem determines the amount of relief supply to be sent from distribution centres to demand points. The authors proposed an $\varepsilon$-constrained method for the multi-objective model as it can generate an exact Pareto front. The authors also proposed approximation-based heuristics that would reduce solution time.

Na and Zhi (2009) used a genetic algorithm to solve the emergency relief transportation problem. Their objective was to minimise transportation time. Nolz et al. (2011) discussed risk approaches in relief distribution. They differentiated risk into five categories: number of alternative paths, unreachability, threshold risk, minimal travel time, and minimal risk. The first three are considered dependent catastrophe hazards. Their objective function has three terms: risk and travel time; minimum facility location criterion; and maximum coverage location criterion. A modified multi-objective memetic algorithm is used to solve the optimisation problem. Afshar and Haghani (2012) developed a deterministic location-distribution model based on the Federal Emergency Management Agency (FEMA) standard. They aimed to minimise unmet demand and their model identified the location of all temporary facilities. It also incorporated equity in distribution.

Recently, Fathollahi-Fard and Hajiaghaei-Keshteli (2018) proposed a bi-objective and bi-level model for optimising the pre-disaster decisions in the case of terrorist attacks. They optimised the cost of the location of facilities and the allocation of customers while minimised the budget of defensive systems to control the disasters. They developed two hybrid metaheuristics by the combination of particle swarm optimisation and genetic algorithms as well as the water wave optimisation and whale optimisation algorithms. They recommended that the vehicle routing decisions and the introduction of robust optimisation are the main continuations of their work. Maghfiroh and Hanaoka (2018) developed humanitarian logistics as an extension to the vehicle routing optimisation in the case of disaster response. Their proposed model optimised the heterogeneous vehicles, multiple trips, and location of facilities with different accessibilities under demand uncertainty. They applied a modified simulated annealing algorithm with a variable neighbourhood search to solve their model. However, their model was not established by the robust and stochastic optimisation. They did not consider a specific type of disaster for their model and one of the future recommendations of their work was to change the models' constraints to meet a specific disaster like floods.

At last but not least, Cavalcante et al. (2019) developed an integrated model with a simulation of machine learning to study the risk of suppliers to analyse the resilience levels of facilities. The disaster type was general and can be applied to different types of disasters.

### 2.2. Stochastic logistics model

Realising how uncertainty is embedded in humanitarian logistics, several authors have incorporated uncertainty in their model. Barbarosoğlu and Arda (2004) developed a two-stage stochastic, multi-commodity, and multi-modal transportation model intended to be used as a decision support tool for disaster response officials. The first stage of the model determines the amount of commodity to be pre-positioned in local distribution centres, and the second stage determines the detailed distribution plan of relief goods. Chang et al. (2007) developed a two-stage stochastic programming model for planning rescue operation logistics in a flood situation. Their model determined the location of distribution facilities, their capacities, and the transportation plan. The authors developed flood scenarios using a GIS system and the problem was solved using the sample average approximation method. Rawls and Turnquist (2012) developed a model for pre-positioning and dynamic delivery of relief supplies in a short-term situation. It was an expansion of an earlier model developed by the same authors (Rawls & Turnquist, 2011). The authors developed a multi-commodity model where two policies were developed for consumable and non-consumable commodities. They developed a reliability measure $\alpha$, which selected a subset of the most likely scenarios from a set of given scenarios.

Rennemo et al. (2014) developed a unique three-stage stochastic model. The first stage considers the location of local distribution centres and pre-position of supply in those centres. The second stage of the model involves generating routes based on the uncertain nature of the network and dispatching of commodities and vehicles. The third stage considers recourse actions for the dispatched vehicles. Distribution equity is achieved in this model by means of utility intervals for each recipient. Ahmadi et al. (2015) developed a two-stage stochastic multi-depot location routing model. The unique features of their model were network failure, multiple uses of vehicles, and relief time limitation constraints. A real-world case study of San Francisco was solved to show the effectiveness of the model. They used a variable neighbourhood search heuristic to solve large instances of the model. In another research, Cao et al. (2018) incorporated the sustainable development goals with disaster management. With the development of a stochastic optimisation model, their objectives were the maximisation of the lowest victims' perceived satisfaction, and the minimisation of the largest deviation on victims' perceived satisfaction. The earthquake disaster was the applicability of their work. In another study, Maharjan and Hanaoka (2018) introduced a multi-objective and multi-period humanitarian supply chain that optimised the location of temporary logistics hub for disaster response. The application of their work was the earthquake disaster in Nepal. At last but not least, with the use of a stochastic model to address the case of flood disaster in Peruvian in Peru, Chong et al. (2019) proposed a resilient humanitarian logistics with different warehouses and distribution centres.

### 2.3. Robust-Stochastic models in humanitarian logistics

In terms of robust-stochastic optimisation, Bozorgi-Amiri et al. (2013) developed a bi-objective, two-stage, robust stochastic model for relief distribution considering demand, supply, and transportation uncertainty. Their objective was to minimise transportation and inventory costs while maximising satisfaction. The first stage model determined the location of the Regional Distribution Centers (RDC) and inventory levels. The final stage determined the detailed schedule of relief distribution. The limitations of their model are that it ignored vehicle flow and time periods.

Haghi et al. (2017) expanded the robust stochastic model developed by Bozorgi-Amiri et al. (2013) by adding casualty transportation. They developed a MOGASA (multi-objective genetic algorithm and simulated annealing) metaheuristics algorithm. They used the $\epsilon$-constrained method to solve it exactly. They also used NGSAII (non-dominated sorting genetic algorithm) to compare the performance with the MOGASA algorithm. Their results showed that although the $\epsilon$-constrained algorithm was efficient for small problems, with larger problems it became extremely time-consuming. On the other hand, NGSAII and MOGASA performed similarly.

Rezaei-Malek et al. (2016) formulated a multi-objective robust optimisation model for perishable commodities that require renewal and disposal after a certain time. This model considers uncertainty in road conditions, and usable supply and demand. The objective functions were to reduce response time and total cost. The reservation level Tchebycheff method was used for multi-objective optimisation. Although this paper incorporated multiple periods in the robust-stochastic model, it did not consider vehicle flow. Similarly, Tofighi et al. (2016) proposed a mixed possibilistic-stochastic model to address resilient humanitarian logistics. They applied a self-adaptive differential evolution as a new metaheuristic to solve its optimality in large-scale networks. They also recommended that the vehicle flow will be an interesting addition to increase the applicability and complexity of their problem.

Recently, Sahebjamnia et al. (2018) with the use of robust optimisation, developed integrated business continuity and disaster recovering planning. They validated their model by a furniture manufacturing company in Iran. They solved their model by the $\epsilon$-constrained method. Finally, Nezhadroshan et al. (2020) proposed a scenario-based possibilistic-stochastic approach to model the humanitarian logistics with resiliency levels. Their model contributes to the multi-modal logistics in the case of earthquake disasters in the Mazandaran province of Iran. In addition to the total cost, the travel time and resiliency levels were their objectives to be optimised. A hybrid of the $\epsilon$-constrained algorithm and a novel technique combining DEMATEL and ANP was applied to solve their case study.

In conclusion, Table 1 provides a comprehensive summary of the literature reviewed. We classified the papers based on the type of the model, multi-objective, multi-period, commodity flow, and vehicle flow as well as location selection. Besides, we have considered the types of disasters like floods, earthquakes and terrorist attacks. Finally, the solution algorithm as one of the main contributions of the several works in the literature is also provided in this table.

Based on the aforementioned papers and findings from Table 1, these research gaps can be found:

- The majority of the papers (around 80 percent) are only considered the commodity flow and location selection as their variables of their models.
- Only three studies simultaneously considered a multi-objective, multi-period, commodity flow, and vehicle flow as well as location selection for humanitarian logistics (Ahmadi et al., 2015; Rennemo et al., 2014; Tzeng et al., 2007). However, their applicability was the earthquake disaster and they did not contribute a robust-stochastic optimisation approach.
- Most of the papers did not consider a specific disaster type or their model was suitable for the earthquake disaster. Only two studies considered the flood disaster type. However, they did not propose a robust-stochastic optimisation and the vehicle flow and multi-objective and multi-period logistics model.

To fill the aforementioned gaps, this paper is the continuation of the similar models in the area of robust-stochastic logistics, while adds several extensions such as the vehicle flows with multiple periods, which give a detailed schedule of relief distribution and vehicle dispatch as well as a real-life case study of a flood.

## 3. Robust optimisation

In a practical situation, uncertain and noisy data are common, and during a disaster, where panic and confusion abound, finding the exact data is almost impossible (Caunhye et al., 2012). In a deterministic model, this uncertainty is dealt with reactively through the use of sensitivity analysis (Mulvey et al., 1995). According to Mulvey et al. (1995), a proactive approach is needed to deal with uncertainty – that is, uncertainty must be built into the model. The stochastic programme is used to incorporate uncertainty in the model. Robust optimisation is an improved version of stochastic optimisation and has some unique advantages over stochastic programming.

### 3.1. Robust optimisation modelling framework

Mulvey et al. (1995) introduced the idea of robust optimisation. They described two types of the robustness of a model: solution robustness and model robustness. Solution robustness is defined as a model's ability to produce solutions for every scenario that is close to an optimal solution. Model robustness is defined as the model's ability to provide a feasible solution for every realisation of scenarios. The authors stated that it is impossible for a linear programme model to be solution robust and model robust at the same time for every scenario. That is why a model is needed with sufficient redundancies built-in. A typical linear programme is given below:

$$\text{Minimize}\, f(x,y) = c^T x + d^T y \tag{1}$$

$$\text{Subject to}\, Ax = b \tag{2}$$

$$Bx + Cy = e \tag{3}$$

$$x, y \geq 0 \tag{4}$$

where $x$ is a design variable vector that is not dependent upon a specific realisation of the scenario; $y$ is a control variable vector that depends upon the realisation of the uncertain scenarios; $A$ and $b$ are deterministic parameters while $B$, $C$, and $e$ are uncertain stochastic parameters. A set of scenarios is defined as $\Omega = \{1, 2, \ldots, s\}$ to model the uncertain parameter. Subset $\{d_s, B_s, C_s, e_s\}$ is the realisation of the parameters for each scenario, $s \in \Omega$. The probability of occurrence of each scenario is $p_s(\sum_S p_s = 1)$. A set of control variables $\{y_1, y_2 \ldots, y_s\}$ is defined for each scenario $s \in \Omega$. A set of deviation vectors is also introduced to allow infeasibility in the model defined as $\{\delta_1, \delta_2, \ldots, \delta_s\}$.

Thus, the robust formulation is provided as below:

$$\text{Minimize}\, \sigma(x, y_1, y_2, \ldots\ldots, y_s) + \gamma\rho(\delta_1, \delta_2, \ldots\ldots, \delta_s) \tag{5}$$

S.t.

$$Ax = b \tag{6}$$

$$B_s x + C_s y_s + \delta_s = e_s,\ \forall s \in \Omega \tag{7}$$

$$x \geq 0,\ y_s \geq 0,\ \forall\, s \in \Omega \tag{8}$$

The first term in the objective function represents solution robustness and the second term represents

**Table 1.** Summary of the literature review.

| References | Model Type | Multi-objective | Multi-Period | Commodity flow | Vehicle Flow | Location Selection | Disaster type | Solution Procedure |
|---|---|---|---|---|---|---|---|---|
| Knott (1987) | DET | | | ✓ | | | General | Exact |
| Haghani and Oh (1996) | DET | | ✓ | ✓ | ✓ | | General | Lagrangian relaxation, Iterative fix and run |
| Özdamar et al. (2004) | DET | | ✓ | ✓ | ✓ | | General | Lagrangian relaxation, Greedy heuristics |
| Barbarosoğlu and Arda (2004) | STOC | | | ✓ | ✓ | | General | Exact |
| Chang et al. (2007) | STOC | | | ✓ | | ✓ | Flood | Exact |
| Yi and Özdamar (2007) | DET | | ✓ | ✓ | ✓ | ✓ | General | Exact |
| Tzeng et al. (2007) | DET | ✓ | ✓ | ✓ | ✓ | ✓ | General | Exact, Fuzzy Multi-objective optimisation |
| Yi and Kumar (2007) | DET | | ✓ | ✓ | ✓ | | General | Ant Colony Optimisation |
| Balcik and Beamon (2008) | DET | | ✓ | ✓ | ✓ | | General | Exact |
| Na and Zhi (2009) | DET | | ✓ | ✓ | | | General | Genetic Algorithm |
| Nolz et al. (2011) | DET | ✓ | | ✓ | ✓ | | General | Memetic Algorithm |
| Afshar and Haghani (2012) | DET | | ✓ | ✓ | ✓ | ✓ | General | Exact |
| Rawls and Turnquist (2012) | STOC | | ✓ | ✓ | | ✓ | Earthquake | Exact |
| Abounacer et al. (2014) | DET | ✓ | | ✓ | ✓ | ✓ | General | Exact, Epsilon constrained optimisation |
| Rennemo et al. (2014) | STOC | ✓ | ✓ | ✓ | ✓ | ✓ | Earthquake | Exact |
| Ahmadi et al. (2015) | STOC | ✓ | ✓ | ✓ | ✓ | ✓ | Earthquake | Variable Neigh-bourhood Search |
| Bozorgi-Amiri et al. (2013) | ROB | ✓ | | ✓ | | ✓ | Earthquake | Exact |
| Tofighi et al. (2016) | ROB | ✓ | ✓ | ✓ | | ✓ | Earthquake | Metaheuristic |
| Haghi et al. (2017) | ROB | ✓ | | ✓ | | ✓ | Earthquake | Exact, NGSA-II, MOGASA |
| Rezaei-Malek et al. (2016) | ROB | ✓ | ✓ | ✓ | | ✓ | Earthquake | Exact |
| Fathollahi-Fard and Hajiaghaei-Keshteli (2018) | DET | ✓ | | ✓ | | ✓ | Terrorist attacks | Hybrid metaheuristics |
| Cao et al. (2018) | STOC | ✓ | ✓ | ✓ | | ✓ | Earthquake | Exact |
| Maghfiroh and Hanaoka (2018) | DET | | ✓ | ✓ | ✓ | ✓ | General | Simulated annealing and Variable Neighbourhood Search |
| Maharjan and Hanaoka (2018) | STOC | ✓ | ✓ | ✓ | | | Earthquake | Exact |
| Sahebjamnia et al. (2018) | ROB | ✓ | ✓ | ✓ | | ✓ | General | Exact |
| Chong et al. (2019) | STOC | | ✓ | ✓ | | ✓ | Flood | Exact |
| Cavalcante et al. (2019) | DET | ✓ | ✓ | ✓ | | | General | Exact, simulation |

*(continued)*

**Table 1.** Continued.

| References | Model Type | Multi-objective | Multi-Period | Commodity flow | Vehicle Flow | Location Selection | Disaster type | Solution Procedure |
|---|---|---|---|---|---|---|---|---|
| Nezhadroshan et al. (2020) | ROB | ✓ | ✓ | ✓ | | ✓ | Earthquake | Exact, Hybrid of DEMATEL and ANP |
| This paper | ROB | ✓ | ✓ | ✓ | ✓ | ✓ | Flood | Exact, Lexi-cographic Tchebycheff Method |

DET, deterministic; STOC, stochastic; ROB, robust-stochastic.

model robustness. The second term is a penalty term that penalises any deviation of the constraint. Model robustness and solution robustness can be traded off using weight $\gamma$. Increasing $\gamma$ value will lead to more feasible solutions but will incur a higher cost and vice versa.

### 3.2. Application of robust optimisation in logistics problem

The original formulation provided by Mulvey et al. (1995) leads to a quadratic variance term which causes computational complexity. Yu and Li (2000) provided an alternative formulation for the logistics problem which was based on approach 2 provided by Mulvey and Ruszczyński (1995).

$$\sum_{s=1}^{S} p_s\left(\sum_{k}\sum_{j} c_{kj}x_{kj}\right) + \lambda\sum_{s=1}^{S} p_s(\theta_s^+ + \theta_s^-) + \sum_{s=1}^{S}\sum_{j=1}^{J}(\omega_{sj}^+\delta_{sj}^+ + \omega_{sj}^-\delta_{sj}^-) \tag{9}$$

$$\text{subject to } Ax \geq b, \tag{10}$$

$$\left(\sum_{k}\sum_{j} c_{kj}x_{kj}\right) - \sum_{s=1}^{S} p_s\left(\sum_{k}\sum_{j} c_{kj}x_{kj}\right) = \theta_s^+ - \theta_s^- \ \forall s \tag{11}$$

$$\sum_{k} x_{kj} - D_{sj} - g_{sj} = \delta_{sj}^+ - \delta_{sj}^- \ \forall j \text{ and } s, \tag{12}$$

$$\text{all } x_{kj},\ D_{sj}, g_{sj},\ \theta_s^+, \theta_s^-, \delta_{sj}^+, \delta_{sj}^- \geq 0 \tag{13}$$

Here $x_{kj}$ is the amount of commodity shipped from location $k$ to location $j$. $c_{kj}$ is the unit cost of transporting a unit of commodity from location $k$ to location $j$. $\theta_s^+$ and $\theta_s^-$ indicate the deviation from the mean, and $\delta_{sj}^+$ and $\delta_{sj}^-$ represent the violation of control constraints., $D_{sj}$ is the demand at location $j$ under scenario $s$; $g_{sj}$ is the unmet demand (or surplus); $\omega_{sj}^+$ and $\omega_{sj}^-$ are weights of the penalty parameters; $\lambda$ is the weight of the deviation parameter. Thus, Equation (9) is the sum of the total cost of transporting commodity, variation from mean and constraint violation penalty. Equation (11) is the variance from mean costs. Equation (12) is the commodity control constraint. Although this approach has the disadvantage of additional variables, it keeps the form of the mixed-integer linear programme intact and avoids computational complexity due to the quadratic problem.

## 4. Problem description

The model is defined as a three-stage logistics model. The first stage consists of Central Supply Depots (CSDs) where commodities and vehicles procured from suppliers are stored until disaster. The second stage consists of Local Supply Depots (LSDs), which receive supplies from CSDs and further distribute them to the lowest level of the model, the points of distribution (PODs). LSDs are temporary facilities and their location and size are determined before the occurrence of a disaster. They can temporarily store commodities and vehicles. PODs are situated in affected areas and these are located where victims of the disaster directly collect relief supplies (such as food, water, medical supplies). An LSD can only serve a cluster of PODs, and which LSD serves which POD will be determined by the decision-maker. Before a disaster occurs, the amount of commodity to be procured and stored is determined according to the expected magnitude of the disaster. The location and size of LSDs are also determined at this stage. After the disaster, commodities are sent from CSDs to LSDs via vehicles. At LSDs, mode transfer can occur if certain types of vehicles cannot reach a POD. From LSDs, commodities are sent to the cluster of PODs the LSDs serve. After delivering to LSDs, empty vehicles may return to CSDs or may wait in LSDs, but vehicles must return to LSDs from PODs after delivery because PODs do not have vehicle storage capacity.

In this study, a two-stage robust stochastic optimisation formulation has been used. In the first stage of the model, the amount of commodity to be procured, and the location and size of the LSDs are determined based on the expected value of the uncertain parameters. In the second stage, scenario-specific variables are determined. Thus, a decision-maker will first procure a determined amount of

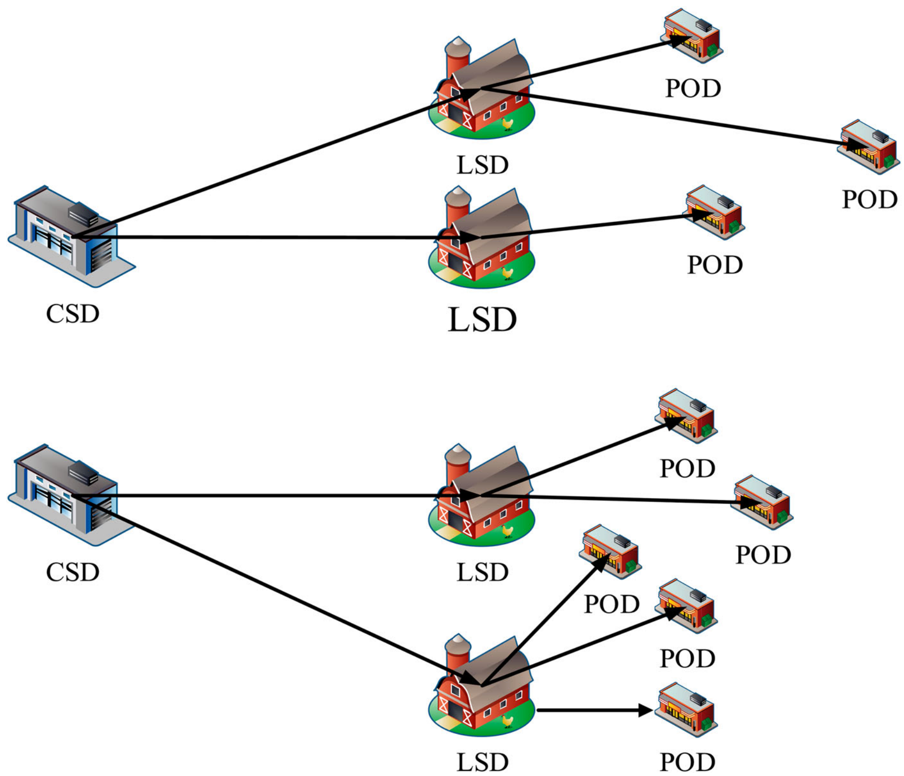


**Figure 1.** Graphical representation of the relief distribution network.

commodity and store it in CSDs until the actual occurrence of a disaster. After the disaster, when a particular scenario is realised, the decision-maker will distribute resources according to the recourse variables.

According to Holguín-Veras et al. (2013), the summation of logistics cost and deprivation cost is the most appropriate objective function for a humanitarian logistics model. Thus, the objective of the model is to minimise the penalty cost of unmet demand at the same time as minimising logistics cost. Logistics cost consists of the procurement cost of both commodity and vehicle, the fixed cost of opening a temporary facility (an LSD), the transportation cost of the commodity, the fixed cost of assigning a vehicle, and the inventory storage cost of the commodity and vehicle. In this model, the penalty cost of unmet demand is used instead of using quantity. The reason behind this is: using the penalty cost of unmet demand allows the decision-maker to prioritise a specific point of distribution, a specific commodity or a specific period separately (Haghani & Oh, 1996) Using cost also relieves the hassle of normalising the objective function. The planning horizon is divided into equal periods. These periods can be minutes, hours, or days. The smaller the time period unit the more accurate and detailed the result will be. However, as the number of periods increases drastically, the model will be more and more computationally demanding (Afshar & Haghani, 2012). Vehicles are considered to be an integer commodity instead of a binary variable as this gives a compact formulation and also gives a detailed vehicle routing and distribution plan (Yi & Özdamar, 2007). A graphical description of the distribution network is given in Figure 1.

In this study, the uncertainty of demand, probable damage to the stocked commodity, and node reachability by a particular transportation mode have been considered. Due to the uncertain nature of any disaster, the demand can vary by quite a lot. Also, some portion of the stock can get damaged due to the disaster and a particular node can become unreachable by a particular transportation mode or become unreachable altogether (Bozorgi-Amiri et al., 2013; Rezaei-Malek et al., 2016). A decision-maker must take these uncertainties into consideration while making a decision. Uncertainty is represented as a finite set of scenarios each with a predetermined discrete probability of occurrence. The probabilities can be determined using geographic data, historical records, simulation of the disaster, or expert opinion. Equity measures can ensure fairness in distribution (Afshar & Haghani, 2012). Thus, two equity measures have been incorporated into this model. The first measure ensures that a certain percentage of demand is met for all PODs and the second measure ensures that a certain percentage of demand is met for all commodities.

As mentioned before, the robust formulation allows the decision-maker to tradeoff between model robustness and solution robustness. In the robust formulation presented by Mulvey et al. (1995) the variance term is quadratic. To prevent the model from transforming to quadratic programming, an alternative approach proposed by Mulvey and Ruszczyński (1995) is used. The alternative approach has been applied to the logistics problem by Yu and Li (2000). In this study, this alternative robust stochastic formulation has been used.

## 5. Model formulation

### 5.1. Model assumptions

We have made the following assumptions in this study:

- Vehicle capacity of the same type is assumed to be the same. The capacity of vehicles of the same type can vary a little but considering different capacities for different vehicles can make the model computationally expensive and make inputting data time-consuming.
- Facility opening cost of a particular size is constant for all candidate locations. Facility opening cost can fluctuate for different locations, but when a problem contains hundreds of candidate locations, inputting opening cost for each size and each location can be quite a daunting task and the number of extra variables may cause computational complexity.
- Distance between two nodes is known and constant for a given transportation mode. Distances will be different for different transportation modes and that has been considered in this model.
- It takes equal time to traverse a route forward and backward. For small periods, i.e. minutes, the travel time can vary for onward and return journey because during the return journey the vehicles are empty, but when periods are larger, i.e. hours or days, the traversal time will be the same. Thus, to avoid this complication the forward and backward route traverse times have been considered equal.

With these assumptions in mind, a robust stochastic mixed-integer linear programme model is formulated as follows.

### 5.2. Model formulation

The following notations are used to describe the robust stochastic model.

#### 5.2.1. Notations

*Sets.*

| | |
|---|---|
| $S$ | Set of scenarios; $s \in S$ is index |
| $T$ | Set of time periods; $t \in T$ is index |
| $M$ | Set of transportation modes; $m \in M$ is index |
| $C$ | Set of commodities; $c \in C$ is index |
| $CSD$ | Set of central supply depots; $i \in CSD$ is index |
| $LSD$ | Set of candidate local supply depots; $j \in LSD$ is index |
| $POD$ | Set of points of distribution; $k \in POD$ is index |
| $L$ | Set of LSD sizes; $l \in L$ is index |

*Parameters.*

| | |
|---|---|
| $CS_l$ | Storage capacity of LSD of size $l$ |
| $CS_i$ | Storage capacity of CSD $i$ |
| $VS_{lm}$ | Vehicle storage capacity of LSD of size $l$ of mode $m$ |
| $VS_{im}$ | Vehicle storage capacity of CSD $i$ of mode $m$ |
| $VP_{lm}$ | Vehicle receiving capacity of LSD of size $l$ of mode $m$ |
| $VP_{km}$ | Vehicle receiving capacity of POD $k$ of mode $m$ |
| $P_{max}$ | Maximum number of LSDs to be built |
| $VC_m$ | Vehicle capacity of mode $m$ |
| $VR_{im}$ | 1 if CSD $i$ can be reached by mode $m$; 0 otherwise |
| $VR_{jms}$ | 1 if LSD $j$ can be reached by mode $m$ under scenario $s$; 0 otherwise |
| $VR_{kms}$ | 1 if POD $k$ can be reached by mode $m$ under scenario $s$; 0 otherwise |
| $V_m$ | Velocity of transportation mode $m$ |
| $CX_{cm}$ | Cost of carrying commodity $c$ via mode $m$ per unit distance |
| $CY_m$ | Fixed cost of assigning a vehicle of mode $m$ |
| $CS_{ict}$ | Cost of supply carryover of commodity type $c$ at CSD $i$ at time period $t$ |
| $CS_{jct}$ | Cost of supply carryover of commodity type $c$ at LSD $j$ at time period $t$ |
| $CDC_{kct}$ | Cost of unmet demand penalty of commodity type $c$ at POD $k$ at time period $t$ |
| $CYC_{imt}$ | Cost of vehicle carryover of mode $m$ at CSD $i$ at time period $t$ |
| $CYC_{jmt}$ | Cost of vehicle carryover of mode $m$ at LSD $j$ at time period $t$ |
| $FC_l$ | Fixed cost of opening an LSD of size $l$ |
| $PC_c$ | Procurement cost of commodity $c$ |
| $S_{jk}$ | 1 if POD $k$ is serviced by LSD $j$; 0 otherwise |
| $D_{ijm}$ | Distance between CSD $i$ and LSD $j$ for transportation mode $m$ |

| | |
|---|---|
| $D_{jkm}$ | Distance between LSD $j$ and POD $k$ for transportation mode $m$ |
| $ED_{kcs}$ | Amount of demand of type $c$ at POD $k$ under scenario $s$ |
| $UD_{ics}$ | Percentage of undamaged pre-positioned commodity $c$ at CSD $i$ under scenario $s$ |
| $P_s$ | Probability of occurrence of scenario $s$ |
| $t_{ijm}$ | Time to traverse route $(i,j)$ via mode $m$ |
| $t_{jkm}$ | Time to traverse route $(j,k)$ via mode $m$ |
| $\gamma^+_{kcst}, \gamma^-_{kcst}$ | Weight assigned to cost variability |
| $\lambda^+_1, \lambda^-_1, \lambda^+_2, \lambda^-_2$ | Weight assigned to model infeasibility penalty |
| $\alpha, \beta$ | Minimum percentage of demand to be met |
| $M$ | Big number |

*Decision variables.*
*First-stage variables.*

| | |
|---|---|
| $Proc_{ic}$ | Amount of commodity $c$ to be procured and pre-positioned at CSD $i$ |
| $loc_{jl}$ | 1 if LSD of size $l$ is placed at candidate location $j$; 0 otherwise |

*Second-stage variables.*

| | |
|---|---|
| $X_{ijcmst}$ | Amount of commodity $c$ to be transferred from CSD $i$ to LSD $j$ at time period $t$ by mode $m$ under scenario $s$ |
| $X_{jkcmst}$ | Amount of commodity $c$ to be transferred from LSD $j$ to POD $k$ at time period $t$ by mode $m$ under scenario $s$ |
| $SC_{icst}$ | Amount of supply carryover of commodity $c$ at CSD $i$ at time period $t$ under scenario $s$ |
| $SC_{jcst}$ | Amount of supply carryover of commodity $c$ at LSD $j$ at time period $t$ under scenario $s$ |
| $DC_{kcst}$ | Amount of demand carryover of commodity $c$ at POD $k$ at time period $t$ under scenario $s$ |
| $Y_{ijmst}$ | Number of vehicles of type $m$ to be sent from CSD $i$ to LSD $j$ at time period $t$ under scenario $s$ |
| $Y_{jimst}$ | Number of vehicles of type $m$ to be sent from LSD $j$ to CSD $i$ at time period $t$ under scenario $s$ |
| $Y_{jkmst}$ | Number of vehicles of type $m$ to be sent from LSD $j$ to POD $k$ at time period $t$ under scenario $s$ |
| $Y_{kjmst}$ | Number of vehicles of type $m$ to be sent from POD $k$ to LSD $j$ at time period $t$ under scenario $s$ |
| $YC_{imst}$ | Number of vehicles of mode $m$ to be carried over at time period $t$ at CSD $i$ under scenario $s$ |
| $YC_{jmst}$ | Number of vehicles of mode $m$ to be carried over at time period $t$ at LSD $j$ under scenario $s$ |
| $\theta^+_{1s}, \theta^-_{1s}$ | Deviation from the mean value for objective function 1 under scenario $s$ |
| $\theta^+_{2s}, \theta^-_{2s}$ | Deviation from the mean value for objective function 2 under scenario $s$ |
| $\delta^+_{kcst}, \delta^-_{kcst}$ | Violation of the commodity flow control constraint of POD $k$ for commodity $c$ at time period $t$ under scenario $s$ |

### 5.3. Mathematical formulation

In this section, we calculate the different costs used in the objective functions. Equations (14)–(20) formulate various costs for the convenience of objective function formulation.

Equation (14) is the procurement cost of the commodity. Procurement cost is the cost of purchasing a commodity. It is calculated as the procurement cost of commodity $c$ time the units of commodity procured at CSD $i$ (Bozorgi-Amiri et al., 2013; Haghi et al., 2017):

$$PC = \sum_i \sum_c Proc_{ic} \times PC_c \tag{14}$$

The fixed cost of opening an LSD at a candidate location is calculated by multiplying the fixed cost of opening an LSD of a particular size with the binary variable $loc_{jl}$ (Haghi et al., 2017):

$$LC = \sum_l \sum_j (loc_{jl} \times FC_l) \tag{15}$$

The transportation cost of the commodity in Equation (16) is the cost of transferring a commodity from one facility to another. It is calculated by multiplying the amount of commodity to be transferred by a particular model with a unit cost of transportation and the distance between two facilities for that transportation mode (Haghani & Oh, 1996):

$$TC = \sum_i \sum_j \sum_c \sum_m \sum_t CX_{cm} \times X_{ijcmst} \times d_{ijm} + \sum_j \sum_k \sum_c \sum_m \sum_t CX_{cm} \times X_{jkcmst} \times d_{jkm} \tag{16}$$

Vehicle assignment cost is the fixed cost of assigning a vehicle to a route (Haghani & Oh, 1996). A separate cost is assigned to forward and backward route traversal. It includes costs like drivers' wages, fuel costs. This cost is defined as the product of the number of vehicles assigned to each route times the unit vehicle assignment cost:

$$VC = \sum_i \sum_j \sum_m \sum_t CY_m \times (Y_{ijmst} + Y_{jimst}) + \sum_j \sum_k \sum_m \sum_t CY_m \times (Y_{jkmst} + Y_{kjmst})\ \forall s \tag{17}$$

Commodity carryover cost or inventory holding cost is the cost of warehousing. It is the cost of holding unused commodity over from one period to the next and calculated by multiplying the unit cost of carryover by the amount of commodity to be carried (Haghani & Oh, 1996; Haghi et al., 2017):

$$IC = \sum_i \sum_c \sum_t CSC_{ict} \times SC_{icst} + \sum_j \sum_c \sum_t CSC_{jct} \times SC_{jcst}\ \forall s \tag{18}$$

Vehicle carryover cost is the cost of holding unused vehicles from one time period to the next (Haghani & Oh, 1996). This is calculated similarly to commodity carryover cost:

$$VI = \sum_i \sum_m \sum_t YC_{imst} \times CYC_{im} + \sum_j \sum_m \sum_t YC_{jmst} \times CYC_{jm}\ \forall s \tag{19}$$

Unmet demand penalty cost is used to penalise the model for not satisfying demand. It is calculated by multiplying unmet demand in a period and unit penalty cost (Afshar & Haghani, 2012; Haghani & Oh, 1996):

$$UC = \sum_k \sum_c \sum_t CDC_{kct} \times DC_{kcst}\ \forall s \tag{20}$$

### 5.4. Objective function

Equation (21) is the objective function 1, which is the logistics cost. It is the summation of all the costs, variability cost, and constraint violation penalty cost. The variability cost is the measure of solution robustness. The constraint violation penalty term is the measure of model robustness. The second objective function, Equation (22), is the deprivation cost. The expected value of the unmet demand penalty cost is taken. The second term is the variability term. The method selected for multi-objective optimisation is the lexicographic weighted Tchebycheff method, which will be discussed later.

(1) Minimise commodity flow, vehicle flow, supply carryover, and vehicle carryover cost:

$$\begin{aligned}\text{Minimize Obj}_1 = {} & PC + LC + \sum_s p_s \times (TC + VC + IC + VI) \\ & + \lambda_1 \times \sum_s p_s(\theta^+_{1s} + \theta^-_{1s}) \\ & + \sum_s p_s \times \sum_k \sum_c \sum_t \times (\gamma^+_{kcst} \times \delta^+_{kcst} + \gamma^-_{kcst} \times \delta^-_{kcst})\end{aligned} \tag{21}$$

(2) Minimise unmet demand penalty cost:

$$\text{Minimize Obj}_2 = \sum_s p_s \times UC + \lambda_2 \times \sum_s p_s(\theta^+_{2s} + \theta^+_{2s}) \tag{22}$$

### 5.5. Constraints

$$UD_{ics} \times Proc_{ic} = SC_{icst}\ \forall i, c, s, t \tag{23}$$

$$SC_{ics(t-1)} = SC_{ict} + \sum_j \sum_m X_{ijcmst}\ \forall i, c, t, s \tag{24}$$

$$\sum_i \sum_m X_{ijcms(t-t_{ijm})} + SC_{jcs(t-1)} = \sum_k \sum_m S_{jk} \times X_{jkcmst} + SC_{jcst}\ \forall j, c, s, t \tag{25}$$

$$ED_{kcs} = DC_{kcst}\ \forall k, c, s, t \tag{26}$$

$$S_{jk} \times \left( DC_{kcs(t-1)} - \sum_j \sum_m X_{jkcms(t-t_{jkm})} - DC_{kcst} \right) = \delta^+_{kcst} - \delta^-_{kcst}\ \forall\ k, c, s, t \tag{27}$$

$$VR_{im} \times \left( \left( \sum_j VR_{jms} \times\ Y_{jims(t-t_{jim})} \right) + YC_{ims(t-1)} \right) = VR_{im} \times \left( \left( VR_{jms} \times \sum_j Y_{ijmst} + YC_{imst} \right) \right. \quad \forall i, m, s, t \tag{28}$$

$$VR_{jms} \times \left(\left(\left(\sum_i \left(VR_{im} \times (Y_{ijms(t-t_{ijm})} - Y_{jimst})\right)\right.\right.\right.$$
$$+ YC_{jms(t-1)} - YC_{jmst}$$
$$\left.\left.\left. + \sum_k \left(VR_{kms} \times S_{jk} \times (Y_{kjms(t-t_{kjm})} - Y_{jkmst})\right)\right)\right)\right)$$
$$= 0 \, \forall j, \ m, s, t \tag{29}$$

$$VR_{kms} \times \sum_j (S_{jk} \times VR_{jms} \times (Y_{jkms(t-t_{jkm})} - Y_{kjmst}))$$
$$= \ 0 \, \forall k, m, s, t \tag{30}$$

$$\sum_c SC_{icst} \leq CS_i \forall i, s, t \tag{31}$$

$$\sum_c SC_{jcst} \leq \sum_l loc_{jl} \times CS_l \forall j, s, t \tag{32}$$

$$VR_{im} \times YC_{imst} \leq VS_{imt} \, \forall i, m, s, t \tag{33}$$

$$VR_{jms} \times YC_{jmst} \leq \sum_l loc_{jl} \times VS_{lm} \quad \forall j, m, s, t \tag{34}$$

$$\sum_j Y_{jkmst} \leq VP_{km} \, \forall k, m, \ s, \ t \tag{35}$$

$$\sum_i Y_{ijmst} \leq VP_{lm} \, \forall j, m, \ s, \ l, \ t \tag{36}$$

$$\sum_i \sum_l loc_{jl} \leq P_{max} \tag{37}$$

$$1 - \frac{\sum_c DC_{kcst}}{\sum_c ED_{kcs}} \geq \alpha; \forall k, s, t \tag{38}$$

$$1 - \frac{\sum_k DC_{kcst}}{\sum_k ED_{kcs}} \geq \beta; \forall c, s, t \tag{39}$$

$$VR_{im} \times Y_{ijmst} \times VC_m \geq \ \sum_c X_{ijcmst} \, \forall i, j, m, s, t \tag{40}$$

$$VR_{jms} \times VR_{kms} \times S_{jk} \times \ Y_{jkmst} \times VC_m$$
$$\geq \sum_c X_{jcmst} \, \forall j, k, m, t, s \tag{41}$$

$$VR_{im} \times Y_{ijmst} \leq \ M \times \sum_c X_{ijcmst} \, \forall i, j, m, s, t \tag{42}$$

$$VR_{jms} \times S_{jk} \times VR_{kms} \times Y_{jkmst}$$
$$\leq M \times \sum_c X_{jkcmst} \, \forall j, k, m, s, t \tag{43}$$

$$X_{jkcmst} \leq M \times \sum_l loc_{jl} \, \forall j, k, m, s, t \tag{44}$$

$$(TC + VC + IC + VI)$$
$$- \sum_s p_s \times (TC + VC + IC + VI)$$
$$= \theta_{1s}^{+} - \theta_{1s}^{-} \forall s \tag{45}$$

$$UC - \sum_s p_s \times UC = \theta_{2s}^{+} - \theta_{2s}^{-} \, \forall s \tag{46}$$

$$X_{ijcmst}, X_{jkcmst}, \ SC_{icst}, SC_{jcst}, DC_{kcst} \geq 0; \, \forall j, k, c, m, s, t \tag{47}$$

$$Y_{ijmst}, Y_{jimst}, Y_{jkmst}, Y_{kjmst}, YC_{imst}, YC_{jmst} \geq 0;$$
$$\forall i, j, k, m, s, t \tag{48}$$

$$loc_{jl} \epsilon \{0, 1\}; \, \forall j, l \tag{49}$$

Equation (23) assigns the undamaged commodity to the supply carryover or inventory of period 1. Equation (24) is the commodity flow control equation for CSDs. It states that the inventory of the last period at CSD is equal to the summation of the commodity sent to LSD and the inventory of the current period. Equation (25) is the commodity flow control equation for LSDs. Equation (26) assigns the demand for the commodity to the demand carryover or cumulative unmet demand of the first period. Equation (27) is the commodity control equation for PODs. It also defines the positive and negative constraint violation penalty. Equations (28)–(30) are vehicle flow control equations for CSDs, LSDs, and PODs respectively. These equations also incorporate vehicle reachability. Equations (25), (27), (29), and (30) also include service coefficients which ensure that a certain LSD only serves a predefined cluster of PODs. Equations (31) and (32) are commodity storage constraints for CSDs and LSDs, respectively. They ensure that inventory does not exceed the storage capacity. Similarly, Equation (33) and (34) are vehicle storage constraints for CSDs and LSDs, respectively. Equations (35) and (36) limit the number of vehicles that an LSD or POD can receive at a time. Equation (37) limits the maximum number of LSDs that can be opened. Equations (38) and (39) are equity constraints. Equation (38) ensures that a certain percentage of demand of each POD is met and Equation (39) ensures that a certain percentage of demand for each commodity type is met. Equations (40) and (41) link the number of vehicles to the amount of commodity. Equations (42) and (43) prohibit any vehicle flow if there is no commodity flow. Equation (43) prohibits any commodity to be sent to a candidate LSD location where no LSD has been opened. Equations (45) and (46) define the deviation from the mean value of the objective functions 1 and 2, respectively. Equations (47)–(49) are non-negativity variables. It should be noted Equation (48) are the integer variables while Equation (49) is the binary variables.

## 6. Solution Procedure

Multi-objective optimisation methods are of three types according to the articulation of preference: a priori, progressive, and posteriori. Among them, a priori methods use parameters that reflect the decision-maker's preference. A priori methods also allow the generation of Pareto front by continuously changing the preference parameter (Marler & Arora, 2004). Weighted min–max or the weighted Tchebycheff method is one such a priori method that is able to generate Pareto optimal solution. The weakness of this method lies in the fact that it may not be able to generate a strong Pareto optimal solution exclusively (Marler & Arora, 2004). The methodology of the model goes as follows:

$$\text{minimize } \rho \tag{50}$$

$$\text{subject to } \omega_i\{\text{obj}_i - \text{obj}_i^o\} - \rho \leq 0, \; i = 1, 2. \tag{51}$$

where $\text{obj}_i$ is the value and $\text{obj}_i^o$ is the utopia point of the $i$th objective function. $\omega_i$ is the weight of the $i$th objective function. The value of $\omega_i$ is set in a way such that $\sum_{i=1}^{2} \omega_i = 1$. By changing the value of the weight, the complete Pareto front can be generated.

The weakness of the aforementioned formulation can be eliminated by a modification provided by Tind and Wiecek (1999). Due to the modification, the possibility of generating a non-unique solution is eliminated. Their method, called the lexicographic weighted Tchebycheff method, only generates a Pareto optimal solution. The methodology is as follows:

(1) The optimum value of $\rho$ is obtained by solving Equation (50) with Equation (51) as the constraint.
(2) The optimum value of $\rho$ is made constant.
(3) With $\lambda$ constant $\sum_{i=1}^{2}[obj_i - obj_i^o]$ is solved with Equation (51) as the constraint.

The simplicity of the method and its ability to generate a Pareto front make it the multi-objective method of choice for this paper.

## 7. A real-world case study

In this section, a case study is presented to show the effectiveness of the model. A flood in Bangladesh is chosen as the case. The reason behind choosing Bangladesh is that it is a disaster-prone country with floods, cyclones, and droughts occurring regularly due to geographical and climatic factors (Abedin et al., 2019). Among them, floods are the most common. Every year, on average, 18% of the total geographical area of Bangladesh is flooded. The worst flood in the history of Bangladesh happened in 1998 in which 65% of the total land was flooded. Previous data indicate that a major flood occurs every 5–10 years. Eight severe floods have occurred in the past half-century in which at least 50% of Bangladesh has been flooded (MoFDM, 1959; Shah Alam Khan, 2008).

For this case study, three flood scenarios have been constructed based on the percentage of flooded land. These scenarios have been developed using historical data from the Flood Response Plan, 2015 by the Disaster Management Bureau of Bangladesh. The probabilities of occurrence of scenarios are given in Table 2. These probabilities have been established using the expert opinions of the disaster management officials. Two CSDs are considered for the case study, situated in Dhaka and Khulna. For LSDs, eight candidate locations have been selected: Mymensingh, Chandpur, Barisal, Rajshahi, Gazipur, Comilla, Bagerhat, and Bogra. Three sizes have been selected: small, medium, and large. Twelve locations have been selected for points of distribution. The demand data for PODs are given in Table 3. As mentioned before, an LSD only serves a certain number of PODs, which is shown in Table 4. The locations of the different centres in the network are shown in Figure 2. Twelve periods have been considered, each period consisting of an hour. Two transportation modes – namely, truck and helicopter – have been considered. According to the severity of the flood, some LSDs and PODs may

**Table 2.** Scenarios and their probability of occurrence.

| Scenario | % of land flooded | Probability of occurrence (%) |
|---|---|---|
| S1 | 25 | 55 |
| S2 | 36 | 30 |
| S3 | 61 | 15 |

**Table 3.** Demand for commodities at points of distribution (PODs).

| POD | Commodity | S1 | S2 | S3 |
|---|---|---|---|---|
| r1 | Rice | 123 | 235 | 278 |
| r2 | Rice | 124 | 237 | 361 |
| r3 | Rice | 125 | 237 | 362 |
| r4 | Rice | 128 | 245 | 373 |
| r5 | Rice | 130 | 252 | 382 |
| r6 | Rice | 120 | 233 | 353 |
| r7 | Rice | 115 | 224 | 339 |
| r8 | Rice | 120 | 233 | 353 |
| r9 | Rice | 122 | 237 | 359 |
| r10 | Rice | 126 | 239 | 365 |
| r11 | Rice | 129 | 244 | 373 |
| r12 | Rice | 177 | 347 | 524 |
| r1 | Water | 234 | 460 | 694 |
| r2 | Water | 247 | 482 | 729 |
| r3 | Water | 251 | 491 | 742 |
| r4 | Water | 246 | 483 | 729 |
| r5 | Water | 243 | 477 | 720 |
| r6 | Water | 243 | 477 | 720 |
| r7 | Water | 249 | 485 | 734 |
| r8 | Water | 252 | 489 | 741 |
| r9 | Water | 241 | 471 | 712 |
| r10 | Water | 235 | 460 | 695 |
| r11 | Water | 243 | 476 | 719 |
| r12 | Water | 225 | 308 | 371 |

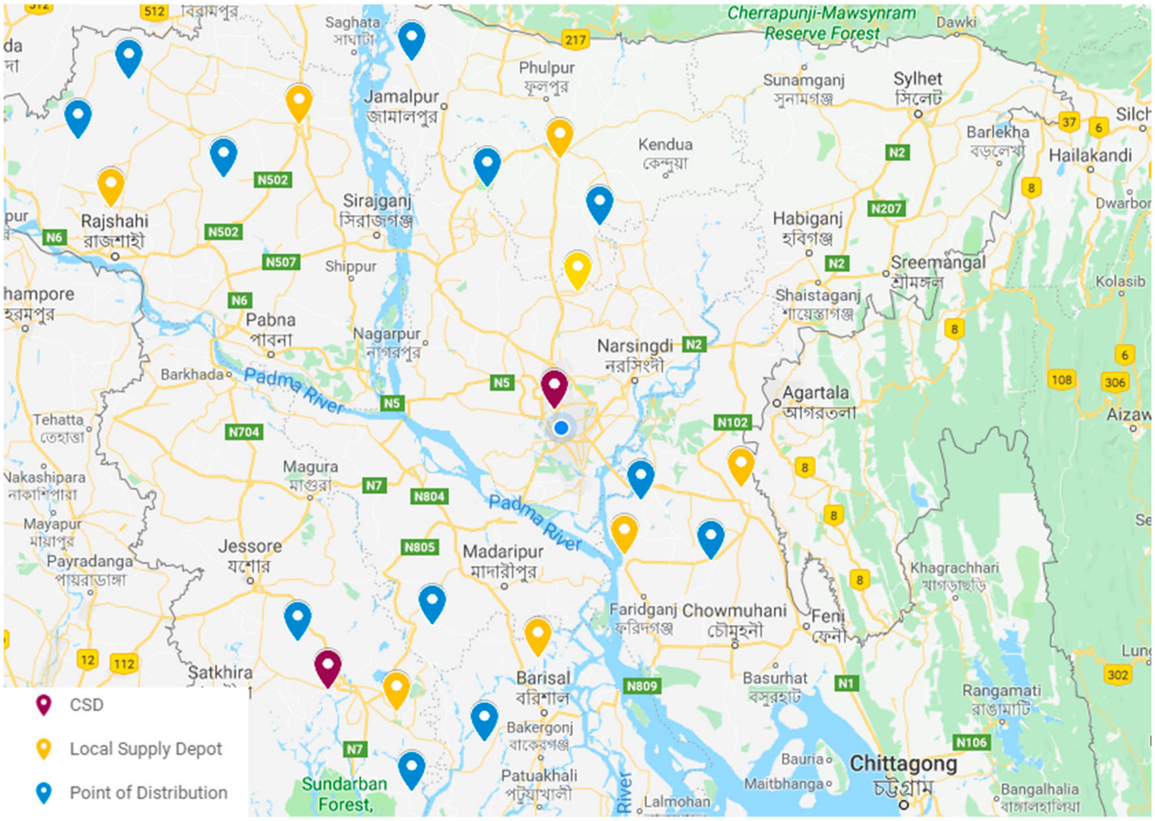


**Figure 2.** Map showing the CSDs, candidate LSDs, and PODs.

**Table 4.** Clustering of PODs.

| LSD | PODs Serviced |
|---|---|
| Mymensingh, Gazipur | r1, r2 |
| Chandpur, Comilla | r3, r4 |
| Barisal, Bagerhat | r5, r6, r7, r8 |
| Rajshahi, Bogra | r9, r10, r11, r12 |

**Table 5.** Transportation cost per unit of commodities per KM.

| | Vehicle | |
|---|---|---|
| Commodity | Truck | Helicopter |
| Rice | 0.1 | 0.5 |
| Water | 0.15 | 0.7 |

become unreachable by truck, but all the centres remain reachable by helicopter at all times. However, all CSDs remain reachable by all modes in all scenarios. Two commodities – rice and water – have been considered for the case study.

Separate distance data have been used for trucks and helicopters. The average velocity of a truck is assumed to be 50 KPH and of a helicopter 300 KPH. The time required to reach a centre is calculated by dividing the distance with the average velocity. The required cost parameters are determined using market observation and expert opinion. The procurement cost of rice is 10,000 BDT per metric ton, and for water, 1000 BDT per metric ton. The cost of assigning a truck is 1,000 BDT and of a helicopter 10,000 BDT.

The transportation cost of commodities via different vehicles per metric ton and per kilometre of distance is given in Table 5. The inventory holding (commodity carryover) cost per period is 10 BDT for rice and 5 BDT for water. The vehicle carryover cost is 25 BDT for truck and 100 BDT for helicopter per period. The commodity and vehicle carryover costs are considered to be the same for all LSDs and CSDs. The unmet demand penalty cost for the first period is given in Table 6. The unmet demand penalty cost increases by 20% per period. This forces the model to satisfy demand as early as possible to avoid higher unmet demand penalty costs. It is to be noted that all costs in the tables are thousand BDT units and all weights are metric ton units.

## 8. Results and sensitivity analysis

In this section, the results of the case study are discussed. The model is coded in GAMS and solved with a CPLEX solver in an Intel Pentium Quad Core 3 GHz pc with 4 GB of ram. Finally, some sensitivity analyses on the key factors are performed.

**Table 6.** Unmet demand penalty cost per unit of the commodity in the first period.

| | Commodity | |
|---|---|---|
| POD | Rice | Water |
| r1 | 6 | 10 |
| r2 | 5 | 13 |
| r3 | 8 | 8 |
| r4 | 9 | 11 |
| r5 | 9 | 15 |
| r6 | 9 | 12 |
| r7 | 7 | 12 |
| r8 | 7 | 13 |
| r9 | 9 | 11 |
| r10 | 5 | 11 |
| r11 | 6 | 15 |
| r12 | 8 | 15 |

Using the lexicographic weighted Tchebycheff method and varying the weight of the objective function, the Pareto front of the model is generated. For this, both $\lambda_1$ and $\lambda_2$ have been set to 0.56, and $\gamma^{+}_{kcst}$ and $\gamma^{-}_{kcst}$ have been set at 10,000. The values $\alpha$ and $\beta$ have been set at 0.7. The generated Pareto front is given in Figure 3.

Sensitivity analysis is the task of understanding the behaviour of the final solution of an optimisation problem because of changes in the input parameters. Sensitivity analysis is very common for the domain of post-optimisation in different areas (Foumani et al., 2020; Foumani & Smith-Miles, 2019). In this regard, a single point having $\omega = 0.7$ in the Pareto front has been chosen. This means that more priority has been given to minimising deprivation cost than minimising logistics cost. For this point, the deprivation cost is 185,346,130 BDT and the logistics cost is 145,681,330 BDT. The selected location and their sizes are given in Table 7. Six candidate locations have been selected and all of them are small. The amount of supply to be procured at different CSDs is given in Table 8. An interesting thing to note is CSD Dhaka is used mostly for storing water whereas CSD Khulna is used to store rice. As intended, the model gives a detailed schedule of the commodity distribution. For demonstration purposes, the distribution schedule of water from CSD Dhaka to different LSDs under scenario 3 is shown in Table 9. Figures 4 and 5 give graphical representations of commodity flows from CSDs to LSDs and from LSDs to PODs, respectively. From Figure 4, it

**Table 7.** Selected locations and sizes of LSDs.

| | Size | | |
|---|---|---|---|
| LSD | Small | Medium | Large |
| Barisal | 1 | | |
| Rajshahi | 1 | | |
| Gazipur | 1 | | |
| Comilla | 1 | | |
| Bagerhat | 1 | | |
| Bogra | 1 | | |

**Table 8.** Amount of commodity to be procured at CSDs.

| | Commodity | |
|---|---|---|
| CSD | Rice | Water |
| Dhaka | 6 | 11,854 |
| Khulna | 5523 | 10 |

**Table 9.** Commodity distribution schedule of water from Dhaka CSD under scenario 3.

| | | | Periods | | | | | |
|---|---|---|---|---|---|---|---|---|
| CSD | LSD | Mode | T1 | T2 | T3 | T4 | T5 | T6 |
| Dhaka | Barisal | Truck | 400 | 370 | 400 | 400 | | |
| | Rajshahi | Truck | 190 | 330 | 400 | 248 | | |
| | Gazipur | Truck | 393 | 400 | 230 | 400 | | |
| | Comilla | Truck | 398 | 40 | 400 | 380 | 150 | 100 |
| | Bagerhat | Truck | 400 | 400 | 140 | 400 | | |
| | Bogra | Truck | 399 | 400 | 160 | 370 | | |

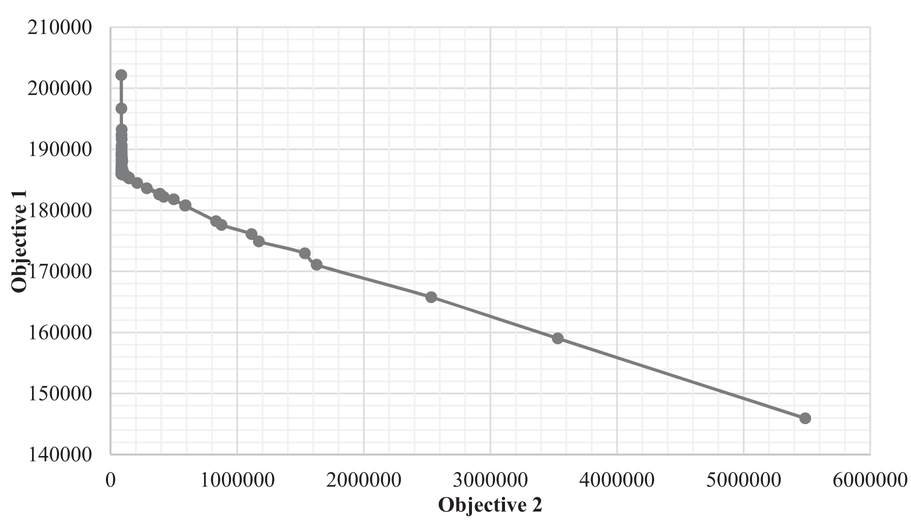


**Figure 3.** Pareto front of the robust formulation.

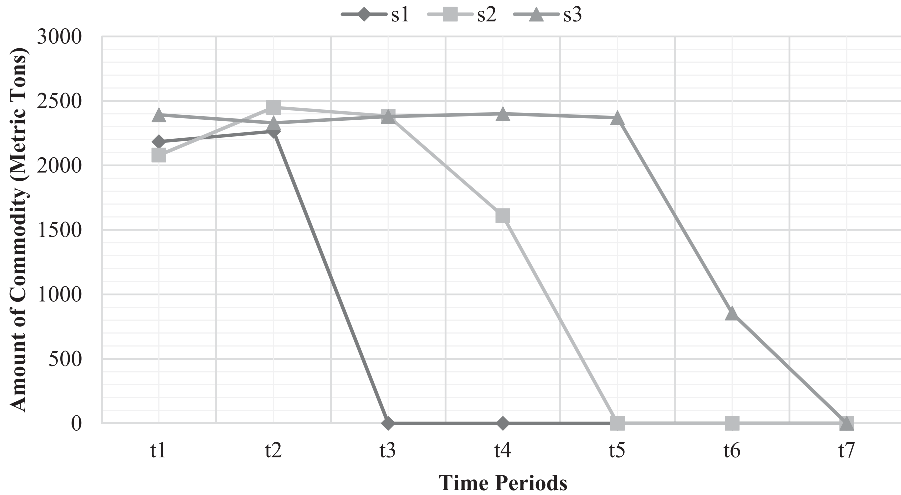


**Figure 4.** Total commodity flow from CSDs to LSDs under different scenarios.

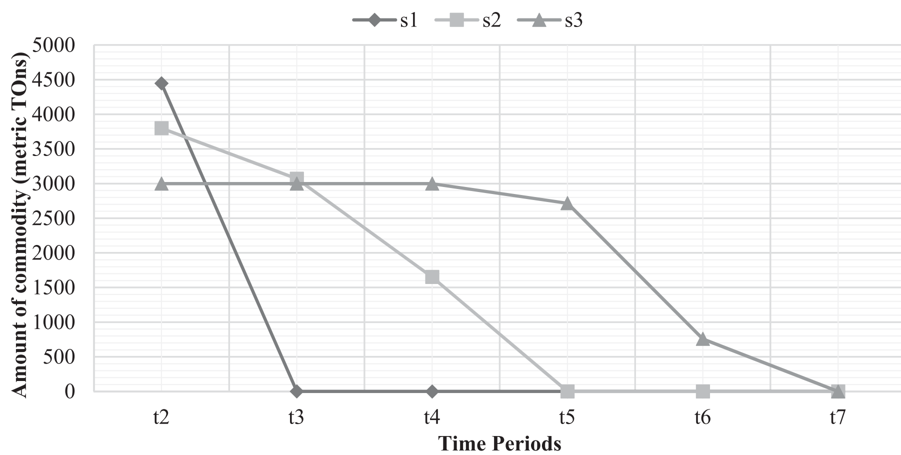


**Figure 5.** Total commodity flow from LSDs to PODs under different scenarios.

can be seen that for scenario 1 commodity flow occurs only until period 3, as scenario 1 has the lowest amount of demand. For scenario 2, flow lasts until period 5 and for scenario 3 the flow lasts until period 7. Scenario 2 has higher demand than scenario 1, and scenario 3 has the highest demand. Thus, commodity flow occurs for a longer time for scenario 3 than for scenarios 1 and 2. From Figure 5, similar trends can be seen. It is to be noted that no commodity flow from LSD to POD occurs until period 2. This is because it takes at least one period for some commodities to reach LSDs from CSDs. For scenario 1, shipments are sent to PODs at period 2 only. For scenarios 2 and 3 shipments are sent until periods 4 and 6, respectively. Note that commodities received from CSD are immediately sent to LSD. For example, shipments received from CSD at period 6 are immediately sent to PODs. Figure 6 shows the cumulative unmet demand over the planning horizon. For scenario 1, shipments received from LSDs at period 2 fulfil all unmet demand. Thus, the cumulative unmet demand reaches 0 in period 2. For scenarios 2 and 3, all unmet demands are met within periods 5 and 7, respectively. The model also gives a detailed vehicle dispatch schedule. For demonstration purposes, the dispatch schedule of trucks from CSD Dhaka to different LSDs under scenario 3 is shown in Table 10. Results from Table 9 correspond to the results in Table 10. For example, 400 metric tons of water are sent from Dhaka CSD to Barisal LSD at period 1. As a truck has a carrying capacity of 10 metric tons, 40 trucks are sent from Dhaka to Barisal at period 1. Figure 7 shows the inventory or supply carryover at CSDs over the planning horizon. The model procures supply based on the expected value of demand and predicted condition of the procured supply after the onset of the disaster. As scenarios 1 and 2 have lower demand than scenario 3, some supplies are expected to remain unused. Figure 7 corresponds with this statement. All the procured commodity is used only for scenario 3, whereas for scenarios 1 and 2,

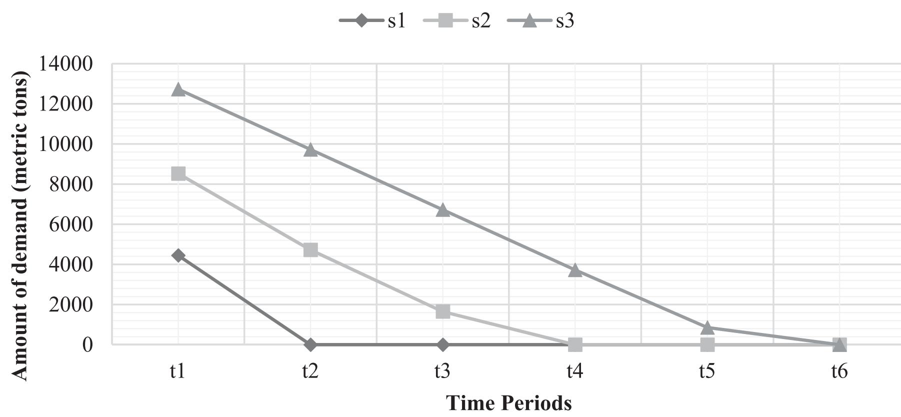


**Figure 6.** Cumulative unmet demand over the planning horizon.

**Table 10.** Truck dispatch schedule from CSD Dhaka to LSDs under scenario 3.

| | | Periods | | | | | |
|---|---|---|---|---|---|---|---|
| CSD | LSD | T1 | T2 | T3 | T4 | T5 | T6 |
| Dhaka | Barisal | 40 | 37 | 40 | 40 | | |
| | Rajshahi | 19 | 33 | 40 | 25 | | |
| | Gazipur | 40 | 40 | 23 | 40 | | |
| | Comilla | 40 | 4 | 40 | 38 | 15 | 10 |
| | Bagerhat | 40 | 40 | 14 | 40 | | |
| | Bogra | 40 | 40 | 16 | 37 | | |

a huge portion of the commodity remains unused. Vehicle carryover is zero for both CSDs and LSDs throughout the entire planning horizon.

The effect of constraint violation penalty weight on objective 1 is shown in Figure 8. At weight 0, the value of the objective function 1 is also zero. This is because when the weight is zero, the entire unmet demand is assigned to constraint violation parameters $\gamma^{+}_{kcst}$. Thus, no commodity flow occurs resulting in zero logistics costs (objective 1). Consequently, constraint violation is highest when the weight is zero, which can be seen in Figure 9. As the weight increases, the violation penalty decreases and reaches zero at about a value of 2000. The objective function 1 first reaches the highest value at $\gamma^{+}_{kcst}$, value 1000, then decreases until 5000. Objective 1 remains relatively unchanged after $\gamma^{+}_{kcst}$ 5000.

A deterministic version of the model has been solved for each scenario and compared with the robust model in terms of logistics cost (objective 1) and deprivation cost (objective 2). The results are shown in Figures 10 and 11. From Figure 10, it can be seen that the deterministic model produces varied logistics costs for different scenarios, whereas the robust stochastic model gives a stable cost. Figure 11 indicates that although the deprivation cost is lower for scenario 1, it is much higher in scenario 3. This means the deterministic model will result in massive unmet demand. Thus, in an uncertain situation, a

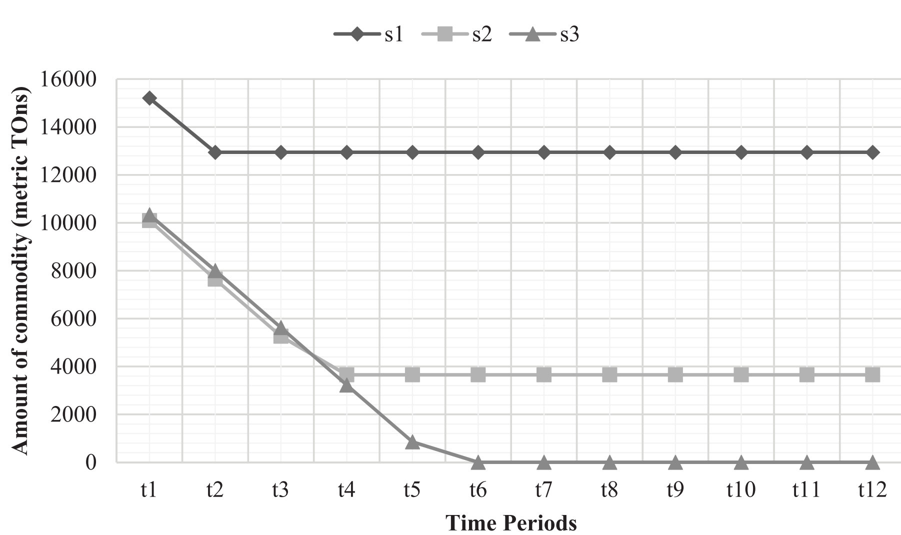


**Figure 7.** Total inventory (supply carryover) at CSDs.

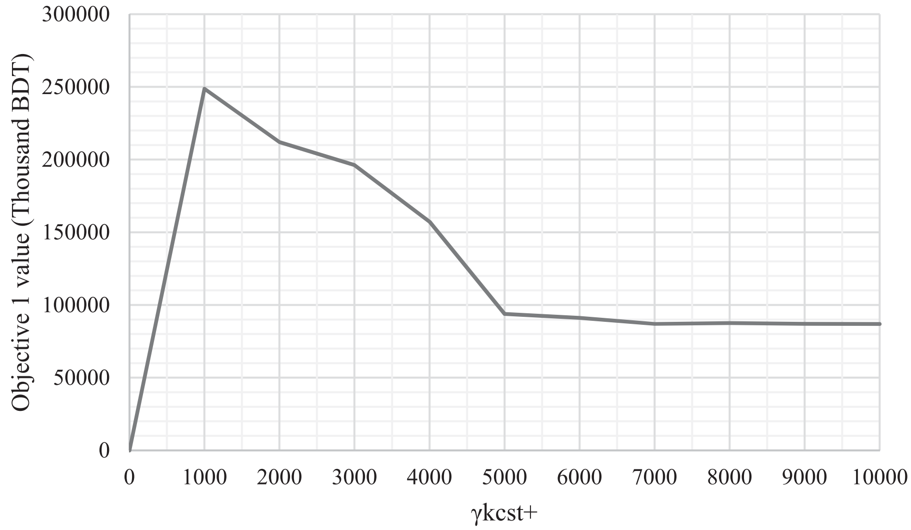


**Figure 8.** Variation in objective 1 with weight of the model robustness parameter.

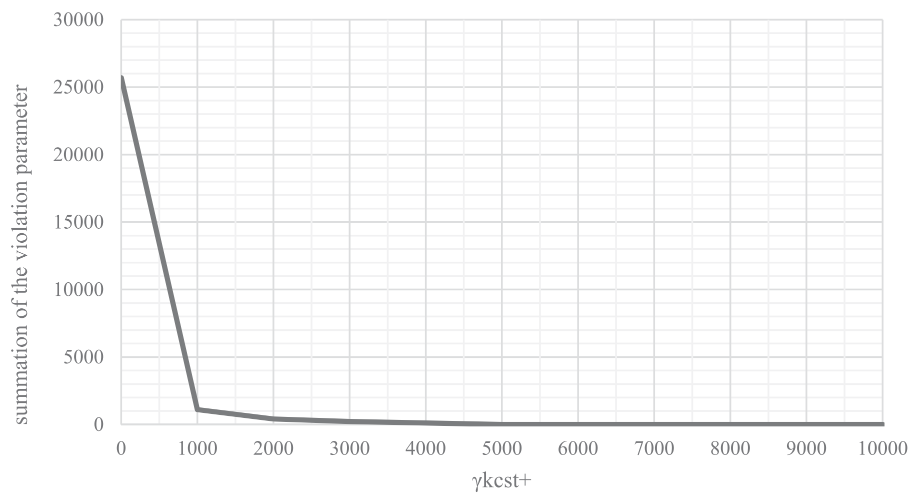


**Figure 9.** Variation in deviation parameter with the weight of the model robustness parameter.

robust stochastic model will be much more beneficial for decision-makers than a deterministic model, although the robust model will be much more computationally demanding.

## 9. Practical and managerial insights

Conventionally, humanitarian logistics decision-making aims to find the optimal locations of facilities and their capacity with regards to a simplified function in making optimal pre- and post-disaster decisions. However, disaster operations management is viewed as a challenging decision problem, especially in developing countries (e.g. Bangladesh). A simplified approach for the management of humanitarian logistics generally cannot deliver satisfactory outcomes in a dynamic environment. In this regard, this study develops a robust-stochastic optimisation model to identify the location of temporary facilities, determine the amount of commodity to be pre-positioned, and to provide a detailed schedule for the distribution of commodities and the dispatch of vehicles.

The proposed model provides great practical benefits to disaster management officials. This model can assist disaster officials in the preparedness phase by determining the optimum amount of relief and optimum locations and sizes of a temporary facility that will make responding immediately after a disaster is easier. The model provides a scenario-specific distribution schedule. Therefore, decision-makers can efficiently distribute relief commodities in the response phase. The decision-makers can also determine the level of equity and thus ensure fairness in distribution. Uncertainties typically encountered and having the most severe effects in real life have been considered in this model, increasing practicality and applicability. Generation of the entire Pareto front

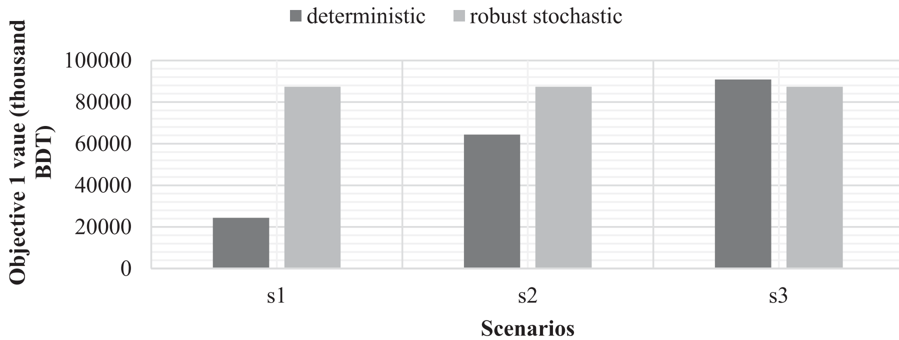


**Figure 10.** Comparison of the robust stochastic and deterministic model in terms of objective 1 (logistics cost).

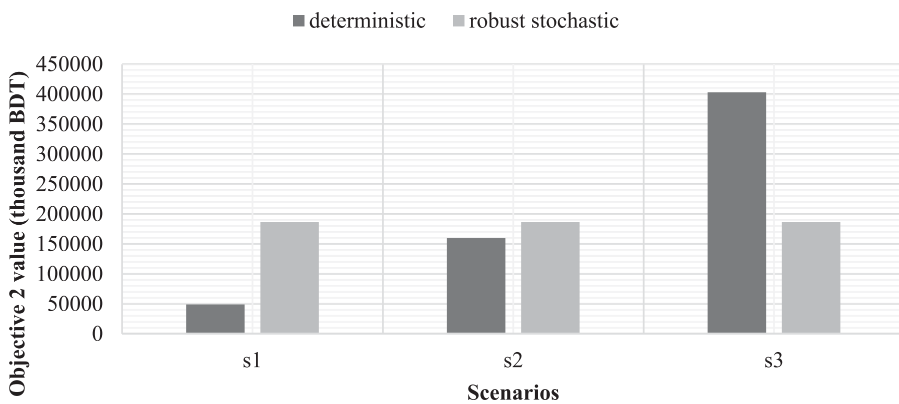


**Figure 11.** Comparison of robust stochastic and deterministic model in terms of objective 2 (deprivation cost).

means that decision-makers have a plethora of options to choose from according to their preference. Although a case study of flood has been conducted, the model can be applied to any natural or human-made disaster that needs rapid relief distribution.

## 10. Conclusion and further research

In this study, a multi-objective humanitarian logistics model has been developed to minimise logistics cost and deprivation cost. A case study of a flood in Bangladesh has been used to test the model. To generate Pareto optimal solutions and Pareto front, Lexicographic weighted Tchebycheff methods have been used. The model determines the location and size of temporary local supply depots and the amount of commodity to be pre-positioned at CSDs. This model also generates a detailed distribution schedule for commodities and a dispatch schedule for vehicles. Uncertainty in demand, node reachability, and condition of pre-positioned supply have been incorporated. A robust stochastic optimisation model has been used as it allows decision-makers to tradeoff cost and solution feasibility. The results show that the model performs satisfactorily in an uncertain disaster situation. The model has been compared with its deterministic variant, and the results indicate that although a robust stochastic model is computationally expensive, it is more effective in predicting cost under uncertainty.

A valuable addition to the research can be the integration of a geographic information system (GIS) to generate location, population, distance, and demand data accurately and automatically. Solving large-scale models can be very time consuming, especially a robust optimisation model where adding scenarios can increase the number of variables and equations drastically. Thus, suitable multi-objective metaheuristics can be developed to reduce solution time. Without a doubt, as the proposed model is complex, an efficient approximation method like the red deer algorithm (Fathollahi-Fard et al., 2020) may be a good continuation of this work to show its complexity in real-scale studies.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

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