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A possibilistic mathematical programming model to control the flow of relief commodities in humanitarian supply chains

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ABSTRACT

In emergency situations, disaster relief organizations are faced with the difficult decision of how to allocate scarce resources in an efficient manner in order to provide the best possible relief action. This paper aims to provide an analytical model that will help relief organizations in reducing human suffering following a disaster while maintaining an acceptable level of cost efficiency. A mathematical model is introduced to optimize the relief distribution problem which considers the social cost —the total sum of logistics and deprivation costs. The fuzzy nature of the deprivation cost function is addressed with possibilistic mixed integer programming with fuzzy objectives to reflect variation in deprivation costs perceptions. The model is solved using the Rolling Horizon method in a sequence of iterations. In each iteration, part of the planning horizon is modeled in detail and the rest of the time horizon is represented in an aggregated manner. The model is tested both empirically and on a case study of internal displacement in northwest Syria. Computational results showed that considering the demographic structure in affected areas and reflecting it to the deprivation cost function helped to reach better prioritization in distribution of commodities. The rolling horizon methodology is also found to be efficient in solving large scale instances and in capturing the dynamic changes in demand and supply parameters.

1. Introduction

Natural and man-made disasters are increasing in frequency throughout the world while the number of people affected as well as the cost of responding are growing considerably (CRED, 2015). Prior to the last decade, most research on disaster management and emergency relief preparedness could be found in areas other than logistics and supply chain. “Much of the research in the disaster management field is targeted to public servants, government agencies, and insurance firms charged with responding in times of crisis and has traditionally focused on crises such as hurricanes, earthquakes, flooding, and fires” (Hale & Moberg, 2005). There is still great potential for enhancing disaster operations management through the use of analytical tools, and thus improving the positive impact on those affected. When compared to business logistics, scientific knowledge about humanitarian logistics (HL) is still emerging. Nevertheless, the high numbers of losses that accompany natural disasters encourage effective contributions of the scientific community to reduce human suffering (Zary et al., 2014). Researchers attempt to adapt analytical formulations developed for the commercial sector to the humanitarian framework. However, the adaptation has some limitations where commercial and humanitarian logistics are radically different and capturing the complexity of HL via analytical formulations designed for traditional logistics could be unreasonable (Holguín-Veras et al., 2012).

The introduction of social cost based objective functions by Holguín-Veras et al. (2013) is an approach among significant contributions in modeling humanitarian logistics. Such costs are experienced by relief groups who are involved in the relief supply plan as well as beneficiaries who are impacted by the plan. The term deprivation cost (DC) is used to express the economic value of the human suffering caused by the lack of access to a good or service (Holguín-Veras et al., 2012). Therefore, the social cost to the relief group is assessed as logistical cost whereas the impact on the beneficiaries is measured as the effects of the relief supply on their DC. Pérez-Rodríguez & Holguín-Veras (2016) developed original mathematical inventory allocation models to maximize the benefits resulting of distributing critical supplies to populations in need in the aftermath of disasters based on the welfare economics and social costs function. Their results establish a promising basis for future model development in this area. Since then, a considerable research effort has been made to develop econometric and proxy approaches to model the deprivation cost function and use it in different HL applications; as summarized in (Shao et al., 2020).

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This paper attempts to contribute to the deprivation cost literature by considering the differences in deprivation vulnerability among different individual groups within the affected population. The basis and experimentation of the paper is inspired by the humanitarian crisis of internally displaced persons (IDPs) in Syria after the start of the prolonged civil war in 2011. The Needs and Population Monitoring (NPM) program conducted by UN partners about Syrian IDPs provided an assessment of vulnerability with regard to specific groups that exhibit a greater susceptibility to risk. These groups include children, women and mentally or physically challenged individuals. "Female headed households, minor headed households, households including a disabled individual among their members, and households where more than 2/3 of their members are dependents (less than 14 or over 65) were considered as vulnerable" (NPM, 2018). Households in which more than one of the above conditions applied were considered extremely vulnerable. These characteristics were selected according to OCHA Humanitarian Needs Overview (HNO) Guidelines published in 2018 (NPM, 2018). The Humanitarian Needs Assessment Program in Syria (HNAP) reported that the current assistance prioritizes recently IDPs with rapid response mechanisms. This can lead to shortcomings in regards to the compounded vulnerability of long-term displaced households, who may themselves face compounded risks of assistance exclusion. HNAP (2019a) analysis revealed that there is very little difference between the rates of vulnerable households receiving assistance compared with fulfilment rates for non-vulnerable households; which highlights the practical gap in adopting vulnerability based distribution models.

This research contributes to the existing models by prioritizing vulnerable individuals for urgent assistance. The relief distribution among different demand nodes is formulated as a possibilistic mixed integer programming (MIP) with fuzzy objective function. The possibilistic model aims to minimize the risk of higher deprivation cost (perceived by vulnerable people), and minimizing the most possible value (perceived by average typical individuals) while maximizing the possibility of lower deprivation cost. Furthermore, unlike many existing literature works, assumptions like equal shipment sizes per node as in Pérez-Rodríguez & Holguín-Veras (2016); or assuming the unit of supply to be sufficient to fulfil demand of an affected area as in Yu et al. (2018), are relaxed in the current model. Moreover, shortage in demand corresponding to each deprivation time is defined as a continuous variable.

The remainder of this paper is organized as follows. Section 2 reviews state-of-the-art literature on humanitarian logistics and deprivation cost models. Section 3 addresses the basic formulation of the post-disaster relief distribution problem under the objective of minimizing total social costs; which adapts and improves upon literature models.. Section 4 extends the proposed model by introducing a possibilistic mathematical programming with fuzzy deprivation cost. Section 5 analyzes the experimental results and implications. Section 6 comprises a case study on humanitarian relief response for IDPs in Northwest Syria. Finally, Section 7 presents conclusions and gaps for future research.

2. Literature review

In the past few decades, humanitarian logistics started to attract the attention of researchers due to the increasing frequency of disasters and conflict situations (Habib et al., 2016). Over the past 35 years there has been immense growth in this research field. Goldschmidt & Kumar (2016) reported that the number of academic articles about HL published per year in the indexed journals has considerably grown since 1980 to reach 165 publications per year as of 2014. This has motivated many authors to conduct literature surveys summarizing the work done so far and highlighting potential areas for further investigation. Examples of literature review include Caunhye et al. (2012) who reviewed optimization models in emergency logistics and categorized them into two classes: pre-disaster and post-disaster models. The pre-disaster operations consist mainly of facility location, stock pre-positioning, and evacuation. The post-disaster operations involve relief distribution, routing and casualty transportation. In addition, models for traffic control and lifeline rehabilitation were reviewed. Areas such as capacity planning, manpower management, facility repair, debris removal, and vaccination of unharmed people to prevent the spread of epidemics were highlighted as gaps for future investigation and have found considerable attention later in the recent HL literature.

Zary et al. (2014) presented a comprehensive analysis of the humanitarian logistics research from the beginning of the twenty first century (2001) up to (2014). Their review was carried out by analyzing the citation and co-citation of related articles in order to provide valuable information about the knowledge network among studies in this area. Kara & Savaşer, (2017) studied and synthesized humanitarian logistics literature based on operations research problems faced in the disaster management cycle with more focus on research conducted in the last 10 years. Other reviews that can be referred to for comprehensive literature on humanitarian logistics include: (Safeer et al., 2014; Anaya-Arenas et al., 2014; Özdamar & Ertem, 2015; Habib et al., 2016; Goldschmidt & Kumar, 2016; Gutjahr & Nolz, 2016; Sabbaghtorkan et al., 2020). In addition, a recent literature review on research progress on deprivation cost based humanitarian logistics can be found in (Shao et al., 2020). In this brief review, focus is paid on articles relevant to the work conducted. The following paragraphs will respectively review research related to the choice of the objective function used in the relief distribution models within the humanitarian context with special attention to deprivation cost function; fuzzy optimization and its use in humanitarian logistics literature, and the methodologies of modeling dynamic decision making over time.

2.1. Deprivation cost and objective functions for HL models

The objective function is crucial to decide how to compromise contradicting goals and optimally allocate limited resources. Attaining high levels of service in the affected regions may require unfeasibly large logistical expenses. On the other hand, minimizing logistic costs without considering the influence on beneficiaries could negatively affect their welfare (Holguín-Veras et al., 2013). Just before the introduction of deprivation cost functions by Holguín-Veras et al. (2013), it should be noted that most of the relief distribution models aimed to optimize one or more of the following objectives: (1) minimizing the transportation or operational cost; (2) minimizing the travel time, flow time, or number of late deliveries; (3) minimizing the travel distance; (4) minimizing cumulative and weighed unmet demand or maximizing the satisfied demand; (5) maximizing the distribution network reliability and security; and (6) maximizing the equity for the satisfied demand. A summary about models under each objective function can be referred to in Özdamar & Ertem (2015). Gralla et al. (2014) grouped the above-mentioned objectives into three main groups of criteria, namely (I) efficiency criteria, (II) effectiveness criteria, and (III) equity criteria. Gutjahr & Nolz (2016) refine these classes by dividing the group "effectiveness" into subgroups including response time, travel distance, coverage, reliability and security; while "efficiency" means cost-efficiency with the different cost components.

Holguín-Veras et al. (2013) suggested the use of social cost, i.e., the total sum of logistics and deprivation costs, as the best objective function to represent the economic value of the human suffering related with lack of access to a good or service in the aftermath of disasters. Gutjahr & Nolz (2016) used the term distress to refer to the social or psychological costs. The introduction of social cost function provides a promising foundation for modeling a reliable objective function in case of HL. This encouraged scholars to study the deprivation cost function both from theoretical and application perspectives. Shao et al. (2020) classified research work on deprivation cost function into two classes: state-of-the-art and state-of-the-practice. The state-of-the-art of deprivation costs refers to the theoretical development including the theoretical proposal and new assessment techniques on the theoretical proposal; proposition, definition and characteristic analyses of new concepts and theories. The state-of-the-practice, on the other hand, refers to evidence of the development of a range of applications for the concept (Shao et al., 2020).

2.1.1. Modeling the deprivation cost function

Holguín-Veras et al. (2016) studied several economic evaluation techniques and came to the conclusion that contingent valuation (CV) and stated choice (SC) are preferred to measure the human suffering. They based their CV on willingness to pay (WTP) and willingness to accept (WTA) measures and integrated the value of life in their model to express the maximum deprivation cost. They also removed the effect of ability-to-pay to avoid bias and unfairness. Multiple linear regression with least square method was adopted to model the data given by the empirical research method.

Cantillo et al. (2018) introduced a mixed logit (ML) model as a type of discrete choice econometric models (DCMs) to capture the influence of socioeconomics variables and random variations among individuals. They explained part of the heterogeneities in the preferences of individuals; where their experiments suggest that: (1) the margin impact of deprivation time is slightly greater for women than men, (2) elderly people (age group >50 years) are more sensitive to deprivation time than young people, and (3) more presence of children in the household provides higher moral obligations. These results are consistent with the UN partners' reports and their definition to vulnerable households – as discussed in the introduction section.

Macea et al. (2018a) evaluated economic impacts of water deprivation in humanitarian relief distribution and combine discrete choice modeling with stated preference techniques to estimate the changes in the individuals' welfare. Their experimental results showed that the deprivation time significantly affects the individuals' stated choices while the effect of socio-economic characteristics were found negligible. Macea et al. (2018b) went a step forward in estimating more explanatory deprivation cost functions by analyzing the influence of psychological factors in addition to the demographic and socio-economic characteristics. They revealed that risk perception, safety culture, and confidence in emergency response system have an important impact on deprivation cost estimations.

Apart from the econometric valuation, Wang et al. (2017) proposed a new method for quantifying human suffering by means of numerical rate scale (NRS) inspired by clinical assessment applications. They studied how deprivation levels change based on deprivation time, relief commodity, and previous experience with disasters. Respondents were first asked to give pairwise comparisons on their preferences for receiving commodity *a* or *b* after different deprivation times. Then they were asked to give a rate scale from 1 to 10 to express their suffering under different scenarios. Curvilinear regression was used to model the deprivation cost function for tents, food, and medicines.

2.1.2. Applications of deprivation cost based models in HL

It is observed that the problem types discussed using deprivation cost cover almost any application in the entire HL research field with no reported disadvantages in any particular area in HL research (Shao et al., 2020). Among the applications where deprivation cost function is applied in HL areas are: facility location e.g. (Pradhananga et al., 2016; Loree & Aros-Vera, 2018; Ni et al., 2018; Chapman & Mitchell, 2018; Cotes & Cantillo, 2019), inventory allocation and relief distribution e.g. (Das & Hanaoka, 2014; Pérez-Rodríguez & Holguín-Veras, 2016; Rivera-Royero et al., 2016), inventory pre-positioning e.g. (Kelle et al., 2014; Condeixa et al., 2017; Ni et al., 2018), resource allocation (Yu et al., 2018); transportation network (Moreno et al., 2018; Paul & Wang, 2019; Cantillo et al., 2019; Gralla & Goentzel, 2018; Rivera-Royero et al., 2020), and casualty rescuing and transportation (Zhu et al., 2019).

Some interesting extended models include Gutjahr & Fischer (2018) who questioned whether the deprivation cost minimization results in achieving equity and proposed to extend the deprivation cost objective by adding a term proportional to the Gini index of inequity. Zhu et al. (2019) proposed the relative deprivation cost and defined it as the difference between deprivation costs in two disaster regions. They assigned priorities to diverse injury degrees based on the probability of survival after the relief intervention. Keshvari Fard et al. (2019) estimated the deprivation cost that can be avoided by fulfilling transportation relief mission to maximize the potential of alleviating human suffering. Huang & Rafiei (2019) extended Huang et al. (2015) and Pérez-Rodríguez & Holguín-Veras (2016) work by comparing different equity measures, namely in fulfillment rates, arrival times and deprivation times under different supply and demand relationships. Then, the trade-offs between equity and efficiency were investigated. Sakiani et al. (2020) developed an inventory routing model and dynamic redistribution of relief goods in post-disaster operations. They categorized the relief supply to consumable and durable goods and reuse the durable commodities when applicable.

2.2. Fuzzy HL models

Fuzzy modeling has the advantage of handling the subjective uncertainty and thus has been used for the extension of many decision making quantitative models. There is no need to generalize reality to fit it into classes; rather the degree of membership to the category is given (Vitoriano et al., 2013). Among the few fuzzy models in the HL literature are the following examples. Tzeng et al. (2007) proposed a fuzzy multi-criteria LP model for a relief distribution system aiming to optimize three objectives: minimizing costs, minimizing travel time and maximizing the satisfaction of demand nodes, some of which might be difficult to reach. Their model maximizes the membership function for the satisfaction of the multiple yet contradicting objectives using fuzzy linear programming (FLP). Adivar and Mert (2010) optimized a simple relief distribution system in which donor countries provide relief items collected at collection points. These items are shipped to points of delivery in disaster affected countries. The type of uncertainty considered is related to imprecise information concerning the quantity of items provided by the donor countries, the procurement items cost at donor country level, and the potential delay at collection point level. The authors dealt with the uncertainty by employing a fuzzy model to consider both the uncertain parameters and the credibility.

Rodriguez et al. (2010) designed a Decision Support System (DSS) for aiding humanitarian organizations based on fuzzy logic. Their DSS, called SEDD, focuses on providing an estimation of the effects after a disaster strikes; i.e., when there is a lack of reliable knowledge on the real magnitude of the emergency. Given a disaster-type and the affected area, SEDD makes use of the data stored in the EM-DAT database to predict the number of casualties, injured, homeless, affected, and the total damage value. The data, technological, and infrastructure requirements make SEDD particularly useful and accessible to NGOs.

Tofighi et al. (2016) developed a novel mixed possibilistic – stochastic model to cope with different sources of uncertainty in HL network design problem. The model copes with two major sources of uncertainties including random disaster scenarios at post-disaster and fuzzy scenario-independent and scenario-dependent parameters in disaster relief operations. Zahiri et al. (2017) proposed a Multistage Possibilistic Stochastic Programming (MSPSP) method which relaxes the subjectivity of probabilities and allows possible perturbation in their values as fuzzy probabilities. It also enables these values to be updated in such a manner that avoids inconsistent values and keeps the summation less than one. Random fuzzy variables are used to treat the scenario dependent variables. A real case study on post-disaster relief distribution in Tehran was presented to validate the model.

Fuzzy logic is also integrated in multi-criteria decision making in the humanitarian aid context. Ismail and Quinteros (2015) developed a hybrid AHP fuzzy TOPSIS model for prioritizing humanitarian aid activities provided by the humanitarian relief foundation (IHH) to Syrian refugees in Turkey. Boltürk et al. (2016) solved the HL warehouse location selection problem using hesitant fuzzy-AHP method and applied it to select the best warehouse location of a relief agency in an earthquake prone area in the northwest of Turkey.

In a related context, fuzzy logic has been widely employed in socio-economic studies to estimate the deprivation index as a measure for multi-dimensional poverty. For some examples, please refer to: (Belhadj, 2012; Najjary et al., 2016; Chakravarty, 2019; and others). The research presented in this paper aims to utilize the fuzzy formulation for modeling the uncertainty in the deprivation cost objective function which, to the best of our knowledge, has not been addressed in the literature. Lai and Hwang (1992) possibilistic linear programming approach, as discussed in Section 4.1, has been used.

2.3. Modeling dynamic decision making in the HL context

One important aspect of research associated with the current work is the methodologies used to model and solve dynamic decision making problems over time. The time space network, a network in which each node in a directed graph is associated with a specific time period, has been approved to support humanitarian operations scheduling and is widely used in the literature (e.g. Yan et al., 2014; Yan & Shih, 2009; Afshar & Haghani, 2012). Yu et al., (2018) developed a dynamic programming model, an optimization over simple recursion, for a multi-period resource allocation dispatch problem designed to address the disaster response phase, with special attention paid to the human suffering resulting from delays in relief deliveries. The Rolling Horizon (RH) approach is another effective method to capture the dynamic nature of humanitarian logistics (Balcik et al., 2008; Huang et al., 2015). "RH is a reactive scheduling method that solves iteratively the deterministic problem by moving forward the optimization horizon in every iteration; assuming that the status of the system is updated as soon as the different uncertain or not accurate enough parameters became to be known" (Silvente et al., 2015). The most common application of the rolling horizon approach is found in the field of lot sizing planning and production scheduling (e.g. Clark, 2005; Araujo et al., 2007; Tiacci & Saetta, 2012). Some other examples are found in the field healthcare supply facility location and distribution (Mete & Zabinsky, 2010) and humanitarian relief operations (Salmerón & Apte, 2010; Huang et al., 2015; Rivera-Royero et al., 2016; Sakiani et al., 2020).

In summary, the literature review shows that Humanitarian logistics and deprivation cost modeling have recently been extensively addressed both from theory and practice perspectives. However, some gaps and potential for new extensions can still be recognized. In this paper, the advantage of fuzzy modeling to handle subjective uncertainty is utilized to reflect the variances in perceiving deprivation cost by different groups of individuals; which have not been studied in the literature. While most of existing literature use stochastic based formulation to model uncertain parameters, the type of uncertainty (vagueness) under study is subjective and depends on individuals' perceptions more than probability of occurrence. Therefore, it is more appropriate to characterize the problem as possibilistic rather than probabilistic. Furthermore, unlike most of related researches which focus on natural disasters, this paper is inspired by the humanitarian crisis resulted from conflict and man-made situations.

3. Problem description and formulation

The model and methodology provided in this research are intended to be used by independent aid organizations. The focus is on the lower end of the humanitarian relief chain, i.e., the distribution subsystem covering local distribution centers and demand nodes at the affected area. In other words, the research considers a relief agency which decides upon distributing critical relief commodities from supplier points (or distribution centers) $i \in SN$ to a set of demand points $j \in DN$. The demand nodes are assumed to have their own store areas and can thus serve as transshipment nodes to transfer relief to other demand nodes if needed. Decisions include the quantities, order, transportation mean, number and types of needed vehicles, routes, and time of deliveries from each supply or transshipment node to each of the demand nodes. The model formulates for multiple transportation modes $m \in M$; i.e., different ways by which goods are transported from one node to the other through land, air or sea. An undirected graph G_m associated with each transportation mode can be defined to represent the inventory routing and aid distribution problem under study; where $G_m = (N; A_m)$ with a set of nodes $N = DN \cup SN$ and a set of arcs $A_m = \{(i; j): i; j \in N; i \neq j\}$ (Espejo-Díaz & Guerrero, 2019). Each arc (i, j) has an associated non-negative finite value τ_{ij}^{m} which represents the travel time between nodes i and j using the path (i,j) through mode m. The travel time for infeasible arcs is set as infinity. Finally, fleets of vehicle types $k \in K_m$ are available for each mode m; with a defined maximum load capacity Q^{km} and transportation cost per time unit C^{km}.

The proposed model aims to control the flow of multiple commodities $c \in C$, (e.g, water, food, nonfood items (NFI)) in a multiperiod time horizon after the occurance of a disaster or in an emergency situation. Let D_{cit} be the demand of node i for commodıty c at time period $t = 1, 2, \dots T$; and a_{cit}^{s} be the supply of commodity c received from external resources to a node i at time t. The length of the time period depends on the planning scale and the frequency of commodities' consumption. It can be expressed in hours, days or any fixed duration of time. In the current model, one time unit is assumed to equal 12 h (half day). Note that the external supply is either received as scheduled replenishments to supply nodes or as local donations to demand nodes. Note also that the demand might change with time due to possible displacement of affected individuals among nodes during the planning horizon. Relief delivery decisions are taken while considering existing inventories, if any, in the local distribution points or at the affected areas. Therefore, the problem is similar to the vendor managed systems (Pérez-Rodríguez & Holguín-Veras, 2016), in which the centralized suppliers (in this case, the relief agencies) are responsible for satisfying the demands from several customers (the beneficiaries in the case of humanitarian logistics). The ultimate goal a relief agency seeks in the aid distribution process is to alleviate the suffer of affected people by minimizing the deprivation costs while ensuring transportation and distribution cost efficiency.

Before introducing the model formulation, some methodological and conceptual foundations are provided in Sections 3.1 through 3.3; respectively discussing the basic concept of deprivation cost function and its formulation, a new proposed way to capture unmet demand per deprivation time and model it as a continuous variable, and some notes on the need of adding arc capacity constraints to the aid distribution model.

3.1. A brief introduction on social and deprivation cost operators.

In their analysis to the appropriate objective function in the HL context, Holguín-Veras et al., (2013) study the impact of the relief distribution of critical supplies from biological, philosophical, and economic points of view. Their main concluding result was that Post-Disaster Humanitarian Logistics (PD-HL) models must be based on welfare economics, which is the field of economics that studies the impact of the resources allocation to ensure that all related impacts are accounted for. This implies considering impacts of the distribution strategy on the relief group itself and the beneficiaries of affected populations through explicitly considering the social cost minimization in the models' objective functions.

To evaluate the social cost, two mathematical operators were introduced in (Holguín-Veras et al., 2013): $\Omega_T^{*}(X,T)$ and $\Gamma_T^{*}(X,T)$ respectively denoting the total logistics and deprivation costs. The setting X is an ordered sequence of relief deliveries to different demand nodes. The deprivation cost at node i at time t is equal to the accumulation of individual costs: $\Gamma_i(X,t) = \gamma_g(\theta_g, d_{it})\pi_{it} \forall i \in DN$. Where, $\Gamma_i(X,t)$ is the deprivation costs experienced at node i at time t as a result of employing the sequence of delivery activities X; $\gamma_g(\theta_g, d_{it})$ is standard deprivation cost function with parameter vector θ_g; d_{it} is the deprivation time for node i at time t, π_{it} is the population size of node i at time t. Note that this is a simplified version of the deprivation cost which assumes that the population π_{it} are observationally identical and equally affected by deprivation and lack of access to different commodities. Therefore, individuals' socioeconomic characteristics were not considered as a factor in formulating the deprivation cost function. See Section 2.1 for extended literature formulations of the deprivation cost.

Obviously, the value of the function $\Gamma_i(X,t)$ drops to zero when a delivery which is large enough to fulfill the needs of all individuals is received at time t. If the delivery partially covers the demand of node i, deprivation costs drop to zero for population receiving the relief assistance, and continue to increase for those who did not. For simplification, Pérez-Rodríguez & Holguín-Veras, (2016) assumed that the supply is received with fixed shipment sizes where the shipment is large enough to serve all beneficiaries in a node for at least one period of time. They broke up nodes with large number of beneficiaries to smaller nodes the maximum demand of which equals the shipment size. As an improved way to deal with the partially fulfilled demand, Huang and Rafiei (2019) categorize individuals into three groups; individuals who receive the relief items in the same period of demand; individuals who do not receive the relief items in the requested period but receive it within the time window; and individuals who could not fulfil their demand due to scarce resource. As the model aims to minimize the deprivation cost and hence deprivation time, the last group of people would be served as the first group in the next actual period (Huang & Rafiei, 2019).

The current model relaxes the assumption of equal shipment sizes and their sufficiency to fulfil the demand for one time period in a demand node. Furthermore, instead of using binary variables to capture the delivery time for the most recent supply and calculate the deprivation time since then, this paper defines the shortage as a number of units for each deprivation time as will be discussed in Section 3.2. This would help to reduce the computational burden resulting from the binary variables. It also provides more realistic representation to the relief delivery process.

3.2. Modeling the unmet demand per deprivation time

If the received relief does not satisfy the demand, people in charge in the demand points can distribute it in such a manner that the demand for each individual is partially covered or priority is given to vulnerable individuals. For example, the general director of the HIHFAD, an active responding organization to Syria crisis, reported that their strategy is to reach all affected communities with some aid better than nothing. They avoid having a comprehensive response to one community that might deprive other communities (personal communication, March 13, 2020). In the current formulation, it is assumed that people in charge of relief distribution are able to track the demand fulfilment for each individual and priority is given for those who have been deprived for a longer time within the same node.

Holguín-Veras et al. (2013) criticized models that consider minimizing the unmet demand as the objective function for the relief distribution optimization models as they generally assume additive demands at the beneficiary nodes. This means that the total unsatisfied demand accumulated over the last past time periods can be satisfied once sufficient supply is received. Obviously, in humanitarian relief models the demand over time cannot be additive which essentially invalidates the objective pursued in that formulation. The model presented in this paper follows a similar reasoning of Huang and Rafiei (2019) and overcomes the above-mentioned limitation by defining the shortage in demand and the corresponding deprivation time for this shortage to calculate the deprivation cost accordingly. The priority is thus given to nodes which have a shortage for longer time even if the unmet demand is less than that of other nodes which have less deprivation time. To illustrate this, Fig. 1 graphs the deprivation cost vs. the unmet demand for three deprivation times: 20 h, 30 h, and 40 h. The deprivation cost formula $\Gamma_c(d) = 0.19(e^{0.126d})$ provided in Holguín-Veras et al. (2016) for the drinkable water deprivation is borrowed here for illustration purposes. The formula assumes that the deprivation cost increases exponentially with the increase of deprivation time; with the multiplier and exponent parameters reflecting the criticality of the relief commodity. As the figure indicates, the cost is more sensitive to the deprivation time than the number of unmet units and the total deprivation cost for 100 units and 40 h of deprivation equals that of 350 and 1200 units for 30 and 20 h of deprivation; respectively.

The parameter $\gamma_{cd} = \Gamma_c(d) - \Gamma_c(d\text{-}1)$ can be defined as the marginal deprivation cost associated with unsatisfying the demand of commodity c for *one individual* at the time period $[d-1, d]$. Let the variable e^d_{cit} be the shortage in supply (i.e., unsatisfied demand) as number of units of commodity c at node i that have not been satisfied for d time periods at time t. For example suppose that the total demand of commodity c for node i at time $t-1$ is 50 units and that the delivered supply at time t is only 30 units; then $e^1_{cit} = 20$ *units*. If the number of units delivered at time $t+1$ is only 10 units, it is assumed that these 10 units will go to individuals who have not received the supply at time t. Hence$e^2_{cit+1} = 10$ *units*; and $e^1_{cit+1} = 30$ *units*. The number of individuals at node i who are deprived from commodity c for d periods at time t is thus $u_c^{-1} e^d_{cit}$, where u_c^{-1} is the reciprocal of the average individual consumption of commodity c per time unit.

3.3. Vehicle flow capacity (arc capacity)

In the context of humanitarian logistics and emergency operations, involved agencies work to ensure the application of simplified inspection and customs procedures in order to speed up the delivery of the

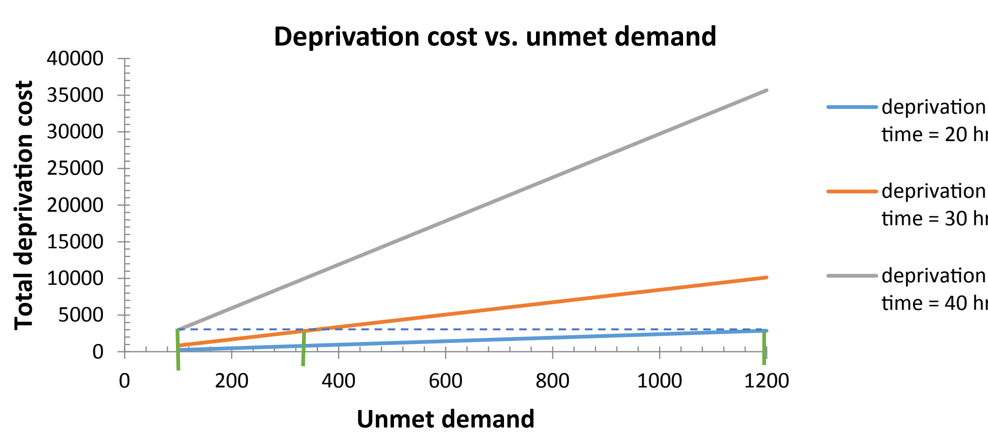


Fig. 1. Deprivation cost vs. unmet demand for different deprivation time units.

humanitarian assistance. This increases the capacity of the relief flow and improves the responsiveness. However, in some cases of *post-conflict* humanitarian operations, authorities may impose restrictions on the inspection process that limit the capacity of the relief flow through the conflict area entry borders. An example for this limitation on the flow capacity is the "Cross Border" relief program from Turkey to Syria where the number of trucks to cross the border is limited to 22 trucks per day (Jardanko Bjelica, supply chain officer - IOM-Turkey, personal communication, May 17, 2017).

For a generalized formulation, it is assumed that some of the arcs between supply and demand (or transshipment) nodes are located in critical zones and are thus subjected to flow capacity constraints. Let $A_m^{'}$ be the set of *capacity constrained arcs* linking nodes in the transportation network with mode *m*, G_{ijt}^m be the capacity of arc (*i*,*j*) expressed as the number of standardized vehicles of mode *m* at time *t*. Let also g_k^m be an index used to standardize the different types of vehicles (*k*) within transportation mode *m* in terms of size and time needed for inspection and processing. For example, $g_k^m = 2\left(\text{respectively } g_k^m = \frac{1}{2}\right)$ for a huge (small) truck which needs processing time twice (half) as the processing time needed for an average sized truck. The formulation of the arc capacity constraint is provided in inequality (3.8) in the next section.

3.4. Model formulation

This section provides the mathematical formulation of the described problem in the light of the above-mentioned foundations. It starts with listing the assumptions based on which the model was built, followed by symbolic notations, objective function, and constraints formulations. As the current model is an extension to Pérez-Rodríguez (2011) and Pérez-Rodríguez & Holguín-Veras (2016), some of the sets, parameters, notation as well as the formulation basis of some constraints are adapted from these resources.

3.4.1. Assumptions

- It is assumed that people in charge of relief distribution have sufficient knowledge about locations of demand nodes, total number of beneficiaries at each node, transportation networks, rate of consumption, the amount and type of goods needed, as well as the possible external supplies and donations to distribution centers or demand nodes.
- Deprivation cost is represented as a function of deprivation time only (exponential DC as introduced by Holguín-Veras et al. (2016) is assumed and linearized for simplification). At this part of the formulation (crisp objective formulation) beneficiaries are assumed to be identical in terms of their needs and perception to deprivation.
- The impact of deprivation is assumed to diminish once the demands are fulfilled (non-hysteric deprivation cost function).
- Backordering for unmet demand is not allowed.
- Vehicles are allowed to wait in nodes and to pick-up commodities from any distribution center or transshipment node in the system.
- Demand nodes can be used as transshipment points to transfer commodities among vehicles.
- People in charge of relief distribution are able to track the demand fulfilment for each individual and priority is given for those who have been deprived for a longer time within the same node.

3.4.2. Notation

Sets	
T	Number of time periods in the planning horizon;
DN	Set of demand nodes which can also serve as transshipment nodes, $\mathrm{DN} \subset \mathrm{N}$;
SN	Set of supply nodes such local distribution centers, warehouses, … etc. $\mathrm{SN} \subset \mathrm{N}$;
N	Set of all relief network nodes, $\mathrm{N} = \mathrm{DN} \cup \mathrm{SN}$;
M	Set of transportation modes;
A_m	Set of all arcs linking different nodes using the transportation mode $m \in M$;
$A_m^{'}$	Set of capacity constrained arcs linking nodes in the transportation network through mode m
C	Set of relief commodities to be distributed during the planning horizon T;
K_m	Set of vehicle types in the transportation mode $m \in M$;
Model Parameters	
u_c	Rate of consumption for commodity $c \in C$, i.e., the quantity of commodity c required to sustain a person for one time period;
τ_{ij}^m	Travel time needed to pass arc $(i,j) \in A_m$ using transportation mode $m \in M$;
t_c^{max}	Maximum deprivation time up to which a person can survive without commodity $c \in C$;
Q^{km}	Load capacity for vehicle type $k \in K_m$; in transportation mode $m \in M$;
c^{km}	Travel cost per unit of time for vehicle type $k \in K_m$ to travel through transportation mode $m \in M$;
w_c	Unit weight of commodity $c \in C$;
a_{cit}^s	Amount of commodity $c \in C$ received from external sources to node $i \in N$ at time t, (e.g., scheduled replenishments to supply nodes or donations to demand nodes).
$\Gamma_c(d)$	Cumulative deprivation cost per individual; associated with not having commodity c for d time periods.
γ_{cd}	$\Gamma_c(d) - \Gamma_c(d-1)$, i.e., the marginal deprivation cost per individual; associated with not having commodity c during period [d-1, d], $d \in 1 \ldots t_c^{max}$
a_{kmit}^v	number of vehicles type $k \in K_m$, mode $m \in M$, added or removed from the fleet at node $i \in N$ at time t
D_{cit}	Demand of node $i \in N$ for commodity $c \in C$ at time t
G_{ijt}^m	Capacity of arc $(i,j) \in A_m$ expressed as the number of standardized vehicles of mode $m \in M$ at time t
g_k^m	An index used to standardize the different types of vehicles $k \in K_m$ within transportation mode $m \in M$ in terms of size and time needed for inspection and processing.
Decision variables	
x_{ijt}^{cm}	Amount of commodity type $c \in C$ sent from node i to node j, $(i,j) \in A_m$, at time t, using transportation mode $m \in M$;
I_{cit}	Inventory level, i.e., amount of commodity type $c \in C$ carried over from time t to time $t+1$ at node $i \in N$;
Y_{ijt}^{km}	number of vehicles type $k \in K_m$, mode $m \in M$, routed from node i to node j; $(i,j) \in A_m$ at time t
V_{it}^{km}	number of vehicles type $k \in K_m$, mode $m \in M$, positioned at node $i \in N$ at time t
e_{cit}^d	shortage in supply (i.e., unsatisfied demand) as number of units of commodity c at node i that have not been satisfied for d time periods at time t

3.4.3. Objective function

The objective function seeks to minimize the social cost, i.e., the total sum of transportation cost and deprivation cost as indicated by formula (3.1).

$$\text{minimize} \sum_{m \in M} \sum_{k \in K_m} \sum_{(i,j) \in A_m} \sum_{t=1}^{T} c^{km} \tau_{ij}^m Y_{ijt}^{km} + \sum_{i \in DN} \sum_{c \in C} \sum_{t=1}^{T} \sum_{d=1}^{\min(t-1, t_c^{max})} u_c^{-1} e_{cit}^d (\gamma_{cd} - \gamma_{c,d-1}) \tag{3.1}$$

The first term calculates the transportation cost considering the travel cost per time unit, number and types of vehicles scheduled in arc *(i,j)* and travel times between nodes *i* and *j* via transportation mode *m*. The second term is a linearization to the deprivation cost function. The incremental increase in the individual's deprivation cost when deprived from commodity *c* for one extra time unit from $d-1$ to d is expressed as $(\gamma_{cd} - \gamma_{c,d-1})$ and summed over the time periods. The term $u_c^{-1} e_{cit}^d$ expresses the number of individuals who are deprived of commodity *c*, for *d* time periods as of time *t*. The deprivation status of individuals in each node is assumed to be checked at the beginning of time period *t*. Therefore, the planning horizon is discretized and is expressed as number of time periods. Note that this section presents the crisp objective function expressing the most possible deprivation cost value (perceived by average typical individuals); while Section 4 presents the fuzzy objective function considering deprivation costs for different groups of individuals.

3.4.4. Constraints

Formulating the relief distribution problem can be thought as a combination of three sub-problems: (a) the allocation of critical commodities from distribution centers to affected nodes; (b) the allocation of commodities to vehicles; and (c) the vehicle routing problem. Pérez-Rodríguez & Holguín-Veras (2016) provided an ideal mathematical formulation combining the aforementioned sub-problems. However, the complexity of such a model is high and needs simplification or heuristic methods to be solved (Pérez-Rodríguez, 2011). One way to reduce the computational burden while still maintaining the problem characteristics is to regard routing decisions as a secondary problem as proposed by Haghani & Oh (1996) and Yi & Özdamar (2007) and used by Pérez-Rodríguez (2011). In their formulation, vehicles are modeled as commodities flowing in a minimum cost network rather than by binary variables. This might require additional post-processing step to extract the vehicle routes from the optimal flows but still helps to solve the problem more efficiently. The current model formulation adopts the same approach in (Haghani & Oh, 1996; Yi & Özdamar, 2007; and Pérez-Rodríguez, 2011) which allocates vehicle to nodes as a separate problem and links it with commodity flow decisions. Therefore, three types of constraints are provided: commodity flow constraints, vehicle flow constraints, and constraints linking commodity with vehicle flows. A fourth set of constraint related to the transportation arc capacity is also introduced in the following.

Commodities flows

$$I_{ci,t-1} + a^{S}_{cit} = I_{cit} + \sum_{m\in M}\sum_{(i,j)\in A_m} x^{cm}_{ijt} \quad \forall i \in SN,\ \ c\in C,\ \ t \in 1\cdots T \tag{3.2}$$

$$e^{d}_{cit} \geq D_{ci,t-d} - I_{ci,t-d} - \sum_{t'=t-d+1}^{t'=t}\left(a^{s}_{cit'} + \sum_{(j.i)\in A}\sum_{m\in M} x^{cm}_{ji,t'-\tau^{m}_{ji}}\right) - \left(\sum_{l=1}^{min(t-d,t^{max}_{c}-d)} e^{d+l}_{cit}\right) \quad \forall c \in C;\ \ i\in DN;\ \ t=1,\cdots T;\ \ d=1,\cdots,\min(t,t^{max}_{c}) \tag{3.3}$$

$$I_{ci,t-1} + a^{s}_{cit} + \sum_{m\in M}\sum_{(j.i)\in A_m} x^{cm}_{ji,t-\tau^{m}_{ji}} - D_{ci,t-1} = I_{cit} + \sum_{m\in M}\sum_{(i.j)\in A_m} x^{cm}_{ijt} - \sum_{d=1}^{min(t-1,t^{max}_{c})} e^{d}_{cit} \quad \forall i \in DN,\ \ c\in C,\ \ t\in 1\cdots T \tag{3.4}$$

$$I_{ci,t-1} + a^{s}_{cit} + \sum_{m\in M}\sum_{(j.i)\in A_m} x^{cm}_{ji,t-\tau^{m}_{ji}} \geq I_{cit} + \sum_{m\in M}\sum_{(i.j)\in A_m} x^{cm}_{ijt} \quad \forall i\in DN,\ \ c\in C,\ \ t \in 1\cdots T \tag{3.5}$$

Vehicle flows

$$V^{km}_{i.t-1} + a^{v}_{kmit} + \sum_{(j,i)\in A_m} Y^{km}_{ji,t-\tau^{m}_{ji}} = V^{km}_{it} + \sum_{(i,j)\in A_m} Y^{km}_{ijt} \quad \forall i\in N,\ \ k\in K_m,\ \ m\in M,\ \ t \in 1\ldots T \tag{3.6}$$

Constraint linking commodity and vehicle flow:

$$\sum_{c} w_c x^{cm}_{ijt} - \sum_{k} Q^{km} Y^{km}_{ijt} \leq 0 \quad \forall (i,j)\in A_m,\ \ m\in M,\ \ t\in 1\ldots T \tag{3.7}$$

Transportation arch capacity

$$\sum_{k} g^{m}_{k} Y^{km}_{ijt} \leq G^{m}_{ijt} \quad \forall m\in M, (i,j)\in A^{'}_{m},\ \ t\in 1,\cdots,T \tag{3.8}$$

Definition of commodity flow variables

$$x^{cm}_{ijt} \geq 0; I_{cit} \geq 0; e^{d}_{cit} \geq 0 \quad \forall c\in C;\ \ i\in N(i,j)\in A_m,\ \ m\in M,\ \ t\in 1\ldots T,\ \ d \in 1,\cdots,t^{max}_{c} \tag{3.9}$$

Definition of vehicle flow variables

$$Y^{km}_{ijt} \geq 0\ \ and\ \ integer;\ \ V^{km}_{it} \geq 0\ \ and\ \ integer \quad i\in N(i,j)\in A_m,\ \ k\in K_m,\ \ m \in M,\ \ t\in 1\ldots T \tag{3.10}$$

Constraints (3.2) through (3.5) balance the commodity flow and denote the shortage of supply for each deprivation time. External supplies received at supply nodes at a given time period are partially distributed to demand nodes upon needs and the remaining is stored for next time periods (constraint 3.2). The number of unmet demand units which have been unavailable for d deprivation time periods is defined in constraint (3.3) as the demand at time $t-d$ minus available inventory at that time minus all supplies received during the period $[t-d+1,t]$. The fourth term in the right hand side of inequality (3.3) represents the sum of shortage in demand for longer deprivation than d time units. Note that transshipment to other nodes is not included in constraint (3.3) based on the assumption that a node does not send to other nodes unless it has excess capacity. Supply excess is either stored or sent to other nodes as explained in equation (3.4). If the demand at time t is greater than the available supply, the difference between demand and supply is regarded as shortage and stored in the shortage variable with the corresponding deprivation time. To better illustrate this, recall the example in Section 3.2 which assumes that the demand for commodity c at a given demand node i for time periods 1 to 3 is $D_{ci1} = D_{ci2} = D_{ci3} = 50$ units. Assuming no stock available in the node at time $t = 1$ and the total amount received at time $t = 2$ and $t = 3$ is 30 units and 10 units respectively. Formula (3.3) will give the shortage at $t = 2$ for one deprivation time period as $e^{1}_{ci2} = 50-30 = 20$ and shortage at $t = 3$ for two deprivation time periods as $e^{2}_{ci3} = 50-30-10 = 10$; while$e^{1}_{ci3} = 50-10- e^{2}_{ci3} = 30$. Plugging the values in equation (3.4) at time $t = 3$ gives $0+10- D_{ci3} = 0+0-e^{1}_{ci3}\ \ -e^{2}_{ci3}$; i.e., $10-50 = -10-30 = -40$ which is the total shortage in demand at time $t=3$. If the received supply is larger than demand, all shortage variables at time$t$ will drop to zero and the excess capacity is either stored or sent to other nodes. However, constraint (3.4) does not necessarily imply that a node cannot store or send to other nodes a larger amount than the amount it already has or received at time t. Therefore, constraint (3.5) is added to the formulation to guarantee feasibility. Constraint (3.6) models the vehicle flow in a similar way of balancing commodity flow. Constraint (3.7) links the commodity flow with the vehicle flow considering the commodity weight and vehicle capacity limits. Note that depending on the commodities and packing characteristics, the weight parameter can be replaced with the volume and the vehicle capacity can be expressed by the maximum allowable volume instead. Constraint (3.8) models the transportation arc capacity as discussed in Section 3.3. Finally, constraints (3.9) and (3.10) respectively model the non-negativity condition for decision variables and integrality of vehicle flow variables.

4. Possibilistic MIP with fuzzy deprivation cost

In this section, an approach to model possibilistic mathematical programming with fuzzy deprivation cost is introduced. Section 4.1 provides a preliminary background and describes Lai & Hwang (1992) as a basis to the current model formulation. Section 4.2 adapts Lai and Hwang's fuzzy approach to model and solve the possibilistic relief distribution problem with fuzzy deprivation cost function.

4.1. Review of possibilistic linear programming with imprecise objective coefficients (Lai & Hwang 1992)

The possibilistic linear programming (PLP) model employed in this paper consider the case of imprecise objective function the coefficients of which are presented as triangular fuzzy numbers (TFN). Consider the cost minimization problem (4.1):

$$min\sum_{i}\mathbf{c}_i\mathbf{x}_i \quad s.t.\ \ \mathbf{x}\in \mathrm{X}\{\mathbf{x}|\mathrm{A}x\leq \mathrm{b}\ \ \text{and}\ \ \mathbf{x}\geq 0\} \tag{4.1}$$

where $\mathbf{c_i} = (\mathbf{c_i^l}, \mathbf{c_i^m}, \mathbf{c_i^h})$, with $\mathbf{c_i^l}, \mathbf{c_i^m}, \mathbf{c_i^h}$are respectively the lowest, most likely, and highest value of the cost fuzzy number. Instead of minimizing the three objectives corresponding to each cost component simultaneously, the model is solved for following three objectives: minimize $z_1 = \boldsymbol{c^m x}$, maximize $z_2 = [\boldsymbol{c^m x} - \boldsymbol{c^l x}]$ and minimize $z_3 = [\boldsymbol{c^h x} - \boldsymbol{c^m x}]$. By doing so, the triangular shape is maintained (normal and convex) and the triangular possibility distribution is pushed in the direction of the left-hand side. In other words, the aim is to maximize (minimize) the left (right) skewness of the triangular fuzzy number. See Fig. 2.

Lai & Hwang (1992) suggest that maximizing region (*I*) and minimizing region (*II*) in Fig. 2 respectively result in maximizing the possibility of lower cost and minimizing the risk of higher costs. Clearly, solution A would be superior to solution B. The solution methodology is to find the positive ideal solution (PIS) for each of the objectives above i.e., min z_1, max z_2, and min z_3 and the negative ideal solution (NIS) by solving for max z_1, min z_2, and max z_3. The linear membership function of these objective functions is computed as:

$$\mu_{Z1} = \begin{cases} 1 & if\ \ Z_1 < Z_1^{PIS} \\ \dfrac{Z_1^{NIS} - Z_1}{Z_1^{NIS} - Z_1^{PIS}} & if\ \ Z_1^{PIS} \leq Z_1 \leq Z_1^{NIS} \\ 0 & if\ \ Z_1 > Z_1^{NIS} \end{cases}$$

$$\mu_{Z2} = \begin{cases} 1 & if\ \ Z_2 > Z_2^{PIS} \\ \dfrac{Z_2 - Z_2^{NIS}}{Z_2^{PIS} - Z_2^{NIS}} & if\ \ Z_2^{PIS} \leq Z_2 \leq Z_2^{NIS} \\ 0 & if\ \ Z_2 < Z_{12}^{NIS} \end{cases} \tag{4.2}$$

μ_{Z3} is similar to μ_{Z1}.

Finally, the optimal solution that compromises the three objectives is obtained by a single objective formulation aiming at maximizing the minimum membership value the solution has with respect to the three objectives, i.e, $maxmin_i\mu_{z_i} : i = 1, 2, 3$ and $x \in X$. The LP formulation defines the decision variable λ as the minimum membership value μ_{Zi} and is to be maximized in the objective function (see model 4.3); where $x \in X$ expresses the set of feasible solution.

$$\mathrm{Max}\lambda;\ \ s.t.\ \ \mu_{Zi} \geq \lambda,\ \ i = 1,2,3\ \ \text{and}\ \ x \in X,\ \ \lambda \leq 1 \tag{4.3}$$

4.2. Relief distribution possibilistic mathematical model with fuzzy deprivation cost

The proposed possibilistic MIP with fuzzy deprivation cost function tries to partially account for the perceptual variation for individual groups and the influence of socio-economic characteristics on the degree of vulnerability to deprivation. To illustrate the fuzzy deprivation cost, we consider the fuzzification of thr deprivation cost formula assumed in Holguín-Veras et al. (2016), $\Gamma(d) = \beta_1 e^{\beta_2 d}$, where d is the deprivation time and β_1 and β_2 are the model parameters derived empirically based

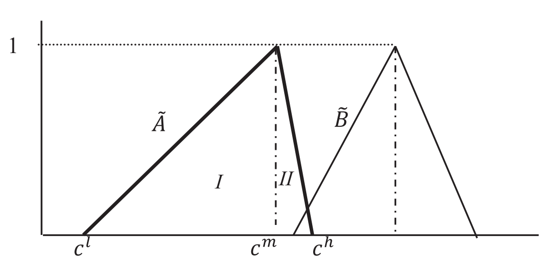


Fig. 2. Lai and Hwang's approach to solve "minimize cx".

on the WTP and WTA econometric valuation measures when individuals are deprived from critical commodities. For high priority products, the values for $\beta_1$andβ_2 are assumed to be 0.19 and 0.12 respectively (Holguín-Veras et al., 2016). Setting β_1 and β_2 as fuzzy triangular numbers; say (0.17, 0.19, 0.21) and (0.11, 0.12, 0.13), the behavior of the deprivation cost function will be as shown in Fig. 3. For example at deprivation time $d = 35\ hr$, $\Gamma(d) = (11.3, 18, 28.2)$ as the membership function indicates.

In this model the Lai and Hwang (1992b) approach described in Section 4.1 is used to deal with imprecision in the objective function coefficients. The rationale behind choosing this fuzzy approach is to increase the responsiveness of our model and attain fairness by highlighting the priority not only based on the expected deprivation cost value but also considering the vulnerability toward deprivation of some items for specific population groups or under given conditions. Consider for example the human suffering if deprived from three different commodities: drinkable water, blankets, and hygiene materials which are all essential supplies in the aftermath of any disaster. Age, health status, and weather conditions justify the differences in evaluating the deprivation cost for the water and blankets. Children, elderly people, and those with health conditions may be more vulnerable to deprivation than young healthy people. On the other hand, hygiene materials are almost of the same importance for all people. To give priority for protecting vulnerable people, the proposed model considers minimizing the difference between the highest estimate and the nominal value of the deprivation cost as one of the optimization criteria.

Let $\widetilde{\gamma}_{cd} = (\gamma_{cd}^l, \overline{\gamma}_{cd}, \gamma_{cd}^u)$ and $\widetilde{\gamma}_{c,d-1} = (\gamma_{c,d-1}^l, \overline{\gamma}_{c,d-1}, \gamma_{c,d-1}^u)$ be the fuzzy deprivation cost associated with not satisfying the demand of commodity c for one individual during the time periods $[d-1, d]$ and $[d-2, d-1]$ respectively. To find the term$\gamma_{cd} - \gamma_{cd-1}$ which appears in the objective function, an appropriate fuzzy subtraction operator that matches the characteristics of the current model is needed. For any two triangular fuzzy numbers$\widetilde{A}$ and $\widetilde{B}$, the standard fuzzy subtraction gives $\widetilde{A} - \widetilde{B} = (A^l - B^u, \overline{A} - \overline{B}, A^u - B^l)$ and $\widetilde{A}/\widetilde{B} = (A^l/B^u, \overline{A}/\overline{B}, A^u/B^l)$ (Chen, 1985). According to the standard fuzzy arithmetic operations, $\widetilde{A} - \widetilde{A} \neq 0$ and $\widetilde{A}/\widetilde{A} \neq 1$.However, in optimization and many applications, it can be desirable to have crisp values for $\widetilde{A} - \widetilde{A}$ and $\widetilde{A}/\widetilde{A}$, i.e., the crisp values 0 and 1 respectively (Gani & Assarudeen, 2012). Furthermore, applying the standard subtraction operator may result in a negative deprivation cost which is considered as illogical to the studied model. Therefore, this study uses Gani & Assarudeen (2012) new fuzzy subtraction operator $\widetilde{A} - \widetilde{B} = (A^l - B^l, \overline{A} - \overline{B}, A^u - B^u)$. The necessary existence condition for this operator is that$A^u - A^l \geq B^u - B^l$. It is clear from Fig. 3 that the spread of the triangular fuzzy deprivation cost increases as we move forward in the deprivation time and the condition is hence satisfied. Thus, the term$\widetilde{\gamma}_{cd} - \widetilde{\gamma}_{cd-1} = (\gamma_{cd}^l - \gamma_{cd-1}^l, \overline{\gamma}_{cd} - \overline{\gamma}_{cd-1}, \gamma_{cd}^u - \gamma_{cd-1}^u)$ is used. To integrate the fuzzy objective function with the current model, the following assumptions are set:

4.2.1. Assumptions

It is assumed that the required input data to the model implementation is available. In particular:

- The demographic and health characteristics of the population at each demand node are assumed to be known and easy to estimate. The population at each node is thus assumed to be classified, according to their characteristics, into three classes: invulnerable, average, and vulnerable individuals. This is represented by defining the parameters p_{ci}^l and p_{ci}^h respectively expressing the percentage of mildly and highly vulnerable groups (people at low and high risks) with respect to commodity c at node i. NPM and HNO criteria for household vulnerability, described in Section 1, provide good guidelines for classifying affected population. See case study in Section 6.

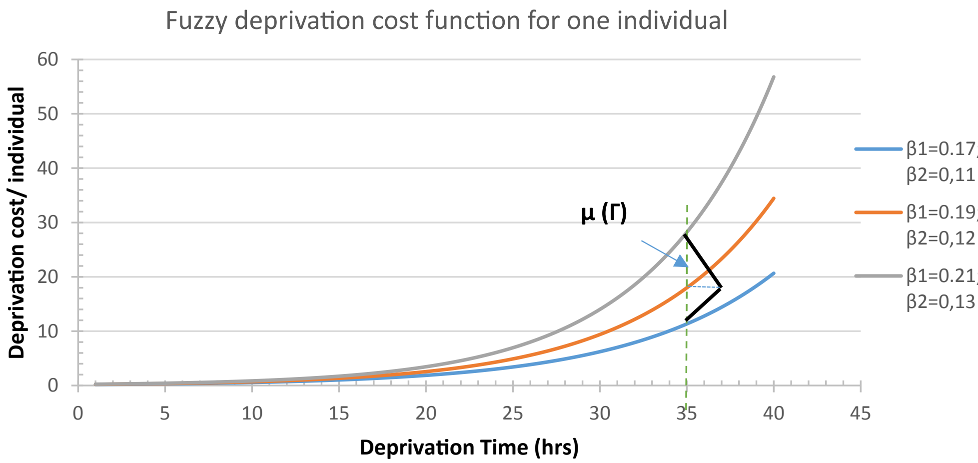


Fig. 3. An example of the fuzzy deprivation cost function.

– The deprivation cost for each commodity is also assumed to be estimated as a TFN in the form $\widetilde{\gamma}_i = (\gamma_i^l, \gamma_i^m, \gamma_i^h)$. Where γ_i^m is the most likely cost or the expected deprivation cost for a typical individual (with moderate age, good health condition, average living standard, etc.). γ_i^l is the minimum possible deprivation cost for a given commodity for people with high potential capacity to endure deprivation. In contrary, γ_i^h is the maximum possible deprivation cost and normally is associated with people at high risks such as elderly people or individuals with medical issues. Furthermore, for some types of non-basic commodities, it is expected that people with high living standards are more affected by deprivation and thus have higher deprivation costs.

4.2.2. *Steps to implement the possibilistic LP with fuzzy objective parameters:*

The methodology employed in this section has a slight modification to Lai and Hwang's approach described in Section 4.1. Namely, instead of solving for $maxz_1$, $minz_2$, and $maxz_3$ to find the NIS, which results in unbounded solutions, the values of z_1, z_2, and z_3 are evaluated for each of the looked-for objective functions and the PIN and NIS are evaluated as stated in steps 1 and 2. Furthermore, weight is assigned to each objective by forcing the membership of the solution to that objective to exceed a predefined threshold (steps 3 and 4).

Step1: Solve the original LP model three times for the three objective functions: minimize z_1, maximize z_2, and minimize z_3, where z_1, z_2, and z_3 are given as:

$$z_1 = \sum_m \sum_k \sum_{(j,i)\in A_m} \sum_{t=1}^{T} c^{km} \tau_{ji}^m Y_{ijt}^{km} + \sum_{c\in C} \sum_{d=1}^{d=t_c^{max}} \left(\left(\overline{\gamma}_{cd} - \overline{\gamma}_{c,d-1} \right) \sum_{i\in DN} \sum_{t=1}^{T} u_c^{-1} e_{cit}^d \right) \tag{4.4}$$

$$z_2 = \sum_{c\in C} \sum_{d=1}^{d=t_c^{max}} \sum_{i\in DN} \left(p_{ci}^l \left[\left(\overline{\gamma}_{cd} - \overline{\gamma}_{c,d-1} \right) - \left(\gamma_{cd}^l - \gamma_{cd-1}^l \right) \right] \sum_{t=1}^{T} u_c^{-1} e_{cit}^d \right) \tag{4.5}$$

$$z_3 = \sum_{c\in C} \sum_{d=1}^{d=t_c^{max}} \sum_{i\in DN} \left(p_{ci}^h \left[\left(\gamma_{cd}^u - \gamma_{c,d-1}^u \right) - \left(\overline{\gamma}_{cd} - \overline{\gamma}_{c,d-1} \right) \right] \sum_{t=1}^{T} u_c^{-1} e_{cit}^d \right) \tag{4.6}$$

Since the transportation cost is expressed as a crisp function, it only appears in $z_1 = \boldsymbol{c}^m\boldsymbol{x}$, and omitted in $z_2 = [\boldsymbol{c}^m\boldsymbol{x} - \boldsymbol{c}^l\boldsymbol{x}]$ and $z_3 = [\boldsymbol{c}^h\boldsymbol{x} - \boldsymbol{c}^m\boldsymbol{x}]$. In each run and for every objective, find the values of the resulting z_1, z_2, and z_3 according to the equations above. In other words, evaluate the resulting z_{1n}, z_{2n}, and z_{3n} with n is the index for the run number related to objective function n.

Step2: Find the positive ideal solution (PIS) and negative ideal solution (NIS) for each z value, where: $z_1^{PIS} = min_n(z_{1n})$, $z_1^{NIS} = max_n(z)$; $z_2^{PIS} = max_n(z_{2n})$, $z_2^{NIS} = min_n(z_{2n})$; and $z_3^{PIS} = min_n(z_{3n})$, $z_3^{NIS} = max_n(z_{3n})$

Step3: Find the compromised solution that balances the three objectives by solving the following LP model:

$$\begin{aligned} & \text{Max } \lambda; \\ s.t. \quad & \mu_{Zi} \geq \theta_i + \lambda, \quad i = 1,2,3 \\ & \chi \in \mathrm{X}, \theta_i + \lambda \leq 1 \end{aligned} \tag{4.7}$$

where $\chi \in \mathrm{X}$ is the set of constraints for the original problem. That is, equations (3.2 through 3.10). The parameter θ_i is defined to add weight for each objective or provide a minimum value for the extent to which the objective is satisfied. For example, if the focus is on minimizing the crisp objective function, then increase θ_1 compared with θ_2 and θ_3. Similarly, if the focus is on minimizing the risk for higher cost, increase θ_3 and so on. The membership function for each objective, μ_{zi}, is defined in equation (4.2).

Step 4: If necessary, adjust the parameter θ_i and check the effect of this adjustment on the final solution and how it is reflected on prioritizing the distribution activities.

5. Model implementation and experimentation

This section discusses the model implementation and describes computational experimentation on randomly generated instances. Section 5.1 presents the methodology to implement the proposed model formulation using the RH solution algorithm. Section 5.2 describes the experimental instances generation. Sections 5.3 and 5.4 respectively present and discuss the computational results for the original model with crisp objective function and the results of the possibilistic LP with fuzzy objectives. The analysis presented in this section is reflected to a real case study of internally displaced persons (IDPs) in Northwest Syria in Section 6.

5.1. *Solution methodology using rolling horizon approach*

The planning horizon is the length of time into the future that is accounted for in the humanitarian relief plan being optimized. Since the complexity of the proposed MIP model increases with the increase of the number of time periods in the planning horizon, the rolling horizon approach provides an efficient way to solve such large scale optimization problems by decomposing the planning horizon into two parts: scheduled and unscheduled horizons. The former refers to early time periods for which a detailed plan is to be maintained while an aggregate plan is provided for the latter. In other words, in the scheduled horizon all problem constraints should be detailed and valid whereas in the remaining time periods a rough estimate of the capacity allocation is sufficient without paying attention to the details of vehicle routes. Therefore, the integrality constraint for the number of vehicles is violated and fractional values are allowed in the unscheduled horizon which will be rescheduled later during the algorithm. The idea is thus to reduce the number of detailed periods and partially deploy the detailed window; where only part of the scheduled horizon is implemented. The algorithm then rolls forward internally and the parameters are updated for the next scheduled horizon until a complete solution is obtained for the original planning horizon. Fig. 4 demonstrates the RH algorithm applied to the current model with the notations listed in Table 1.

The algorithm starts with initializing the parameters and setting the steps count to zero. The model objectives and constraints are generated as in the basic model except the violation of the integrality constraint for the number of vehicles in $t > StC + ScH$. Since the linear relaxation of some integral variables will cause an optimistic solution which is obviously less than the real objective value, extra cost has been added for transferring items with relaxed vehicles. The capacity of vehicles belonging to the relaxed planning duration has also been reduced. This is temporary and approximate compensation for the unrealistic enhancement in the objective value resulting from relaxing some variables. By doing so, the model avoids unnecessary postponement of demand fulfillment to later periods in the unscheduled horizon. The partially relaxed model is then solved and only the solution for the step size (the implementation period Δ) is stored in the solution array. The next decision point is then found as the step count plus the step size and the same process is repeated until the step count plus step size is greater than or equal to the planning horizon. Finally, the model calculates the overall objective function based on the stored solution array and computes the percent relative difference of the exact or best bound. If the relative difference is satisfactory the algorithm stops, otherwise, RH parameters are tuned and the algorithm is run again.

It should be noted that the parameters tuning and comparison with best bound is performed for the purpose of experimentation and algorithm's parameters setting. In reality since the model is periodically fed with new information about real supply and demand, there is no benefit of comparing solution with best bound given the estimated supply and demand data. The choice of parameters such as length of scheduled horizon and step size could be based on periodicity of information update instead. To illustrate the benefit of the RH method when the model parameters are dynamic and unstable, an illustrative example is briefed in box 1. The example compares the objective value when solving a simple problem based on supply and demand pre-estimations with the objective value resulted from applying the RH approach which updates the model parameters with actual values once available.

5.2. Experimental instances generation

The model is tested on two groups of instances. Small sized instances consist of five nodes (two supply and three demand nodes), two relief commodities, two vehicle types, and the planning horizon is 8 time periods. The large sized instances include 15 nodes (3 supply and 12 demand nodes), three commodities, two vehicle types and the planning horizon is 14 time periods. Although generated randomly, the supply and demand parameters were governed by some rules to cover a wider range of possibilities as explained below.

- **Demand**: For each demand node j the initial population size is chosen randomly between 500 and 3000 people. The possible internal displacement among nodes and the allowance for mortality are accounted for by updating the population size at every node after each time period. The increase / decrease in the population size per time period is chosen randomly and ranges from -100 to 100. The demand per commodity is then calculated by multiplying the population size by average consumption per capita.
- **Supply:** The initial inventory at supply nodes as well as the external supply received at supply or demand nodes are generated randomly in a manner which satisfies a predefined supply/demand (S/D) ratio. For each commodity, four levels of demand satisfaction were defined: 100%, 75%, 50% and 35%. Therefore, instances that cover all possible combinations of the satisfaction level for different commodities are generated. For large instances there are three commodities and hence the number of combinations is $4^3 = 64$. For small instances there are two commodities resulting in $4^2 = 16$ combinations. The time periods at which external supplies take place were also selected randomly in the planning horizon.
- **Transportation Vehicles***:* It is assumed that the number of available vehicles at supply nodes is sufficient to cover all distributions and is randomly generated accordingly.
- **Travel Time among nodes:** The distance, expressed as travel time, between every two nodes is generated randomly between 0.5 and 3 time units. (One time unit is assumed to equal 12 hrs.).

The instance generation criteria described above are inspired by Pérez-Rodríguez & Holguín-Veras (2016) who tested their inventory allocation model empirically for instances with different service levels expressed by the ratio between available inventory at supply nodes and total demand at affected areas. The assumption that vehicles at supply nodes is sufficient to cover all distributions is reasonable for humanitarian distribution problems because, unlike commercial supply chains, responders must rely on volunteers and local vehicles to transport supplies (Pérez-Rodríguez & Holguín-Veras, 2016). Other problem parameters are fixed for all instances and assumed as shown in Table 2.

Note that the assumption of deprivation cost function for drinkable water was borrowed from Holguín-Veras et al. (2016) and adapted for the definition of time unit (12 hrs). For other commodities, the parameters of the deprivation cost function are adjusted to roughly reflect the priority of the commodity with respect to drinkable water priority.

5.3. Results and discussion (for crisp objective function)

The model is run over the generated instances using Gurobi optimizer 8.1 - Java interface. The planning horizon is fixed with 14 time periods for large instances and 8 time periods for small instances. The scheduled horizon and step size are tuned during the run to reach the pre-specified threshold for the relative difference from the exact/ best bound values. For small sized instances, three random instances are generated for each S/D combination resulting in a total of 48 instances. The average relative deviation from the exact solution as well as solution times are reported for each combination. The results are satisfactory and the relative deviation did not exceed 0.22% in all combinations (See Table 3). Although solution times for the exact method were reasonably small, the RH approach showed a considerable improvement in the solution time without much sacrifice of optimality. The benefit of using RH can, however, be more justified with large instances where exact solutions are not available. The results showed that the level of resource scarcity expressed by S/D ratio, does not have significant effect on the algorithm performance and solution time. In fact, the complexity of an instance depends on the problem setting defined by the travel time among nodes, times for expected supply deliveries, the dynamic nature of the demand patterns and route availabilities. This justifies why some instances require more time to be solved by exact methods than others.

For large sized instances the original mixed integer programming model with default branch and bound solution is first run and the run stops when the gap between the lower bound and best found upper bound is reasonably small (0.5% – 1%). The RH model is then run and the results are compared with the best found bound by the branch and bound method. The scheduled horizon and step size parameters are tuned during the run to improve the deviation from the best found

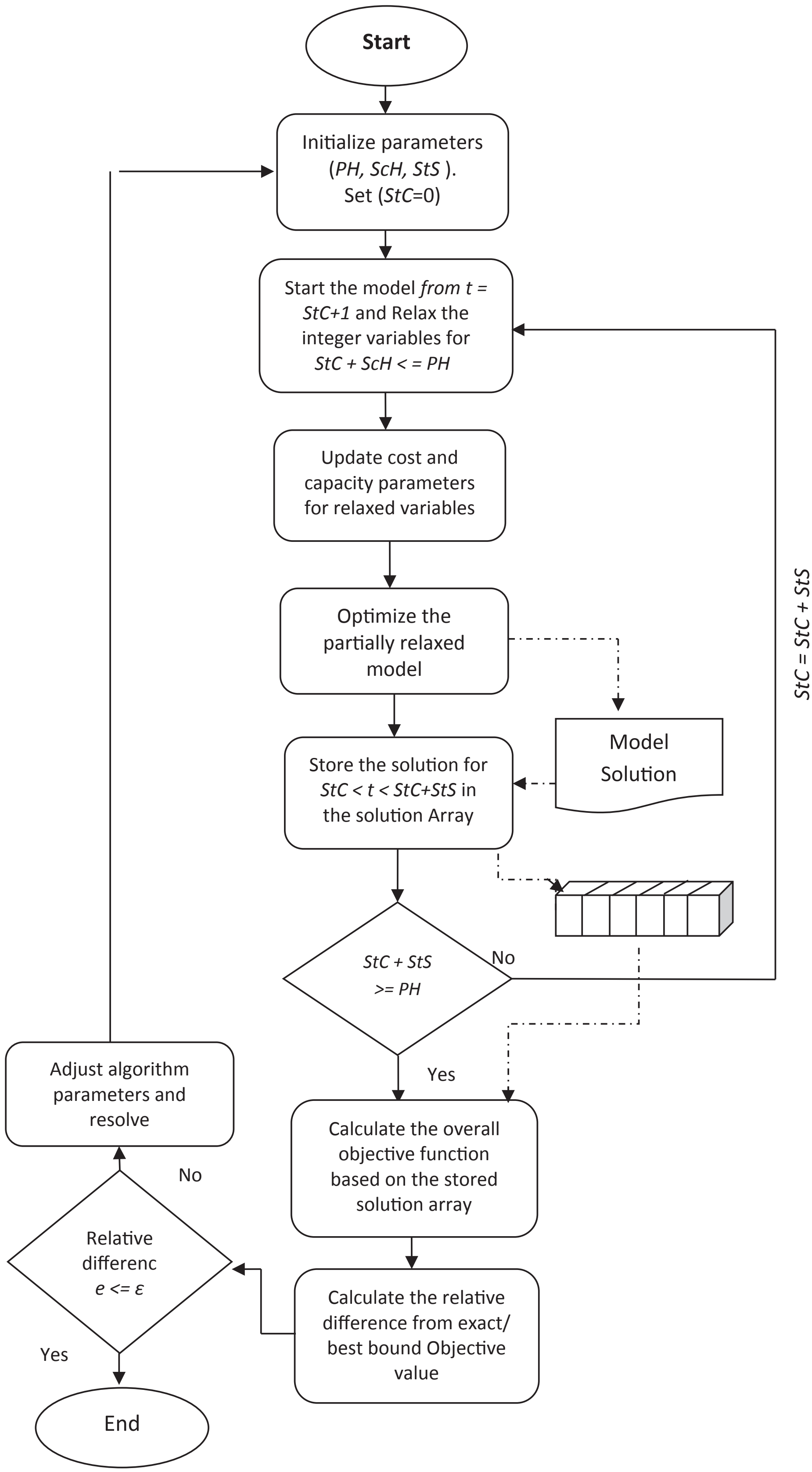


Fig. 4. Flow chart for applying the rolling horizon approach to our model.

Table 1
parameters' notation for the rolling horizon approach.

Parameter	Explanation
PH	Length of the planning horizon
ScH	Length of the scheduled horizon (assumed to be fixed)
StS	Step size: number of time periods in the scheduled horizon to be implemented before moving to next decision point.
StC	Steps count: number of time periods counted so far. In other words, number of time periods in which the solution is implemented and fixed so far.
ε	Threshold for the percent relative difference between the objective value resulted from rolling horizon and exact or (best bound) objective value.

bound. The RH algorithm succeeded to reach the target threshold of 2% or less in 45 instances (i.e., 70% of the total instances). Even with instances that exceeded the deviation threshold, the relative difference between RH solution and best upper bound was around 10% which is reasonable. For the branch and bound solution to reach the targeted gap, it took an average of 30 – 60 min for each instance. The solution time for the RH method largely depends on the choice of the scheduled horizon and step size. For the experimental instances with the reported deviations from the best bound, it took an average time of 5–15 min per instance.

Fig. 5 shows the best-found objective function using the RH approach and compares it with the best bound for the original MIP model. Expectedly, as the S/D ratio decreases, the total social cost increases. This is reflected in Fig. 5 as the scarcity of supply increases when we move forward in the instance index as described in Table 3. Although the performance of the branch and bound approximation is slightly superior to the RH performance, the advantage of the RH approach lies in: (1) its computational efficiency and (2) the benefit of updating the dynamic status of the model parameters once revealed. Since a considerable part of integer variables is relaxed in the unscheduled horizon during each stage, the time to solve the RH is much less than finding a good solution bound in the regular branch and bound approach. For the benefit of the RH method when the model parameters are dynamic and unstable, see the illustrative example previously discussed in box 1.

5.4. Results and discussion of the possibilistic MIP model

The procedure described in Section 4.2 is implemented to represent the fuzzy deprivation cost. A deprivation function $\Gamma(d)$ is assumed as $\Gamma(d) = \beta_1 e^{\beta_2 d}$, where d is the deprivation time. Three relief commodities are assumed in the experimental examples: drinkable water, food, Non-Food items (NFI). Inspired by the deprivation cost function defined for drinkable water commodity in Holguín-Veras et al. (2016), the fuzzy parameters for each commodity are assumed considering the level of essentiality for each commodity as in Table 4.

The model is verified and validated by running it on the generated instances described in Section 5.2 and the findings are consistent for all instances giving a good indication on the model validity. The output of the model is expressed as possible values of each objective function alongside their membership function. An example is given in Fig. 6 where the solid lines present the linear membership function for each objective as described in equation (4.2). This can be used to estimate the resultant total social cost expressed as an interval (in the given example [55000, 450000]). It can also be represented as a TFN considering that the parameters $\widetilde{\beta}_1, \widetilde{\beta}_2$ where originally expressed as TFNs. See the dashed-line triangle in Fig. 6.b.

To evaluate the effect of objectives' weights, the model was run with different configurations of the parameters ($\Theta_1, \Theta_2, \Theta_3$). For example, in the result shown in Fig. 6.b, ($\Theta_1, \Theta_2, \Theta_3$) = (0, 0, 0) indicating that the three objectives are of the same level of importance. Running model (4.7) resulted in optimum $\lambda = 0.6$ meaning that each objective is satisfied at least with 60%. Fig. 7 shows the resultant solution if ($\Theta_1, \Theta_2, \Theta_3$) = (0.3, 0, 0.5) which gives the highest weight to z_3 and the least to z_2. Running the model with this Θ configuration has resulted in $\lambda = 0.35$. This means that the membership for the first objective satisfaction is ($0.3 + 0.35 = 0.65$). The memberships for second and third objectives are 0.35 and 0.85; respectively. Therefore, the compromised objective function = [80,000; 236,500] or as TFN, (80,000 98,000 236,500). That is, with increasing the weight for z_3 over z_1 and z_2, the maximum possible cost is reduced by 213,500 cost units, whereas the minimum possible cost is increased by 35,000 cost units.

The choice of ($\Theta_1, \Theta_2, \Theta_3$) is also reflected on the percentage of demand satisfaction at each demand node and hence helps in attaining a higher level of equity by considering the different levels of vulnerability for each individuals group. For example, if the demographic characteristics at node i indicate vulnerability of a larger group than node j; increasing the weight of the third objective (associated with minimizing the maximum possible cost) will give higher priority to cover demand at node i than node j. Fig. 8 compares the percentage of demand satisfaction in three nodes of a random instance. The characteristics of population in the three nodes for the given example are assumed to follow the distribution given in Table 5.

The percentage of demand satisfaction at each node is calculated by dividing the total supply received at the node during the planning horizon by the total demand at the same node. The purpose of this comparison is only to find out the effect of objectives' weights on defining the priorities of distribution rather than studying the factors affecting the distribution decisions. For example, at Θ configuration (0,0,0) the reason that node 1 receives more supply than node 3 can be explained by several factors such as the ease of accessibility of node 1. Another possible reason is that the demand of node 3 increased at the end of the planning horizon compared with its beginning which indicates less deprivation time. What concerns here is that all the factors are fixed and only Θ setting is changed.

Since node 3 has the highest percentage of people at high risk, the percentage of demand satisfaction at node 3 increases from 46% to 68% when Θ_3 is increased from 0 to 0.5. Similarly, for node 1 which has the highest percentage of people at low risk. Increasing Θ_2 from 0 to 0.5 slightly affects the demand satisfaction at node 1 from 83% to 75% where, on average, one unit shortage at node 1 has less cost than that at other nodes. To generalize the findings, the model is run over the generated random instances described in Section 5.2 (after generating random percentages for population classes at each node) and the percentage of demand satisfaction is analyzed for different Θ_i values where the observation above is verified for the majority of instances. Such findings support the claim that possibilistic LP with fuzzy objectives can have some useful practical implications for better achievement of equity and risk reduction. It is hoped that this extension partially overcomes the inequality gap of minimum deprivation cost based models highlighted by Gutjahr & Fischer (2018). However, it is worthy to assess the level of equity for the demand nodes considering their population demographic distribution with the new fuzzy representation of the objective function using standard equity measures in the literature. This can be a highlighted extension for further investigation.

In the next section, the validity of the model is tested on a practical case study describing the relief supply to internally displaced people in Northwest Syria.

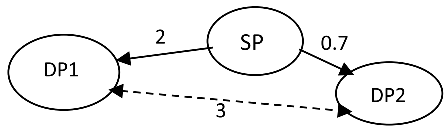
6. Case study – Internal displacement in northwest Syria

Halfway through the eighth year of conflict and violence, the humanitarian situation in Syria remains dire. A total of 5.9 million Syrians have been internally displaced and more than 5.7 million Syrians live as refugees seeking protection (HNAP, 2019a). The intensive ground fighting between non-state armed groups (NSAGs) and Government of Syria (GoS) forces as well as airstrikes and shelling, since late January 2020, continued to affect communities in Idleb area and western Aleppo governorates. "The humanitarian situation for people in northwest Syria

Box 1
Illustrative example - The benefit of RH in dynamic parameters settings.

ILLUSTRATIVE EXAMPLE

Consider a simple optimization problem of the relief distribution for one commodity from one supply point to two demand points. The expected demand and supply parameters are given for ten time periods as shown below.



Initial inventory at supply point = 393 units. Vehicle capacity = 1500 units. Transportation cost per time unit is 90 monetary unit

Supply and demand estimations:

Period t	1	2	3	4	5	6	7	8	9	10
Supply to SP	1500	1200	1600	450	2000	600	0	1200	980	0
Supply to DP_1	0	0	0	800	200	0	300	150	0	0
Supply to DP_2	500	200	0	0	150	630	420	0	0	120
Demand of DP_1	2000	2000	1800	1800	1750	1500	1500	1800	1800	2000
Demand of DP_2	800	850	950	950	1000	1200	1200	1100	1100	1000

Running the model for the parameters above results in solution with objective function value of ***10,530 monetary units.*** However, this objective value is only true if the real values of the parameters are exactly the same as expected. Let's assume that at time period 3, an unexpected increase (decrease) in the demand occurred at DP_1 (DP_2). This increase (decrease) continues until time period 9 when the demand suddenly drops at DP_1 and jumps at DP_2. Such variations in the demand can be referred to the internal displacement of beneficiaries among demand nodes, mortality, and other possible factors. Assume that the *real* demand and supply parameters for the same problem are:

Period t	1	2	3	4	5	6	7	8	9	10
Supply to SP	1500	1200	600	450	0	1600	2000	1500	980	0
Supply to DP_1	0	0	0	400	200	0	0	450	0	0
Supply to DP_2	500	200	0	0	150	200	420	100	150	120
Demand of DP_1	2000	2000	2200	2200	2200	1800	1800	1800	1200	1200
Demand of DP_2	800	850	750	750	900	1100	1200	1100	1600	1600

The actual social cost when applying the optimum solution, which is based on the estimated parameters, is calculated and it reached ***13,110 monetary units***, while optimizing the real problem gives a solution with optimum objective of ***11,800 monetary units.***

The advantage of the rolling horizon method is that decisions misled by wrong estimations are only implemented for the short-term future while the model is able to adapt the next decisions to the updated information about actual supply and demand. For the current example, the scheduled horizon was chosen to equal four time units and the step size Δ is two time units. This means that the decisions for the first two time units are based on the supply and demand estimations and could be misled by the inaccurate estimations. The next stage starts at time 3 where part of the actual information is revealed; leading to more guided decisions. Applying the RH method for the problem above with partially revealing the information at each stage had led to a solution with objective function of ***12,354 monetary units,*** which is closer to the optimum than solving the mixed integer programming problem for the whole planning horizon based on the estimated parameters.

Table 2
Fixed parameters for experimental instances.

Parameter	Value
Transportation cost / time unit (c^{km})	For large vehicles: $c^{11} = 120$ monitory units per time period For small vehicles: $c^{21} = 80$ monitory units per time period
Vehicle capacities (Q^{km})	For large vehicles $Q^{11} = 2000$ kg For small vehicles $Q^{21} = 1000$ kg
Weight per unit of commodities (w_c)	1 unit of water $w_1 = 1$ L = 1 kg 1 Food meal $w_2 = 0.5$ kg 1 hygiene kit $w_3 = 0.8$ kg
Deprivation cost($\Gamma_c(d)$)	For water$\Gamma_1(d) = 0.25(e^{1.62d})$ For food meals$\Gamma_2(d) = 0.12(e^{1.07d})$ For hygiene kits$\Gamma_3(d) = 0.05(e^{0.58d})$
Consumption per capita (u_c)	$u_1 = 3$ L water / day → 1.5 L / time unit $u_2 = 2$ meals / day → 1 meal / time unit $u_3 = 1$ hygiene kit / week
Maximum allowable deprivation time (t_c^{max})	$t_1^{max} = 3$ days for water = 6 time units $t_2^{max} = 5$ days for food = 10 time units Unlimited for hygiene kits

Table 3
% Deviation of RH results with respect to exact solution for small instances.

Instance #	S/D ratio for C1	S/D ratio for C2	Average Solution time by exact method (Sec)	Average Solution time by RH method (Sec)	Average % deviation of RH obj. value w.r.t exact obj. value
1 to 3	1	1	14	2	0.05%
4 to 6	1	0.75	134	4	0.22%
7 to 9	1	0.5	31	1	0.02%
10 to 12	1	0.35	4	2	0.16%
13 to 15	0.75	1	6	1	0.11%
16 to 18	0.75	0.75	10	1	0.15%
19 to 21	0.75	0.5	2	2	0.08%
22 to 24	0.75	0.35	13	1	0.11%
25 to 27	0.5	1	15	2	0.12%
28 to 30	0.5	0.75	14	2	0.03%
31 to 33	0.5	0.5	13	2	0.16%
34 to 36	0.5	0.35	80	2	0.07%
37 to 39	0.35	1	6	2	0.02%
40 to 42	0.35	0.75	5	1	0.12%
43 to 45	0.35	0.5	73	3	0.10%
46 to 48	0.35	0.35	10	3	0.13%

is at the most critical points due to ongoing hostilities, harsh winter conditions, and existing needs that were already severe; highlighting the provision of humanitarian assistance as immense priority" (OCHA, 2020). HNAP (2020) conducted a population assessment in north-west Syria on 1st March 2020, collecting data at the community level which was then been disaggregated by those displaced since 1 December 2019. Fig. 9 visualizes the total number of IDPs as well as the recently displaced individuals as of Feb. 2020. The map highlights rural Idleb and northwest Aleppo to have the highest displacement burden and will therefore be the focus of this analysis.

The prolong crisis in Syria allowed the acting humanitarian parties to reach a comprehensive and effective organization of relief programs therein. Led by UNHCR, the Camp Coordination and Camp Management (CCCM) cluster coordinates the efforts of active member organizations providing assistance in northwest Syria. CCCM cluster activities focus on informing the humanitarian community on the needs in IDP Sites, tracking IDP movements and coordinating the provision of multi-sectoral assistance in IDP Sites (UNHCR, 2019). The information used in this study depends on published reports issued by UN acting parties as well as interviews with NGO's and humanitarian agencies such as: IOM-Turkey, HIHFAD, OCHA, and HNAP program officers.

The CCCM Cluster_ IDP Sites Integrated Monitoring Matrix (ISIMM), January 2020 is used to estimate the demand in each sub-district in rural Idleb and northwest Aleppo. Vulnerability of IDP households is also analyzed in each sub-district by identifying the number of Female-headed households, number of disabled persons, and percentage of minors per household. We aggregated and disaggregated some of the statistics in some districts/ sub-districts depending on the displacement burden for analysis purposes. Fig. 10 presents the network of distribution centers and demand points based on the information provided by HIHFAD relief agency as well as the CCCM cluster reports. The location of each node and distances between nodes are taken from google maps (with adding 30 mins for unloading at each node).

Three relief commodities are analyzed: ready to eat (RTE) food rations, emergency food baskets, and hygiene kits. Table 6 shows the total

Table 4
Fuzzy parameters of the deprivation cost function for each commodity.

Commodity	β_1	β_2
1	(0.21, 0.25, 0.35)	(1.55, 1.62, 1.85)
2	(0.07, 0.12, 0.15)	(0.85, 1.07, 1.21)
3	(0.05, 0.07, 0.15)	(0.33, 0.58, 0.9)

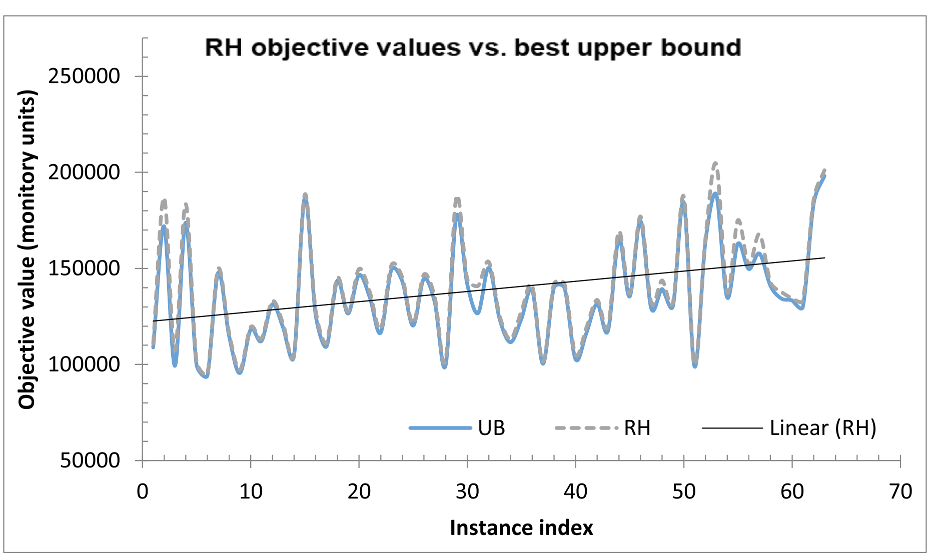


Fig. 5. Branch and bound upper bounds vs. RH objective values.

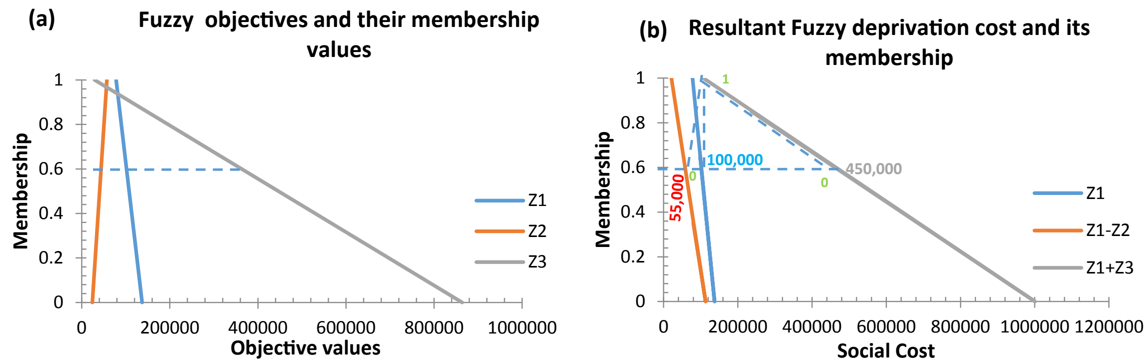


Fig. 6. a) Fuzzy objectives and their membership values; b) Resultant fuzzy social cost and its membership for $\Theta = (0,0,0)$.

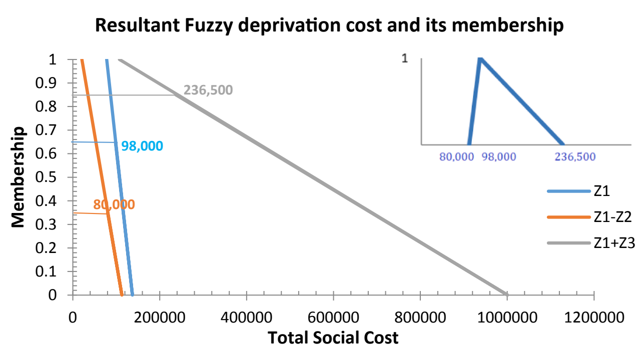


Fig. 7. Resultant fuzzy social cost and its membership for $\Theta = (0.3,0,0.5)$.

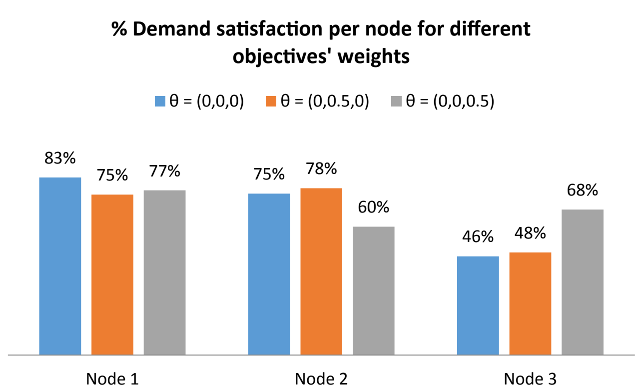


Fig. 8. Comparison of demand satisfaction per node for different fuzzy objectives' weights.

Table 5
Classification of population with respect to their vulnerability at risk.

Node	% of individuals at low risk	% of average typical individuals	% of vulnerable individuals (at high risk)
1	35%	60%	15%
2	10%	70%	20%
3	12%	28%	60%

number of IDPs in each demand node as well as number of IDPs with food and hygiene kits need. The type of shelter is added to estimate the best type of food supply (e.g. we assume that RTE are supplied to tented shelters whereas food baskets to buildings and container shelters). The total demand is estimated by reviewing the percent of needs coverage in each relief sector which are published in the aforementioned reports.

Planners should be aware that displacement in north-west Syria is highly–fluid. Therefore, at any given time numbers may significantly vary to what has been reported. CCCM and HNAP continually work to update figures to match rapidly changing mobility dynamics (HNAP, 2020). This highlights the benefit of using the rolling horizon (RH) approach to cope with the dynamic updates.

The computational case study is designed using the information reported above with few assumptions regarding the missing information. For the supply side, OCHA has published figures about their total supply and interventions during February both in food and hygiene sectors as a response to above mentioned demands; one can refer to (OCHA, 2020) for supply data. Furthermore, it is assumed that the local community participates in 5% of the supply through family-to-family support. Parameters such as transportation cost and maximum truck capacity have been set based on NGOs interviews whereas the boxes volumes of each commodity were standardized and assumed as shown in Table 7. The standard RTE ration box is sufficient for one family for 3–5 days while both food basket and hygiene kits are sufficient for two weeks. Holguín-Veras et al. (2016) formula for deprivation cost function is used after adjusting the function parameters to adapt the type of commodities under study and the definition of the time unit.

Since the security situation is unstable and is always at risk, relief agencies tend to send only one truck until it reaches its final destination to make sure no obstacles before sending the next truck. This puts limitations on the maximum number of trucks that can be sent in the day shift; especially between nodes in different governorates i.e., Aleppo and Idleb. This is reflected by imposing constraint (3.8) for arcs connecting Afrin distribution center with demand nodes in Idleb and for arcs connecting Bab-al-Hawa with Aleppo sub-districts.

A case of a relief agency working to respond to demand data in Table 6 is studied. The planning horizon is one week (14 time units) during which some random changes (displacement from node to node or newly displaced comers) are assumed. The supply reported in (OCHA, 2020) covers approximately 80% of food needs and 69% of hygiene needs. We assume that this supply has received to the distribution centers in different time units during the planning horizon. At each time period, the demand is updated as the demand minus supply received in the previous period plus (minus) the demand of new comers (leavers). The demand of the original group who already received supply is updated at the end of the consumption sufficiency period (e.g. after three days for RTEs). Figs. 11 and 12 respectively show the resultant percentage of demand coverage at each demand node by the end of the planning horizon and average deprivation cost per household experienced during all time periods in the planning horizon.

Although not equally covered, the results show no exclusion or significant under-fulfilment for any node. However, at early stages in the planning horizon, the deprivation cost in all nodes is relatively small and there are no much differences between nodes, putting more weight on the transportation cost. This justifies the early fulfilment (lower average deprivation cost) of closer nodes to the distribution centers such as south Dana and Markez Harim compared with Jesr al-shoghour which is the

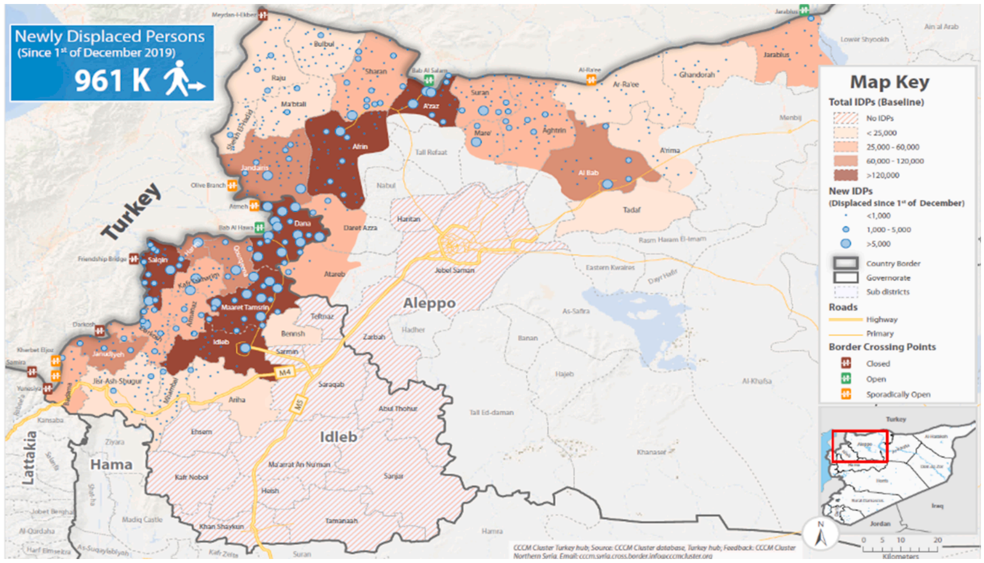


Fig. 9. Internal displacement in northwest Syria, HNAP (2020).

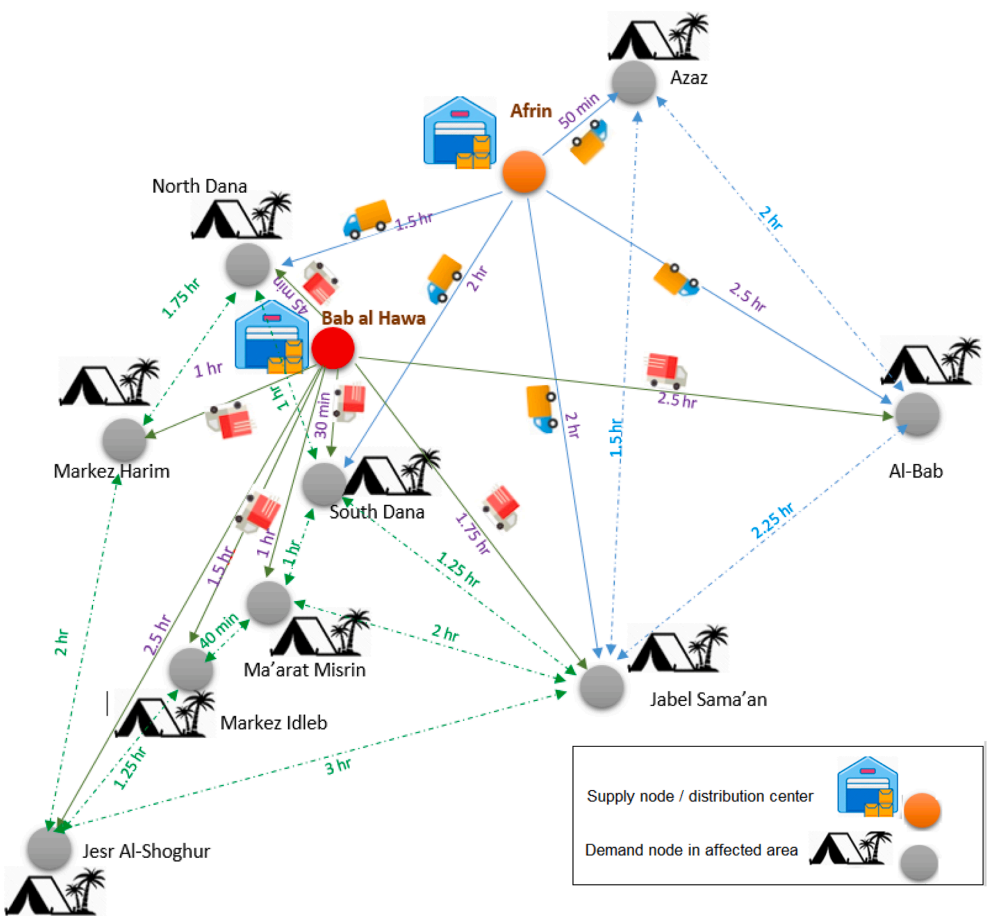


Fig 10. Relief distribution network in northwest Syria.

farthest point and exhibits the highest average deprivation cost per household. After few time periods the increase of deprivation cost in Jesr al-shoghour is higher than the difference in transportation cost which forces the model to give it priority in next periods. In some sense, the model outperforms other models aiming to minimize unsatisfied demand or external costs without the inclusion of the deprivation cost which may exclude or disregard difficult-to-access nodes. In another sense, however, an explicit adoption of equity criteria is still needed to further minimize the differences of average deprivation cost among different nodes.

Vulnerability of IDPs in each nodes is evaluated by analyzing the demographic characteristics in each community according to CCCM published reports. The population segment of the age group between 14 and 45 is regarded as the less vulnerable individuals. Highly vulnerable

Table 6
IDPs and their needs in different camps at northwest Syria.

Governorate	Demand point name	Included sub-districts / communities	Type of shelters	Total number of IDP's	IDPs with food needs	IDPs with Hygiene kits needs
Aleppo	Al Bab	Al bab- Al Raie	Tented shelters	21,012	502	0
	Azaz	Azaz – Suran	55% tented shelters 40% containers and tents 5% mixed tents and buildings	146,795	58,859	68,999
	Jabel Samaan	Jrablus - Atareb	96% tented shelters 4% mixed tents and buildings	46,847	10,153	27,762
Idleb	North Dana	Atmah – Aqrabat – Qah – Mashhad Ruhin	22% tented shelters 78% mixed tents and buildings	291,142	254,927	20,921
	South Dana	Bab al Hawa – Deir Hassan – Hezreh – Hezri – Tal karameh – Sarmadah – Kafr Rayan	48% tented shelters 48% mixed tents and buildings 4% Buildings	270,827	79,475	185,201
	Markez Harim	Salqin – Markez Haim - Armanaz	70% tented shelters 30% mixed tents and buildings	38,989	38,989	38,949
	Ma'arat Misrin	Kelly – Hazano -Maaret Elekhwan – Haranbush	40% tented shelters 60% mixed tents and	111,567	94,585	95,080
	Jesr Al-Shoghur	Badama – Janudiye – Darkoush	37% tented shelters 63% mixed tents and buildings	38,551	38,283	3,343
	Markez Idleb	Bennsh + Markez Idleb	90% tented shelters 10% mixed tents and buildings	7,096	7,096	4,545
	TOTAL			**972,826**	**582,869**	**444,800**

Table 7
Case study parameters.

Parameter	Value/formula
Transportation Cost	\$250 per hour for smaller trucks \$400 per hour for larger trucks
Truck capacity	20 ft truck, with dimensions (19′6″ × 7′8″ × 7′2″) and volume capacity 1016 ft^3 40 ft truck, with dimensions (39′ × 7.8′ × 7.8′) and volume capacity 2400 ft^3
Supply box dimensions	RTE rations (8.5″ × 17.5″ × 13.5″) = 1.16 ft^3 Food baskets (12.2″ × 20″ × 16.1″) = 2.3 ft^3 Hygiene kit (15.5″ × 12.5″ × 9.5″) = 1.06 ft^3
Deprivation Cost (crisp)	For food supply $0.15e^{1.2d}$ For hygiene kits $0.07e^{0.58d}$
Deprivation Cost (fuzzy)	For food supply Ae^{Bd}, $A = (0.1, 0.15, 0.25)$, $B = (1.05, 1.2, 1.55)$ For hygiene kits Ae^{Bd}, $A = (0.04, 0.07, 0.1)$, $B = (0.38, 0.58, 0.85)$

groups include female-headed and minor-headed households, households with disabled individuals, and households with more than three minors or independents in the family. Table 8 shows an approximate classification of IDP households according to their vulnerability.

The possibilistic LP model is run considering the fuzzy deprivation cost function in Table 7 and IDPs classification in Table 8. The results described in Section 5.4 were consistent with case findings; where changing the weight of the three objectives z_1, z_2, and z_3, explained in Section 4.2, has a noticeable impact on improving demand coverage and average deprivation cost; especially for nodes with highly vulnerable individuals such as Jesr al shoghour.

7. Conclusions and future work

In this paper an optimization model for relief allocation decisions in the aftermath of a disaster or conflict situation has been introduced. The model aims at improving the responsiveness and robustness of the humanitarian supply chain. The paper introduces extensions for some models in the literature which provided a mathematical foundation on modeling the human suffering as a deprivation cost function. The extensions are focused on providing an alternative presentation to the deprivation cost as a function of the unmet demand as well as accounting for the perceptual variations to deprivation through introducing fuzzy deprivation cost formulation. Possibilistic mixed integer programming approach is used to deal with the fuzzy objective function coefficients in an attempt to minimize the risk of higher cost and minimize the most possible cost value while maximizing the possibility of lower cost. To capture the dynamic aspects of humanitarian logistics, the distribution model is based on a time space network formulation and the solution methodology is built on the rolling horizon approach. This is especially suitable for real time decision support in the humanitarian relief response.

The computational analysis is based both on randomly generated instances and a real case study of IDPs in northwest Syria. The generated instances cover a wide range of possible scenarios regarding resource availability. The experimental results approved the efficiency of the proposed model and its adaptability to the dynamic parameters change. The fuzzy objective formulation provides a more realistic representation of the human perception to deprivation by considering the characteristics of different groups of individuals and hence their vulnerability to risk. Computational results show that possibilistic LP formulation with fuzzy representation to the deprivation cost helps to achieve a higher level of equity by reprioritizing the delivery decisions based on the urgency of need and individuals' vulnerability. The proposed approach can be practically useful to overcome the gap highlighted by HNAP in distributing reliefs to IDP's in Syria, where their analysis showed no differences between rates of vulnerable households receiving assistance and non-vulnerable households.

The model can be further improved upon by considering the uncertainty in the model's other parameters such as supply, demand, and travel time. The author is currently working on research to integrate robust optimization with uncertain supply, demand, and travel time with the current possibilistic LP model. This paper assumes that the deprivation cost is already estimated. Techniques and methods to estimate the deprivation cost -as the economic value of human suffering

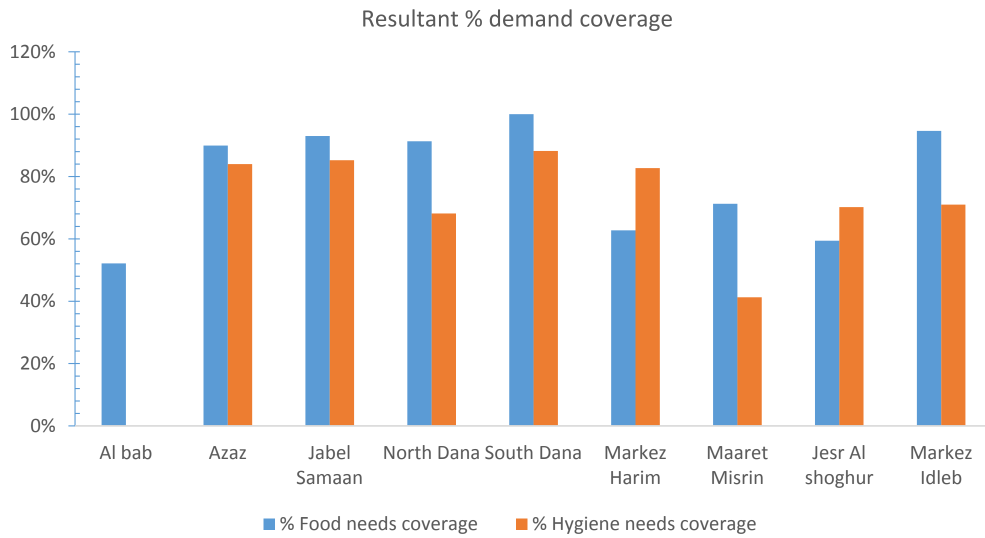


Fig. 11. Resultant percentage of demand coverage.

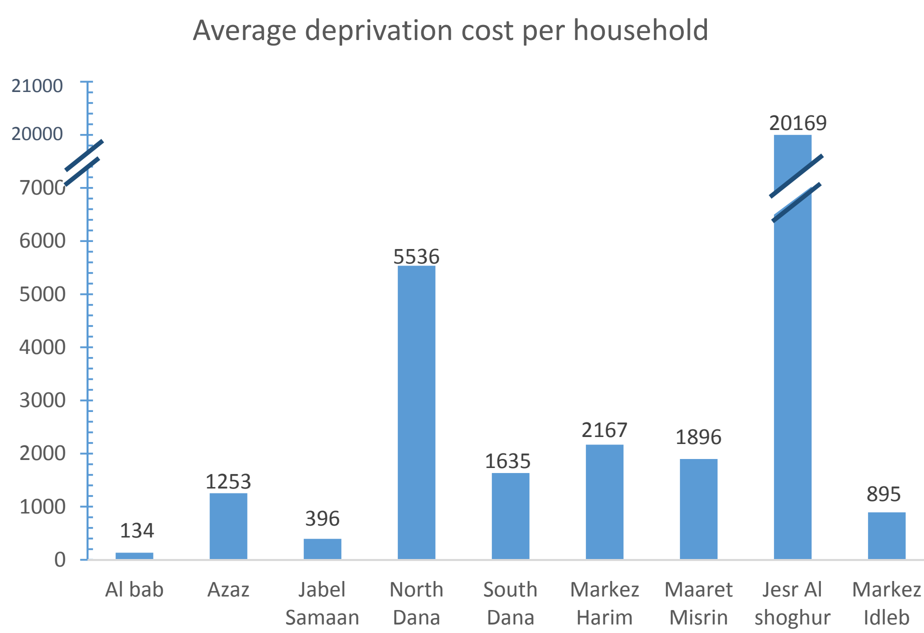


Fig. 12. Average deprivation cost per household.

Table 8
Classification of IDPs households with respect to their vulnerability at risk.

Demand node	less vulnerable	average	highly vulnerable
Al bab	13%	80%	7%
Azaz	11%	72%	17%
Jabel Samaan	12%	82%	7%
Dana N	11%	68%	21%
Dana S	11%	78%	11%
Markez Harim	9%	80%	10%
Maaret Misrin	10%	72%	18%
Jesr Al shoghur	12%	62%	26%
Markez Idleb	8%	70%	22%

resulting from the lack of access to a good or service -for different groups of IDPs is highlighted as an area for future research.

Author contributions

The author confirms sole responsibility for the following: study conception and design, literature review, methodology, data curation, analysis and interpretation of results, and manuscript preparation.

Declaration of Competing Interest

The author declares that she has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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