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A Robust Multi-Commodity Rebalancing Process in Humanitarian Logistics

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Abstract. After disasters occurred, many refugees have to suffer a lot. To relieve this detrimental situation, various commodities are distributed to the pre-determined warehouses. However, the initial multi-commodity distribution may be imperfect, which results in some warehouses having surplus commodities compared to other unmet warehouses. Hence, it is necessary to rebalance commodities among those warehouses. Because of the uncertain environment after a disaster, the demand is usually uncertain. To plan this multi-commodity rebalancing process appropriately, it is usually assumed that the collected data are uncontaminated. However, this assumption can be easily violated due to the uncertain environment or human error, which results in the biased estimation of the solution. In this study, we propose a strategy for remedying the difficulties associated with data contamination so that a set of robust decisions are obtained. Through a case study, we show that the proposed strategy facilitates effective decision-making in the multi-commodity rebalancing when the data contamination is involved.

Keywords: Robust optimization, Nonlinear, Mathematical programming, Humanitarian logistics.

1 Introduction

Based on the Emergency Event Database (EM-DAT, www.emdat.be), large-scale natural or man-made disasters had occurred frequently since the 1900s. Recently, large-scale disasters such as the 2008 Wenchuan Earthquake in China, 2011 Earthquake and Tsunami in Japan, 2018 Earthquake and Tsunami in Indonesia, 2019 Forest Fire in Australia, 2019 COVID in the world, and 2019 Plague of Locusts from Kenya result in a great number of refugees. To relieve this detrimental situation, medical and living commodities should be distributed to and stocked at the pre-determined warehouses.

As the initial multi-commodity distribution happened before the disasters, it is impossible to match with the practical situation, which results in some warehouses having surplus commodities compared to other unmet warehouses. The undersupply of commodities worsens human suffering and results in an increased mortality rate. In contrast, the oversupply of commodities may also occur in some other affected areas. To make full use of any surplus commodities, it is necessary to conduct a multi-commodity rebalancing process to rebalance the commodities among the warehouses. However, the collected information about the demand may be inaccurate during the critical hours right after disasters [1]. Also, the collected data may be contaminated due to human error. The above two factors result in a biased rebalancing strategy. Neither strategic approaches nor quantitative models to handle this multi-commodity rebalancing under data contamination. Thus, we investigate the multi-commodity rebalancing problem with data contamination and propose a robust optimization model for remedying the data contamination so that a set of robust decisions can be obtained.

The remainder of this paper is organized as follows. Section 2 reviews previous studies about commodity rebalancing (also referred to as redistribution) in humanitarian logistics, highlighting the novelty of this study. In Section 3, we present the problem description and propose a strategy for remedying the problem with data contamination. Then a mixed-integer nonlinear programming (MINP) model is formulated for the problem. Next, a linearization approach is applied to linearize the model. In Section 4, we compare different methods in a case study. Finally, Section 5 concludes this study with contributions and further directions.

2 Literature review

The logistics related problem in disaster response has been extensively studied by many researchers [2-6]. However, the commodity rebalancing is also an important part in relief supply chain planning [7, 8]. However, this commodity rebalancing has been received insufficient attention in the past. In what follows, we review the studies about commodity rebalancing in disaster response. Then the research gap is discussed and the novelty of this study is summarized.

To the best of our knowledge, the commodity redistribution was firstly proposed by Lubashevskiy [9, 10] who implemented the required redistribution of vital resources between the affected and neighboring cities in the disaster area. However, they did not consider any uncertainty. Then Gao and Lee [11] considered a multi-commodity redistribution problem under demand uncertainty. Based on the above study, Gao and Lee [12] considered the multi-commodity redistribution process happens in a multi-modal transportation system when multiple disaster areas are involved. Sarma, Das [13] and Sarma, Das [14] also introduced different mathematical models for humanitarian logistic applying the fact of redistribution of resources. After that, Gao [8] and Gao [15] modified the terminology from "multi-commodity redistribution" to "multi-commodity rebalancing" as its appropriate and suitable description to the problem. Later Gao [7] defined the multi-commodity rebalancing in disaster response, which is given by "*The multi-commodity rebalancing process in disaster response is to rebalance the commodities from the oversupplied nodes to unmet nodes over the transportation network to satisfy the potential demand at all nodes (relief centers)".* And the relief centers were divided into three groups, namely (i) complete supply relief centers, (ii) complete demand relief centers, and (iii) potential demand or supply relief centers, where the multi-commodity rebalancing process was conducted among these three groups of relief centers.

As the collected data is easily contaminated due to human error and inaccurate information right after disasters, it results in a biased rebalancing strategy. For more details on the data contamination and its effect, one should refer to Park [16]. However, neither strategic approaches nor quantitative models to handle this multi-commodity rebalancing under data contamination. To address this challenge and fill this research gap, a robust approach that is less sensitive to the outliers or noises is warranted. As a consequence, we investigate the multi-commodity rebalancing problem under data contamination and propose a strategy for remedying the difficulties associated with data contamination so that a set of robust decisions can be obtained.

3 Robust optimization model

3.1 Problem description

Suppose that a large-scale disaster strikes an area where a set of warehouses have been pre-identified to stock the commodities. These stocked commodities are used to support basic lives. Inevitably, some warehouses end up having surplus commodities, whereas others end up having insufficient commodities. To reduce human suffering and make full use of any surplus commodities, it is necessary to plan a multi-commodity rebalancing strategy to rebalance the commodities among the warehouses.

The complex and dynamic nature of a large-scale disaster creates a highly uncertain environment. It is difficult to determine how much of a particular commodity a warehouse will require in the future, which makes the demand uncertain. Here, the demand is classified into several independent scenarios. The uncertain demand is represented as a set of discrete stochastic quantities, and a specific realization is considered as a scenario. For each commodity type, there is a set of scenarios Ξ. For a particular scenario $\xi \in \Xi$, there is a probability of occurrence $p(\xi)$ such that $p(\xi) \geq 0$ and $\sum_{\xi \in \Xi} p(\xi) = 1$. As the inaccurate information usually exists, the demand quantity is considered as the outlier in this study. What we need to is identifying these warehouses and determine the outgoing and incoming shipments at the warehouses. Before the model is proposed, an assumption is stated in advance. Each of the warehouses is a separate unit and the weighted values of the warehouses are given.

3.2 Notations

The parameters and decision variables used in this model are shown as follows:

Sets

$\mathcal{R}$ Set of warehouses, indexed by $r \in \mathcal{R}$, $(r \neq c)$.

$\mathcal{E}$ Set of commodity types, indexed by $t \in \mathcal{T}$.

Ξ Set of scenarios, indexed by $\xi \in \Xi$.

Parameters

W_r Weight of warehouse r.

S_{rt} Stock level of commodity-type t at warehouse r.

D_{rt}^{ξ} Demand of commodity-type t at warehouse r in scenario ξ.

P_{rt}^{ξ} Probability of occurrence for D_{rt}^{ξ}.
O_{rt}^{ξ} Outlier demand for commodity-type t at warehouse r in scenario ξ.
N Number of scenarios in Ξ.
Decision variables
qo_{rt} Quantity of outgoing commodity-type t at warehouse r.
qi_{rt} Quantity of incoming commodity-type t at warehouse r.

3.3 Robust strategy

To copy with the uncertain demand, many researchers use expected demand [7, 17, 18]. Given a set of discrete demand quantities $D_{rt}^{1}, D_{rt}^{2}, \dots, D_{rt}^{N}$ with corresponding probabilities P_{rt}^{1}, P_{rt}^{2}, …, P_{rt}^{N}, such that $\sum_{\xi\in\Xi} P_{rt}^{\xi} = 1$, the expected demand is given by

$$\mathbb{E}(D_{rt}^{\xi}, \xi) = \sum_{\xi\in\Xi} D_{rt}^{\xi} P_{rt}^{\xi} \tag{1}$$

The above-expected demand can be considered as the weighted mean. However, the weighted mean is not a robust outlier-resistant location estimator. As the median is a robust outlier-resistant location estimator [19], instead of using weighted mean, we use the median to represent the demand at warehouse r, which is denoted by $\mathbb{M}(D_{rt}^{\xi}, P_{rt}^{\xi}, \xi)$ and given by

$$\mathbb{M}\left(D_{rt}^{\xi}, \xi\right) = \text{Median}(D_{rt}^{1}, D_{rt}^{2}, \dots, D_{rt}^{N}) \tag{2}$$

3.4 Robust optimization model

The problem is formulated as the following MINP model.

$$\text{Min}\, \Psi_1 = \sum_{t\in\mathcal{T}} \sum_{r\in\mathcal{R}} W_r[\text{Median}(D_{rt}^{1}, D_{rt}^{2}, \dots, D_{rt}^{N}) - (S_{rt} + qi_{rt} - qo_{rt})] \tag{3}$$

s.t.

$$\sum_{r\in\mathcal{R}} qi_{rt} = \sum_{r\in\mathcal{R}} qo_{rt} \quad \forall\, t \in \mathcal{T}. \tag{4}$$

$$qo_{rt} \le S_{tr} \quad \forall\, r \in \mathcal{R}, t \in \mathcal{T}. \tag{5}$$

$$qi_{rt} \cdot qo_{rt} = 0 \quad \forall\, r \in \mathcal{R}, t \in \mathcal{T}. \tag{6}$$

$$S_{rt} + qi_{rt} - qo_{rt} \le \text{Median}(D_{rt}^{1}, D_{rt}^{2}, \dots, D_{rt}^{N}) \quad \forall\, r \in \mathcal{R}, t \in \mathcal{T}. \tag{7}$$

$$qi_{rt} \text{ and } qo_{rt} \text{ are nonnegative variables} \quad \forall\, r \in \mathcal{R}, t \in \mathcal{T}. \tag{8}$$

The objective function (3) aims to minimize the total weighted unmet demand at warehouses. Constraint (4) ensures the balance between incoming and outgoing shipments. Constraint (5) restricts that the outgoing shipment is not greater than the stock level. Constraint (6) ensures that either outgoing or incoming shipments could happen. Constraint (7) restricts that the commodity after rebalancing is not greater than the demand. Constraint (8) defines the decision variables.

3.5 Linearization method

The above model is nonlinear due to Constraint (6). It is significant to propose a linearization strategy for the above MINP model so that it can be solved by using CPLEX. Consequently, we introduce a big positive value M and two auxiliary binary variables into the model. These two auxiliary binary variables are given by

$$i_{rt} = \begin{cases} 1 & \text{if } qi_{rt} > 0 \\ 0 & \text{otherwise} \end{cases} \quad \forall\, r \in \mathcal{R}, t \in \mathcal{T}. \tag{9}$$

$$j_{rt} = \begin{cases} 1 & \text{if } qo_{rt} > 0 \\ 0 & \text{otherwise} \end{cases} \quad \forall\, r \in \mathcal{R}, t \in \mathcal{T}. \tag{10}$$

Then the MINP model can be reformulated as the following mathematical model.

$$\text{Min } \Psi_1$$

s.t.

Constraints (4), (5), (7), and (8)

$$i_{rt} + j_{rt} \leq 1 \quad \forall\, r \in \mathcal{R}, t \in \mathcal{T}. \tag{11}$$

$$qi_{rt} \leq i_{rt} M \quad \forall\, r \in \mathcal{R}, t \in \mathcal{T}. \tag{12}$$

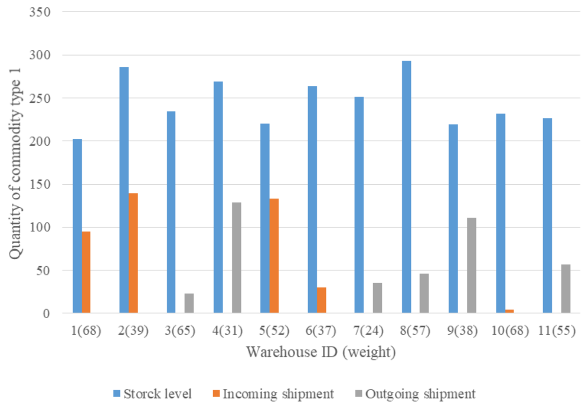
$$qo_{rt} \leq j_{rt} M \quad \forall\, r \in \mathcal{R}, t \in \mathcal{T}. \tag{13}$$

Constraint (11) guarantees that either an outgoing or incoming shipment could happen. Constraints (12) and (13) restrict the quantities of incoming and outgoing shipments, respectively.

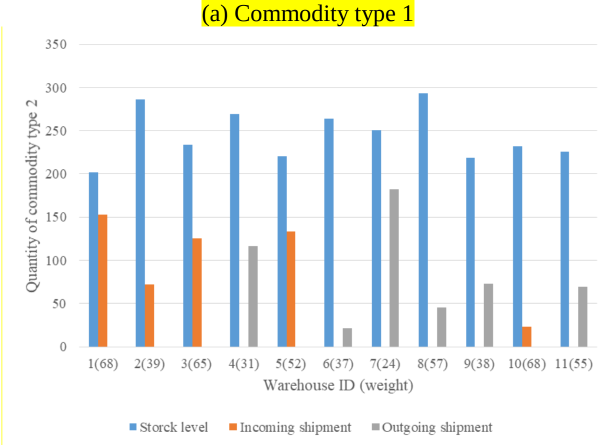
4 Numerical example

This study considers a numerical example that includes eleven warehouses and two commodity types based on the study of Gao [7]. Let the outlier value be 10000, which exists in warehouses 1, 5, and 9. The proposed mathematical model is implemented in the CPLEX (Version: 12.6). All the experiments are run on a computer with an Intel(R) Core(TM) i7-7700 CPU@3.6 GHz under the Windows 10 Pro system.

To evaluate the robustness of the proposed robust optimization model against the outliers, we compare the results for the numerical example using different models. We first present the optimal solution in Fig. 1 without considering data contamination and then compare different methods and present the results in Table. 1 when the data contamination is involved.



(a) Commodity type 1



(b) Commodity type 2

Fig. 1. Commodity rebalancing strategy for two commodity types

As shown in Table. 1, it provides an outlier resistance behavior for commodity type 1 in different models. The solution obtained using the robust optimization model is quite close to the solution through the method in Gao [7]. After considering the outlier, the method in Gao [7] is strongly sensitive to the outlier, whereas the proposed model is quite stable to obtain the solution that is still quite close to the true optimal solution.

Table 1. Comparison of commodity rebalancing strategies.

ID	Without outlier				With outlier in warehouses 1, 5, and 9							
	Gao [7]		Robust model		Gao [7] $O_{11}^{N} = 10^4$		Gao [7] $O_{51}^{N} = 10^4$		Gao [7] $O_{91}^{N} = 10^4$		Robust model	
	qo_{r1}	qi_{r1}	qo_{r1}	qi_{r1}	qo_{r1}	qi_{r1}	qo_{r1}	qi_{r1}	qo_{r1}	qi_{r1}	qo_{r1}	qi_{r1}
r=1	0	89.8	0	95	0	1051.3	0	89.8	0	89.8	0	95
r=2	0	134	0	139	0	95.9	0	96.1	0	75.5	0	139
r=3	10.6	0	23	0	282	0	282	0	282	0	23	0
r=4	123.7	0	129	0	274	0	274	0	274	0	129	0
r=5	0	137.3	0	133	0	137.3	0	1098.6	0	137.3	0	133
r=6	0	34.6	0	30	0	34.6	0	34.6	0	34.6	0	30
r=7	33.5	0	35	0	285	0	285	0	285	0	35	0
r=8	49.8	0	46	0	300	0	300	0	300	0	46	0
r=9	115	0	111	0	115	0	115	0	0	866.9	111	0
r=10	0.5	0	0	4	0.5	0	0.5	0	0.5	0	0	4
r=11	62.6	0	57	0	62.6	0	62.6	0	62.6	0	57	0

5 Conclusion and future study

This study focused on the multi-commodity rebalancing problem under data contamination in disaster response. We proposed a robust optimization model to formulate the problem. Then we applied a linearization method for the model so that it could be solved in CPLEX. Next, the solutions were obtained to illustrate the effectiveness of the proposed method. Finally, we compared the results of different methods in a case study to verify the outperformance of the proposed method in overcoming the outlier in the multi-commodity rebalancing problem. The limitation of this study is that the data contamination only exists in the demand for commodities.

In future work, some directions are meaningful that could be explored deeply from the following two perspectives. This study only focuses on the multi-commodity rebalancing process. However, it would be interesting to consider how to transport these commodities among the warehouses. Another future consideration is to develop a more reliable multi-commodity rebalancing by considering a multi-period process.

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