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LOGÍSTICA HUMANITARIA: MODELADO Y APOYO AL DISEÑO DE POLÍTICAS DE GESTIÓN FRENTE A LA PREVENCIÓN, SOCORRO Y RESTAURACIÓN

TESIS PARA OPTAR AL GRADO DE
DOCTOR EN SISTEMAS DE INGENIERÍA

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Resumen

El presente documento resume el desarrollo de una investigación conducente al grado de Doctor en Sistemas de Ingeniería, Universidad de Chile. Se presenta un análisis exhaustivo de 178 artículos, incluyendo estudios en el campo de la logística humanitaria de los últimos 10 años, identificando teorías, conceptos y métodos de investigación relevantes en el área, así como temas para futuras investigaciones. Sobre la base de estos análisis, con una perspectiva actualizada y estructurada de la literatura, se identifican oportunidades en torno a la incorporación de: aspecto social y comportamiento humano/organizacional; coordinación y modelos multiobjetivo; presencia de múltiples actores; incertidumbre, dinámica y riesgo; decisiones integradas, pre y post emergencia; contexto, asuntos políticos y culturales; métodos de resolución y escala, proporcionando direcciones y focos integrados para investigaciones futuras con el fin de realizar mejoras en las áreas donde se detecta la falta de investigación. Lo anterior mejorará la comprensión del tema, sirviendo como una guía para el crecimiento, desarrollo y la difusión de este conocimiento científico para responder mejor a los problemas humanitarios.

En segunda instancia, y en base a las brechas y desafíos identificados por la revisión bibliográfica, se propone un modelo integrado de planificación y respuesta a un desastre mediante decisiones de aprovisionamiento, compras, localización y distribución de un suministro crítico como es el agua potable. Se considera una función objetivo que incorpora la sensibilidad a los tiempos de respuesta y el componente social asociado al comportamiento humano y la privación, así como fenómenos de convergencia de materiales, además de los costos asociados a las deciciones logísticas. Se considera un entorno donde la incertidumbre se manifiesta de manera mixta, a través de escenarios con probabilidad conocida que describen localización, cobertura e impacto de los desastres, estado de la red, tiempos de respuesta e inventarios disponibles o dañados, así como información imperfecta o imprecisa respecto a parámetros asociados a la operación logística, los cuales no cuentan con leyes de probabilidad definidas y pueden variar dentro o entre cada escenario. Esta situación es trabajada con un modelo robusto y posibilista, en tanto que se busca minimizar el riesgo en una función objetivo aversa a la variabilidad de los costos globales. Se incorporan medidas de credibilidad y lógica difusa para trabajar la incertidumbre epistémica en los parámetros. Finalmente, reconociendo la presencia de costos sociales y logísticos, se formulan modelos multiobjetivo, resueltos mediante programación por compromisos.

Abstract

This document summarizes the development of an investigation leading to the degree of Doctor of Engineering Systems, University of Chile. An exhaustive analysis of 178 articles is presented, including studies in the field of humanitarian logistics of the last 10 years, identifying relevant theories, concepts and research methods in the area, as well as topics for future research. Based on these analyzes, with an updated and structured perspective of the literature, opportunities are identified around the incorporation of: social aspect and human / organizational behavior; coordination and multiobjective models; presence of multiple actors; uncertainty, dynamics and risk; integrated decisions, pre and post emergency; context, political and cultural issues; resolution and scale methods, providing integrated directions and foci for future research in order to make improvements in the areas where the lack of research is detected. The above will improve the understanding of the subject, serving as a guide for the growth, development of this scientific knowledge to better respond to humanitarian problems.

In the second instance, and based on the gaps and challenges identified by the literature review, an integrated planning and disaster response model is proposed through supply decisions, purchases, location and distribution of a critical supply such as drinking water. It is considered an objective function that incorporates sensitivity to response times and the social component associated with human behavior and deprivation, as well as phenomena of convergence of materials, in addition to the costs associated with logistic decisions. It is considered an environment where uncertainty manifests itself in a mixed way, through scenarios with known probability that describe the location, coverage and impact of disasters, network status, response times and available or damaged inventories, as well as imperfect or inaccurate with respect to parameters associated with the logistics operation, which do not have defined probability laws and may vary within or between each scenario. This situation is worked with a robust and possibilistic model, while it is sought to minimize the risk in an objective function that breaks down the variability of global costs. Credibility and fuzzy logic measures are incorporated to work on epistemic uncertainty in the parameters. Finally, recognizing the presence of social and logistic costs, multiobjective models are formulated, resolved through compromise programming.

Al Instituto de Sistemas Complejos de Ingeniería de la Universidad de Chile, a mis profesores, compañeros y amigos, a mi familia y en especial a mi hija por inspirarme cada día en este largo proceso que termina, y da inicio a uno nuevo.

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INTRODUCCIÓN

En 2018, se registraron 315 eventos de desastres naturales con 11804 muertes, más de 68 millones de personas afectadas y 131 mil millones de dólares en pérdidas económicas en todo el mundo. En relación con la década anterior (2008-2017), destacan algunos desastres masivos, como el terremoto de 2010 en Haití (222,500 muertes); la sequía 2015/2016 en la India (330 millones de personas afectadas); y el terremoto y tsunami de Japón de 2011 ($ 210 mil millones en daños), por mencionar algunos (EM-DAT, www.emdat.be).

Como se aprecia, la ocurrencia de desastres naturales alrededor del mundo ha provocado la reiterada pérdida de vidas humanas, desintegración de los mundos de quienes sobreviven, condiciones de precariedad que se profundizan para muchos, consecuencias ambientales, destrucción de fuentes de empleo e ingresos, daños en infraestructura, y costos asociados a la mitigación y reconstrucción. Ello transmite a la gestión de desastres naturales una fuente permanente de desafíos para expertos provenientes de distintos ámbitos del quehacer humano, incluyendo las ciencias, la política, la ingeniería, la tecnología, la innovación, la sociedad civil y las organizaciones gubernamentales, así como la sociedad en su conjunto.

El presente documento reune el trabajo realizado como tesis doctoral, consistente en dos artículos. El primero consta de una revisión bibliográfica exhaustiva y estructurada de la literatura en logística humanitaria, con foco en la modelación matemática y optimización de decisiones logísticas, así como en la contextualización de un proceso eminentemente sociotécnico. Lo anterior dado porque todo proceso humanitario lo constituyen las personas y organizaciones, por cuanto es fundamental revisar el comportamiento humano y la psicología del desastre, aspecto no integrado hasta ahora en revisiones de la literatura en logística humanitaria.

Desde ahí se analizan y seleccionan 178 artículos donde la logística humanitaria sea abordada mediante modelos de optimización, incluyendo diversas revisiones disponibles en la literatura, así como estudios, problemas y modelos específicos en estructura, contexto, supuestos, mecanismos de resolución y aplicación. Se identifican oportunidades en torno a la incorporación de: aspecto social y comportamiento humano/organizacional; coordinación y modelos multiobjetivo; presencia de múltiples actores; incertidumbre, dinámica y riesgo; decisiones integradas, pre y post emergencia; contexto, asuntos políticos y culturales; métodos de resolución y escala, proporcionando direcciones y focos integrados para investigaciones futuras con el fin de realizar mejoras en las áreas donde se detecta la falta de investigación.

El segundo artículo toma en consideración las brechas indentificadas en el primer estudio, conforme a lo cual se propone un modelo estocástico de optimización multiobjetivo, robusto y posibilista para decisiones de localización, asignación de inventarios y distribución. Este modelo es construido y resuelto con instancias de que la literatura propone con soluciones y contextos específicos para el análisis y comparación de rendimientos y resultados. Al respecto, se acepta incorporar el *costo de privación* en la modelación, que conceptualmente se define como el valor económico del sufrimiento humano causado por la falta de acceso a un bien o servicio, siendo una función del tiempo de privación y las características socioeconómicas del individuo (Holguín-Veras *et al.*, 2013a, Holguín-Veras *et al.*, 2013b, Holguín-Veras *et al.*, 2016).

Junto a lo anterior, se incluye un segundo impacto social dado por el comportamiento de los donantes y un alto fraccionamiento o pobre coordinación entre múltiples agentes involucrados en la toma de decisiones logísticas, tales como la distribución y localización de suministros críticos. Este fenómeno es conocido como la convergencia, definida como el movimiento masivo de personas, mensajes y suministros hacia el área afectada por la emergencia, incluyendo convergencia del personal, convergencia de información, y la convergencia de materiales, además de la afluencia de curiosos, ansiosos y explotadores a las zonas afectadas después de la ocurrencia de una emergencia (Fritz y Mathewson, 1957).

Dado que la logística humanitaria debe hacerse cargo de entornos donde predomina la incertidumbre, respecto de las demandas y privaciones, así como de los parámetros propios de la logística tradicional (tiempos de viaje y estado de la red, capacidades y stock utilizable, entre otros), en esta investigación se propone una versión aversa al riesgo de un modelo estocástico. En este modelo, la función objetivo tiene funciones generales de penalización que robustecen el modelo y su solución, ponderadas con un parámetro destinado a capturar las preferencias del modelador. Para ello se busca minimizar la suma del valor esperado y la varianza del costo total de la cadena de socorro, separando el aspecto de la logística tradicional del impacto social y la privación. Se penaliza además la inviabilidad de la solución debido a la incertidumbre de parámetros asociados a la convergencia de materiales de un suministro crítico como el agua potable.

Para construir un modelo posibilista, se incluye además la incertidumbre epistémica provocada por la impresiciónen el cálculo de parámetros, cuando no hay suficientes datos históricos para modelar datos inciertos. Ello permite enriquecer el tratamiento de la programación estocástica basada en planificación de escenarios, por cuanto permite complementar el que cada escenario de emergencia siga un proceso estocástico con cierta probabilidad de ocurrencia, junto con parámetros independientes de los mismos y que se pueden formular como distribuciones de posibilidad.

Finalmente, se resuelve el modelo para instancias de la literatura asociadas a huracanes en EEUU. Se comparan los desempeños de modelos multiobjetivo estocásticos, robusto y posibilista, constatándo que este último proporciona costos globales menores en la operación logística, así como menor impacto social asociado a costos de privación y convergencia de materiales. Se evalúan las redes y se comparan estructuras logísticas, junto con proporcionar una herramienta de apoyo a la toma de decisiones, incorporando la gestión de incertidumbre e imprecisión en parámetros para la planificación por escenarios y la optimización multiobjetivo.

Para terminar, este documento proporciona una guía para el desarrollo de una línea de investigación en logística humanitaria, identificando desafíos para futuros proyectos de investigación. Estos últimos se relacionan con la profundización en el estudio de la psicología de los desastres naturales, comportamiento de comunidades y redes sociales; el estudio de fenómenos de congestión, ruteo de vehículos y convergencia de materiales; cálculo de costos de privación para modelos multiproducto; modelos multiobjetivo y estructuras jerárquicas para la toma de decisión.

CAPÍTULO 1

HUMANITARIAN LOGISTICS AND EMERGENCY MANAGEMENT - NEW PERSPECTIVES AND OPTIMIZATION APPROACHES FOR A SOCIOTECHNICAL PROBLEM

Abstract

In this document, we thoroughly and comprehensively review the recent literature in humanitarian logistics and disaster response operations. Special emphasis is set on the underlying sociotechnical phenomenon, analysing optimization models, increase of data, dynamic nature of disasters, uncertainty and multiple objectives present in a supply chain under the presence of a natural disaster. Disaster psychology and human behaviour, organizational failures and the role of institutionalism is described as supplement. This document presents a thorough analysis out of 178 articles, including studies of humanitarian logistic area from the past 10 years, identifying theories, concepts and relevant research methods in the field, as well as topics for further research. In terms of data base analysis, an updated structured and literature perspective, opportunities in modelling to adequately incorporate relevant aspects such as: social aspect and human/organizational behaviour; coordination and multiobjective modelling; presence of multiple stakeholders; uncertainty, dynamics and risk; integrated decisions, prior to and after the emergency; political and cultural context; resolution methods and scale, etc. are identified. Alignments for further research are provided, with concrete proposals to optimize the response to better face humanitarian problems that come up in the aftermath of a disaster.

1.1. INTRODUCTION

Humanitarian logistics addresses the integration of social sciences and analytical research, incorporating mathematical characterization and modelling of diverse aspects of relief efforts, together with an intense field work. Levels of knowledge and understanding of humanitarian challenges, in the field of logistics, has quickly raised the specialized literature providing more sophisticated models, which are better adapted to the context and to specific needs, presenting at the same time, a set of challenges inherent to a complex phenomenon, in terms of stakeholders involved, society behaviour, emergency dynamics and uncertainty (Anaya-Arenas *et al.*, 2014; Holguín-Veras *et al.*, 2013b).

Scientific knowledge about humanitarian logistics is still incipient compared to commercial logistics. Nevertheless, based on several losses that come with natural disasters, the scientific community is compelled to contribute to effectively reduce human suffering. According to the Emergency Events Database (EM-DAT, www.emdat.be) 11,495 natural disasters occurred worldwide between 1980 and 2015, with more than 6 billioneople affected, more than 135 million homeless, more than 2.5 million deaths and reported $2.71 USD billion damage value. Main disasters of recent years include: tsunami in Southern Asia (2004); hurricane Katrina in United States (2005); earthquakes in Pakistan and Java (Indonesia), Chile (2010) and Japan (2011), among others. Although these events could not have been avoided, their impacts could have been reduced by improving preparedness and response efforts (Noham y Tzur (2017)).

Humanitarian logistics is defined as a sociotechnical process that allows individuals to be organized as a social network comprised by a set of activities. In general terms, these activities can be split in phases, as it is presented in Figure 1, which are comprised by actions conducted in stages prior to and after the emergency occurrence:

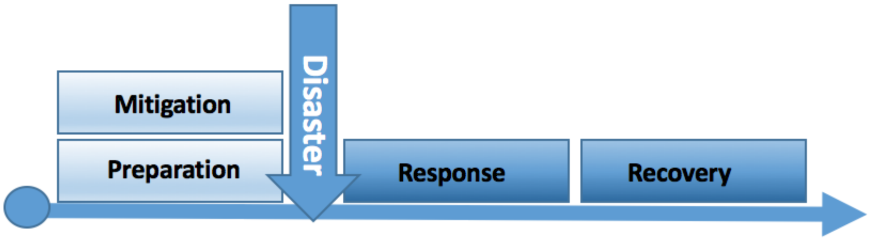


Figura 1.1: Emergency Management Anaya-Arenas *et al.*, 2014

- Preparedness: It includes facilities location, goods pre-positioning, resource allocation (capacity and inventory), transport planning and design of supply contracts and distribution strategies prior to an emergency;
- Mitigation: It includes network design, allocation and critical supply routing, location of early warning systems and aid facilities, as well as implementation of facilities protection systems;
- Response: It begins, in some cases, when early warning systems or hazards monitoring alerts prompt the authorities of an imminent disaster. Activities and logistic

decisions include supply allocation (flow, routing and vehicle scheduling, temporary facility location), transportation of people and/or evacuation, inventory management (allocation and availability of stock), network recovery (roads, bridges, information systems and energy, etc.) among others;

- Recovery: It includes debris and garbage removal, network restoration, aid distribution for reconstruction and recovery of households, safety, functioning of markets and community operations in general.

These decisions and activities depend on the nature of the emergency itself, which offers a set of difficulties and challenges at the time of making or designing management support tools. In fact, most part or the whole structure built by the community is strongly impacted, including facilities and operational bases of the emergency organisms, local officials cannot always comply with their regular work, nearby community aid may not be necessarily provided, most of the community daily functions (if not all) are acutely and simultaneously interrupted, the media create more catastrophes than the disaster itself from a social perspective, human suffering in its cognitive and affectional dimensions make difficult to determine and to project their needs, mass emigration during long periods of time are observed, etc. (Wachtendorf *et al.*, 2010).

The humanitarian logistic allows to understand challenges at conception and to model an unexpected event that jeopardizes lives and goods. Such events demand a quick or immediate response with the use of resources and procedures (more or less structured or organized), very often exceeding the capacity of the affected zone, and therefore, affecting bordering or remote zones that are interested in collaborating. The above, in line with goals intended to save lives and/or preserve properties, allow to maintain social, ecological, economic and political stability of the affected region, as well as achieving efficient and effective operations in the logistic response.

In terms of techniques to build mathematical models as a support to decision making, new and novel research challenges arise. These include the use of disaster psychology and knowledge about human behaviour, welfare economy and data (decisions and incentives), use of econometrics and big database management (relationships between variables, assessments and scenario building, risks and impacts simulations and projections); multi-objective, multi-level, stochastic and dynamic optimizations for multiple products and multiple periods. The use of multiple resources coming from multiple entities that would coordinate, compete and/or collaborate must be also assessed.

This article presents a thorough bibliographic revision that provides a comprehensive analysis of some of the above-mentioned elements, also incorporating humanitarian logistics outcomes and social perspective. As pointed out by previous revisions, for instance, Holguín-Veras *et al.* (2013a)), and based on differences between commercial and humanitarian logistics, there are research gaps that must be completed in order to improve both humanitarian logistic efficiency as well as realism of mathematical models designed to support it, since humanitarian logistics is such a wide field is impractical to pigeonhole it as a single definition of operational conditions and relate it to logistic management. On one hand there are humanitarian logistic efforts for long term disaster recovery, and humanitarian aid, where operational efficiency, similar to commercial logistics, is a primary consideration. Among other types of problems, humanitarian logistic operations after a disaster implicate disaster response with recovery activities of short term, where a very different operational environment is observed, very often absorbed by chaotic realities where urgent needs, life or death decisions, and management of resource shortages are priorities.

In this article, we conduct a detailed analysis and classification of the literature that would allow to face emergencies by means of humanitarian logistics, providing a global and specific outlook over results and conclusions obtained by many qualitative as well as quantitative studies (the latter based on mathematical models to represent all issues and impacts associated with the emergency) provided by researches on this field. For this, together with a exhaustive literature review, we present classification criteria and analysis of research gaps in order to guide the development of future work in this field in terms of: social and human-organizational behaviour aspects, coordination and roles in multiobjective environments, convergence of materials and organization failures, application and political and/or cultural issues, treatment of uncertainty and/or risk aversion, systems dynamics and integration in phases prior to and after the emergency. In addition to that, methodological aspects of interest are detailed, such as resolution and logistic decision-making mechanisms, types of emergencies, and nature of the data used in numerical studies.

Finally, considering the dimensions previously pointed out, a comprehensive work framework is proposed for the development of future research, based on pending challenges (both in scientific research field and in realistic proposals for handling emergencies), focusing on how to address relevant aspects, such as classification criteria, data sources, stakeholders, modelling approaches, optimization techniques and transference of results.

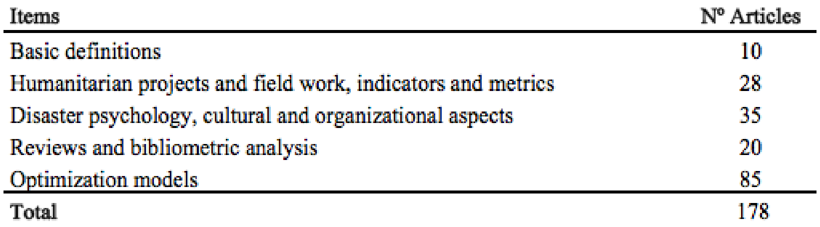
The review is organized as follows: In the next section a through bibliographic revision in regard to general concepts of humanitarian logistics and emergency management is developed, emphasizing the main differences with commercial logistics differences. Then, the sociotechnical system triggered by a disaster is described in terms of logistics management, highlighting the fact of explicitly incorporating theories and models coming from social sciences and disaster psychology. An analysis of diverse contributions proposed in the literature and disaster logistic papers is presented next, particularly presenting the topics discussed in previous bibliographic revisions. Then, a set of studies are chosen to focus on optimization models and objective functions, proposed constraints, mathematical structures and social or organizational considerations of the problem, dynamic nature, competence, stakeholder collaboration and coordination, stochastic nature, uncertainty and risk, multiobjective approaches and empiric nature. Finally, we conclude with research gaps and opportunities to tackle problems related to humanitarian logistics in a systematic manner and with appropriate models

1.2. LITERATURE REVIEW

People and organizations are relevant for every humanitarian process. Reviewing humanitarian logistics articles, we realize that human behaviour and disaster psychology are aspects not properly integrated in the specialized literature so far. Articles where humanitarian logistics is addressed through optimization models, including diverse revisions available in the literature, as well as studies, problems and specific models in structure, assumptions, solution methods, etc., are analysed from that perspective.

Thus, by taking into consideration the importance of the application of these studies, a revision of documents and studies related to indicators, metrics, and humanitarian projects are incorporated in the literature review, which may be used as reference at the moment of analysing the impact that different initiatives related to humanitarian logistics of communities effected by natural emergencies may have. This is a relevant point for this revision, as it is observed, many articles aim rather to academic improvements and not necessarily to a political, social and/or economic context where researches would provide applied solutions.

Overall, 178 articles were reviewed, classified in the topics mentioned above (see Table 2.1), taking in consideration platforms, databases and articles thoroughly analysed in relation to the humanitarian logistic field study, from the beginning of 2010 up to date, out of more than 80 scientific journals whose details are presented later on.



Items	Nº Articles
Basic definitions	10
Humanitarian projects and field work, indicators and metrics	28
Disaster psychology, cultural and organizational aspects	35
Reviews and bibliometric analysis	20
Optimization models	85
Total	**178**

Tabla 1.1: Bibliographic revision, topics and articles

1.2.1. PREVIOUS LITERATURE REVISIONS

Regarding former reviews of humanitarian logistic research, it is noteworthy the effort that different authors have conducted to establish the foundations on which challenges and gaps are built for future research works, over which the present work outspreads and integrates ideas to a framework that allows tackling problems under a systematic outlook.

Altay y Green (2006) revised the literature in order to address possible research directions in disaster operations, identifying that one of the main activities in the affected areas are humanitarian logistic operations, which can be defined as the process of planning, implementing and controlling flow, as well as the effective storage of goods and materials. Moreover, humanitarian logistic operations require data from the point of origin up to the point of consumption, in order to comply with the final requirements of people affected by the disaster. Overstreet *et al.* (2011) reviewed 51 articles published until 2009, classifying the literature using eight logistics key elements which are: staff organization, equipment and infrastructure, transportation, information and communications technology, planning, policies and inventory management procedures. On the matter, the authors developed a research framework, defining and delimiting system, boundaries, primary and secondary entries and humanitarian logistics outcomes.

Among other revisions, De la Torre *et al.* (2012) provided guidelines for practical application of optimization models available in the literature, classifying optimization models in terms of allocation policies, needs assessment, supply and demand uncertainty, vehicles and roads. Caunhye *et al.* (2012) reviewed 74 articles about optimization models in emergency logistics, which are studied in terms of types of models, decisions, objectives and constraints.

Kunz y Reiner (2012) used a content analysis methodology to cover humanitarian logistic literature, analysing 174 works published in 68 journals up to 2011. Liberatore *et al.* (2013) presented the main concepts used in emergency and disaster management through a revision of the literature related to models and support systems for aid decisions applied to humanitarian logistics, classifying works according to the phase considered in the disaster management, and the specific problem addressed. They also highlight the different ways to tackle the uncertainty in the context of disaster management.

Huang *et al.* (2012) pointed out that literature can also address more complicated problems of relief supply allocation, capturing complexities inherent to humanitarian relief, including multiple raw materials, multiple transport modes or types of vehicles, multiple periods, supply and demand uncertain levels or variables, transportation network conditions and delivery time windows.

Holguín-Veras *et al.* (2013b) conducted a work where humanitarian logistic models are assessed in virtue of objective functions and the incorporation of social aspects related to human suffering, including allocation, distribution and routing issues.

Özdamar y Ertem (2015)) analysed mathematical models developed in humanitarian logistics, classifying them in terms of vehicle representation structures, networks and their functionality, discussing relationships between these characteristics and the model size, detailing objectives, constraints and structures of mathematical models, as well as solution methods. In addition, they studied information systems applications and integration of models with IT.

Leiras *et al.* (2014), aim towards identifying trends, suggesting some directions for further research, where 228 articles were reviewed, prompting a more extensive review in this area. Seven classification criteria are proposed, highlighting the perspective of stakeholders and coordination. Hoyos *et al.* (2015) provided a literature revision about mathematical models applied to disaster operations management considering uncertainty, analysing techniques used by different authors to deal with stochasticity.

Mora-ochomogo *et al.* (2016) conducted an analysis of key features related to inventory management for humanitarian operations, classifying the papers according to crucial criteria and identifying trends, gaps and challenges, finding that the less-considered features in the literature are human resources variability, different political and cultural affairs, expiration and obsolescence. The most relevant detected critical aspects of inventory management in this context are: delivery times, number of items, backlogging, donations uncertainty, shortages and/or surplus, prioritization, supplier's development and store locations.

Another work to highlight is Gutjahr y Nolz (2016), who reviewed recent literature about multi-criteria optimization applied to natural disaster management, epidemics or other forms of humanitarian crisis. Different optimization criteria are discussed as well as multi-criteria decision-making approaches applied to this field. Literature available is classified according to several attributes, such as emergency stage, techniques used (multiobjective optimization, lexicographic optimization, scalability, goal programming, analytic hierarchy process, etc) and objective function components (such as cost, time, coverage, reliability, safety, equity, distress, psychological costs).

Karagiannis y Costas (2016) discussed software solutions developed in the phase of preparation to an emergency in order to reduce uncertainty during the response and expedite the operational planning process.

Finally, Boonmee *et al.* (2017), provided a summary of facility location problems in relation to emergency humanitarian logistics, classifying models, type of problems, disasters, objectives, constraints and solution methods. He looked over the layout of facilities prior to and after the disaster, considering the distribution of stores, shelters, debris elimination sites and health centres.

1.2.2. Humanitarian logistic definitions and context

Humanitarian activity includes logistics support derived from phases prior to and after the occurrence of a natural or anthropic disaster. A disaster can be defined as a non-routine event which exceeds the capacity to respond of the affected zone in such a way that lives can be saved, properties can be preserved, and social, economic and political stability can be maintained in the affected region. In some cases, it is referred as catastrophe, where most part or the whole structure built by the community is strongly impacted, facilities and operational bases of most emergency organizations are affected by the event, local officials cannot perform their usual jobs, aid from nearby communities cannot be provided, and most, if not all, daily tasks of the community are simultaneously interrupted severely (Wachtendorf *et al.*, 2010). In what follows, we will refer to an emergency, which could be a disaster or a catastrophe depending on the intensity of the effects described

Van Wassenhove (2006) classified disasters in four types: (i) Sudden, abrupt and natural: such as earthquakes, tornadoes or hurricanes; (ii) of a natural and slow onset, such as famine, drought and poverty; (iii) from a sudden man-made onset, such as a terrorist attack or a coup d'état; (iv) and slow man-made onset, such as political crisis.

Despite this wide list of situations where humanitarian logistics take place, Scarpin y De Oliveira Silva (2014) pointed out that humanitarian logistics is an emerging field, in which more rigorous empiric research should be conducted, mainly in developing countries. In fact, Kovács y Spens (2009) pointed out that about 80 per cent of costs related to humanitarian aid can be allocated to material costs plus delivery costs. Therefore, they are classified as logistics costs, and there are several proposals to build objective functions to support decision making about them.

There is a clear economic impact on decision-making and activities derived from humanitarian logistics. Then, the processes of planning, implementation and control, all focused on relief vulnerable people's suffering at a low-cost of movement of flows along with storage of goods, from point of origin to point of consumption (Blecken, 2010; Scarpin y De Oliveira Silva, 2014). Then, an array of activities must be considered which includes planning, preparation, transportation, acquisition, storage, monitoring and tracking (fleet, supply and people), similar to what has traditionally been observed in commercial logistics.

Some authors such as Halilagic y Folinas (2016)have identified principles and practices of supply chain management (SCM) and lean thinking (LT), inherent to the commercial scope, that can be adapted to humanitarian operation as illustrated in Figure 2. Application of these principles and tools must emphasize the differences with a traditional-commercial logistic process.

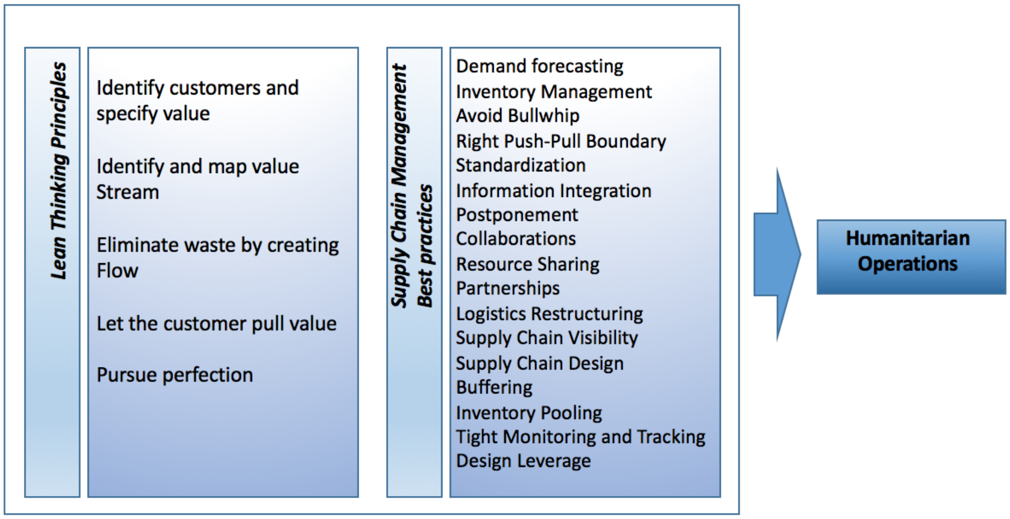


Figura 1.2: LT and SCM principles applied to humanitarian logistics - fuente: Halilagic y Folinas (2016).

Humanitarian logistics presents substantial differences with respect to commercial logistics. Holguín-Veras *et al.* (2013a) pointed out that commercial logistics is mainly focused on optimization of different manufacturing, distribution and waste recovery stages comprising a wide array of activities that need specific analytical models. However, humanitarian logistics comprises a wide array of activities occurring in any of the emergency management phases, including preparation, mitigation, response and recovery when a disaster or catastrophe occurs (FEMA, 2007).

Thus, within the humanitarian context logistic activities can be considered as sociotechnical processes. Around these activities, seven key components are identified which makes evident the differences with the commercial scope, namely: pursued objectives, origin of flow of goods to be transported, knowledge about the demand, decision-making structure, periodicity and volume of logistic activities, status of social networks and support systems (Holguín-Veras *et al.*, 2013a). Moreover, Van Wassenhove y Martinez (2012) pointed out that humanitarian logistics must represent three basic humanitarian principles: neutrality, impartiality and humanity. *Neutrality* means that humanitarian stakeholders should not take part on neither hostilities nor political, racial, religious, ideological nature controversies; *impartiality* means that humanitarian actions must be conducted only based on the need, giving priority to the most urgent cases of distress and not making differences based on nationality, race, genre, religious belief, social class or political opinion; finally, the principle of *humanity* establishes the purpose of protecting life and health, guaranteeing the respect for human beings

In addition, the intertemporal characteristics of disasters and humanitarian logistics prime a transitory nature to the work of preparation and response, mainly conducted by volunteers participating for limited periods of time. This feature hinders the collection of experiences for the development of knowledge (Holguín-Veras *et al.*, 2015). We also highlight the fact that each disaster is unique, and every relief organization has its own set of practices and policies to face a disaster (De la Torre *et al.*, 2012).

Recalling the sociotechnical nature of humanitarian logistics, logistic activities imply convergence of three complementary components: a social network, technical activities conducted by this network and underlying support systems (Holguín-Veras et al., 2013a).

1.2.3. Challenges in modelling

As the pursued objectives are not exactly the same as those of traditional commercial logistics, the decision-making structure in humanitarian logistics has its own nature. This is observed in aspects such as: Little standardization or uncertainty regarding supply and demand information, changes in the status and available capacity of the network for distribution and routing, high fragmentation of storage and generation of aid streams, little coordination and materials convergence, strongly decentralized decision making, misaligned incentives, intertemporal effects, human suffering and social network participation (Blecken, 2010; Holguín-Veras *et al.*, 2007, 2012, 2013a, 2013b).

Such aspects add a set of difficulties and challenges to the process of abstraction, inherent to modelling and mathematical representation of objective functions and ad-hoc constraints in case of humanitarian logistics. In addition to the above, and given that decisions involve sociotechnical processes, it must be considered the features, conditions and context of people, societies, cultures and institutions involved in the occurrence and assistance of an emergency.

Kovács y Spens (2011) indican que, una de las principales preocupaciones de la investigación logística humanitaria es trabajar con datos empíricos para el modelamiento, a través de encuestas, estudios de casos o investigación cualitativa; por ejemplo, incluyendo estudios longitudinales, análisis de encuestas, desarrollo de marcos genéricos (Pettit y Beresford, 2009) y teorías (véase Jahre *et al.* (2009)).

This explains that many studies in the humanitarian logistics literature use primary source contributions, namely, sources registered by witnesses of a fact or an even. Thus, most of the research has been performed through in-depth interviews and surveys conducted directly to people involved in relief efforts, together with collection, revision and analysis of news and reports generated by agencies and institutions involved in management of the emergency studied (Holguín-Veras *et al.*, 2007, 2012; Gralla *et al.*, 2014; Aldunce *et al.* 2014, 2015; Sheu, 2014).

Kovács y Spens (2011) pointed out that some major concerns regarding research in humanitarian logistic are related to the use of surveys, case studies, or qualitative research based on empirical data for the analysis and modelling humanitarian logistics ((Pettit y Beresford, 2009); Jahre *et al.* (2009)).

Some authors such as Anaya-Arenas *et al.* (2014); Caunhye *et al.* (2012) recognize that emergency logistic research is performed separately on decision making and solution approaches. Integrated models (combining different operations and decisions) are limited, as there are discrepancies on the pursued objectives of different levels of decision, as well as on the hypothesis built around supply and demand responses, planning horizons and the need to coordinate efforts.

The above explains that emergency logistic researchers seem reluctant to apply multiobjective models, and that they may find problems such as resource oversupply. This leads to difficulties in the coordination and aid efficacy, together with irregularities in the distribution and routing, as well as the creation of organizations not well structured, as it is discussed later in this review.

In terms of objective functions to build optimization models, minimization of logistic cost prevails, followed by minimization of penalties, considering weighting factors for multiple objectives, while minimization of unsatisfied demand comes as a third option in the literature related to humanitarian issues in emergency logistics (Holguín-Veras *et al.*, 2013b).

The same authors, together with Anaya-Arenas *et al.* (2014); Caunhye *et al.* (2012); Kovács y Spens (2011); De la Torre *et al.* (2012) suggested a set of tasks required to develop proper humanitarian logistics models, in terms of adequate definition of objective functions, variables, parameters and constraints, namely:

- Definition of adequate objective functions: There are discrepancies regarding metrics to be used in humanitarian logistic models, which must consider multiple philosophical and economic considerations inherent to human behaviour before a disaster or an emergency.
- Material convergence: There is an urgent need to systematically study and characterize diverse dynamics related to origin/nature of converging material streams, after

the occurrence of an emergency under an inadequate coordination.

- Decision-making structure: There are challenges in understanding of organizations, institutionalism and humanitarian operations, as well as tracking and assessing results through adequate indicators of efficacy, quality of service, efficiency, interactions and coordination.
- Knowledge of demand: It becomes necessary the estimation of resource requirements for demands generated by the emergency, incorporating estimation of immediate resource needs to support decisions on supply, allocation and transportation. In addition, updates from predefined scenarios or humanitarian logistic decision-making simulations are needed.
- Social aspects: There is still lack of effective incorporation of human behaviour and the functioning of social networks as parts of the response process when an emergency occurs. It is necessary to quantify vulnerability and resilience capacity of the communities, individuals and networks involved in humanitarian logistics.
- Decision support: Humanitarian logistic analysis provides support on decision making through optimization models aimed to: distribution, routing and inventory allocation, reverse logistic analysis and material convergence, pre-positioning and network planning prior to the emergency and dynamic resource allocation for post emergency management,

In what follows, we highlight recent literature stating the major challenges in this area, starting with the incorporation of social aspects from human behaviour and disasters psychology in the models. Then, contributions of the literature considering integration, collaboration, material convergence, dynamic aspects and uncertainty in humanitarian logistics problems, will be analysed. Different innovative objective functions used for proper humanitarian logistic formulations are then discussed in this review.

As shown in Tables 1.2 and 1.3, the relevant literature can be classified based on the aspects mentioned above, together with analysis of decision-making variables and integration of approaches in stages prior to or after the occurrence of an emergency. In what follows, we review each of the criterion summarized in Tables 1.2 and 1.3 highlighting the most relevant references and their contributions:

	№ Articles
Emergency stage	
Pre disaster	21
Post disaster	66
Integrated	18
Decisions	
Inventory	36
Location	36
Disribution	60
Routing	20
Other	49
Fleet	16
Unused stock	8
Capacity / acquisitions	6
Transportation injured / evacuation	9
Unsatisfied demand/ shortage	29
Time arrival	3

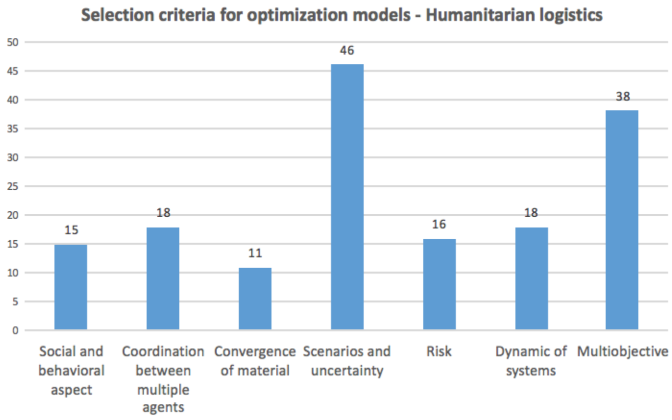


Tabla 1.2: Summary of humanitarian logistic optimization models

Authors	
Balcik 2016; Burkart et al., 2016; Gutjahr & Dzubur, 2016; Hu & Sheu, 2013; Hu et al., 2016; Khayal al., 2015; Kirac et al., 2015; Ni et al., 2017; Pérez-Rodriguez & Holguín-Veras, 2015; Pradhananga et al., 2016; Salmeron & Apte, 2010; Sheu, 2014; Vitoriano et al., 2011; Yushimito et al., 2012	Social and behavioral aspect
Adivar & Mert, 2010 ; Al Theeb & Murray, 2016; Bozorgi-Amiri et al., 2011; Burkart et al., 2016; Camacho-Vallejo et al., 2014; Campbell et al., 2011; Davis et al., 2013; Fereiduni et al., 2016; Fetter & Rakes, 2012; Garrido et al., 2015; Gutjahr & Dzubur, 2016; Lin et al., 2011; Lorca et al., 2016; Nagurney et al., 2016; Najafi et al. 2013a; Najafi et al., 2014; Ozdamar & Demir, 2012; Ransikarbum & Masona, 2016; Sheu, 2014	Coordination between multiple agents
Davis et al., 2013; Fetter & Rakes, 2012; Hu & Sheu, 2013; Hu et al., 2016; Kelle et al., 2014 ; Lorca et al., 2016; Ni et al., 2017; Rawls & Turnquist, 2010; Rezaei-Malek & Tavakkoli-Moghaddam, 2014; Tofighi et al., 2016; Zhang et al., 2012	Convergence of material
Adivar & Mert, 2010; Barzinpour et al., 2014; Ben-Tal et al., 2011; Bozorgi-Amiri et al., 2011; Campbell et al., 2011; Davis et al., 2013; Garrido et al., 2015; Haghi et al., 2017; Hong et al., 2014; Hu et al., 2016; Irohara et al., 2013; Kelle et al., 2014; Klibi et al., 2017; Kulshrestha et al., 2011; Li et al., 2012 ; Liberatore et al., 2014; Lin et al., 2011; Liu & Zhao, 2012; Manopiniwes & Irohara, 2016; Maya et al., 2016; Najafi et al. 2013a; Najafi et al., 2013b; Najafi et al., 2014; Ni & Zhao, 2014; Ni et al., 2017; Noham & Tzur, 2017; Noyan et al., 2016; Ozdamar & Demir, 2012; Pradhananga et al., 2016; Ransikarbum & Masona, 2016; Rawls & Turnquist, 2010; Rawls & Turnquist, 2012; Rennemo et al., 2014; Rezaei-Malek & Tavakkoli-Moghaddam, 2014; Rottkemper et al., 2012; Sahebjamnia et al., 2017; Salmeron & Apte, 2010; Sheu, 2010; Taskin & Lodree, 2011; Tofighi et al., 2016; Vitoriano et al., 2011; Zhan & Liu, 2011; Zhan et al., 2014; Zhang & Jiang, 2013; Zhang et al., 2012	Scenarios and uncertainty
Adivar & Mert, 2010 ; Ben-Tal et al., 2011; Bozorgi-Amiri et al., 2011; Fereiduni et al., 2016; Haghi et al., 2017; Hong et al., 2014; Hu et al., 2016; Kelle et al., 2014; Klibi et al., 2017; Kulshrestha et al., 2011; Najafi et al., 2013b; Ni et al., 2017; Nolz et al., 2011; Rezaei-Malek & Tavakkoli-Moghaddam, 2014; Tofighi et al., 2016; Zhang & Jiang, 2013	Risk Protection
Khayal al., 2015; Kirac et al., 2015; Li et al., 2012; Liu & Zhao, 2012; Maya et al., 2016; Najafi et al. 2013a; Najafi et al., 2014; Ni & Zhao, 2014: Noyan et al., 2016; Ozguven & Ozbay, 2012; Peng et al., 2014; Rawls & Turnquist, 2012; Rottkemper et al., 2012; Sahebjamnia et al., 2017; Sheu, 2010; Zhan et al., 2014; Zhang et al., 2012	Dynamic of systems
Adivar & Mert, 2010 ; Barzinpour & Esmaeili, 2014; Barzinpour et al., 2014; Ben-Tal et al., 2011; Bozorgi-Amiri et al., 2011;Burkart et al., 2016; Camacho-Vallejo et al., 2014; Fereiduni et al., 2016; Gutjahr & Dzubur, 2016; Haghi et al., 2017; Hu et al., 2016; Irohara et al., 2013; Klibi et al., 2017; Kulshrestha et al., 2011; Li et al., 2012; Liberatore et al., 2014; Lin et al., 2011; Liu & Zhao, 2012; Manopiniwes & Irohara, 2016; Najafi et al. 2013a; Najafi et al., 2013b; Najafi et al., 2014; Ni et al., 2017; Nolz et al., 2011; Ransikarbum & Masona, 2016; Rath & Gutjahr, 2014; Rath et al., 2015; Rennemo et al., 2014; Rezaei-Malek & Tavakkoli-Moghaddam, 2014; Rottkemper et al., 2012; Sahebjamnia et al., 2017; Salmeron & Apte, 2010; Sheu, 2010; Tofighi et al., 2016; Vitoriano et al., 2011; Zhan & Liu, 2011; Zhan et al., 2014; Zhang & Jiang, 2013; Zhang et al., 2012	Multiobjective

Tabla 1.3: Summary of papers and humanitarian logistic optimization models

1.2.3.1. Social aspect and human behaviour

The first challenge in modeling humanitarian logistic processes is including the social cost to the objective functions (Holguín-Veras *et al.*, 2013b). The social component in the objective function is characterized by Holguín-Veras *et al.* (2013,2016) as the minimization of human suffering, considered in many cases through equity constraints, such as: maximum allowable time for delivery, minimum amounts of delivery and multiple ways to satisfy the incoming demand. Other approaches simply pursue the minimization of insatisfied demand, or the maximization of delivered loads, not taking into consideration the amount of time that a population could be without receiving supplies (Holguín-Veras *et al.*, 2013b; Dore y Singh, 2013).

Holguín-Veras *et al.* (2013b) state that most of support models for decision-making on humanitarian logistic, should be reformulated to explicitly consider logistic costs, as well as social impacts of product and service delivery. Social costs should include opportunity costs and intertemporal benefits of deprivation and suffering related to waiting (Varian, 1992; Holguín-Veras *et al.*, 2013b). Within this framework, three main agents can be distinguished at any point of the network: relief groups, aid beneficiaries and individuals who do not receive aid for the entire post-emergency planning horizon (Holguín-Veras *et al.*, 2007, 2013a, 2013b).

Conceptually, deprivation cost is defined as the economic value of human suffering caused by lack of access to a good or service. As such, it is likely that deprivation cost may be a function of deprivation time and of the individual's socioeconomic characteristics, for instance, age, genre, physical condition (Holguín-Veras *et al.*, 2013a, 2016). In addition to logistics costs, social cost can be computed as the sum of deprivation costs in the time that aid deliveries were conducted, plus the sum of deprivation costs for all pending demands at the end of the planning horizon (Holguín-Veras *et al.*, 2013a).

Then, it is necessary to empirically estimate the functions of deprivation cost, eliminating the need to use equity constraints as well as proxy indicators of human suffering, providing a better way to assess impacts from delivery actions. Holguín-Veras *et al.* (2016) used econometric techniques and stated preference experiments to obtain a function of deprivation for drinking water. It is worth to mention that a non-linear behavior of these functions was obtained, which is particularly relevant in the context of disasters, where people's lives involved are directly affected (Haghani y Oh, 1996; Lodree y Carter, 2016).

Deprivation costs are clearly relevant in the context of humanitarian logistics; therefore, it is necessarily the study of adequate methods to give value to life or to quantify the impact of human suffering under the conditions experienced after an emergency Maxwell D; Caldwell R (2008) focused on alimentary problems and the impact of food aid programmes in humanitarian emergencies; Byrne y Albu (2010) analysed the benefits of a tool developed to conduct market analysis in emergency situations; Ryckembusch *et al.* (2013) introduced an analytical tool to be used before the implementation of initiatives related to nutritional objectives, and to help identify the most profitable intervention; Gold *et al.* (2002) discussed the health-adjusted life years measures (HALYs) , which are used to estimate the impact of illnesses under an economic perspective.

In Chile, Ministerio De Desarrollo Social (2017) set a statistical value of life to be used in the National Investment System (Sistema Nacional de Inversiones -SNI) to establish social benefits due to projects that may reduce mortality rates. Moreover, the Statistical Value of Life is defined as the monetary valuation that society assigns to efforts for reducing the likelihood of people dying (Braathen *et al.*, 2010; de Blaeij *et al.*, 2000)

Recalling the analysis of objective functions, Gralla *et al.* (2014) suggested a careful analysis of the experts preferences to define a proper objective function to decide relief distribution strategies. Nevertheless, these functions are not explicitly incorporated into the humanitarian logistics objective functions, as it does occur with deprivation costs (Pérez-Rodríguez y Holguin-Veras, 2015).

Yushimito *et al.* (2012) provided ideas to localize a finite number of distribution centres that would provide a fast response time for disaster relief, incorporating social costs within a modelling framework. They proposed a model that maximises coverage of affected regions and minimizes human suffering using a social cost function. If further distances would imply greater deprivation time due to the cycle times (Holguín-Veras *et al.*, 2013a), deprivation time can be set in terms of distance, using a function of urgency that grows with the distance, provided that its growth represents an increase of time of the aid delivery.

Hu y Sheu (2013) presented a methodology to minimize not only disaster logistic costs but also the psychological trauma experienced by people affected by an earthquake while they were waiting for aid. In this work, the psychological stress induced during the reverse logistic process of waste, is computed as the integral of a marginal function of waiting time for medical treatment and waste disposal. Incremental psychological intensity generated by the waiting can also be calculated using formulas for psychological cost of waiting time for service systems, through multivariate regression models (Egna, 1995; Osuna, 1985).

Other objective functions have been conceived through concepts found in the psychology of a survivor. For example, Sheu (2014) proposed structural equation models and empirical studies, building a survival-attitude-resilience conceptual model which establishes the emergency logistic operational decisions. This work characterizes the attitude of survivors towards emergency logistic responses by the government, in both, cognitive and affective domains. Here, resilience refers to the capacity of a survivor to face adversity and to recover, psychologically and physically, from an emergency (Aldunce *et al.* 2014, 2015).

Aldunce *et al.* (2015) collected and classified the studies about resilience in the face of a disaster. We can mention community resilience (Paton *et al.*, 2001), psychological aspects of personal resilience to the emergency (Paton *et al.*, 2000), institutional resilience (Tompkins, 2005), urban resilience (Godschalk, 2003), social and community resilience (Tobin, 2011), economic resilience (Handmer y Hillman, 2004), political resilience (Barnett, 2001), and socioeconomic resilience in emergency management(Adger *et al.*, 2005; Berkes, 2007; Renaud *et al.*, 2010). For revisions of resilience definitions in the face of an emergency, please refer to (Bahadur *et al.* (2010); Buckle (2006); Djalante y Thomalla (2011); Norris *et al.* (2008)).

Another relevant aspect within the conceptualization of resilience in the face of an emergency is the capacity of preparation to mitigate, prevent and minimize losses, suffering, and social disorganization (Bruneau *et al.*, 2003). It is worth stressing that decision makers linked to humanitarian logistics and emergency management have started to include resilience ideas as a core element in international documents, policies and programmes at national level (Djalante y Thomalla, 2011).

Despite the above, and as it is argued by Aldunce *et al.* (2014, 2015), the application of the resilience concept to natural emergencies has happened without enough theoretical and empirical foundations in social sciences. Then, this concept becomes ambiguous, and therefore, its use in humanitarian logistics is unclear and it creates controversy. Only over the last decade, the concept has gained more attention and credibility in the field of disaster and logistics management (Moser *et al.*, 2008), mainly after the adoption of the "Hyogo Framework for Action 2005-2015: Strategy for Disaster Reduction"(UN / EIRD, 2007).

Another aspect to consider is that resilience is preceded by vulnerability levels in the groups affected by the emergency. Hence, to asses vulnerability of people and communities it is important to include variables that represent personal and collective conditions of people and the communities in the face of emergencies, such as living conditions and recovery, social and communities' self-protection (for instance, mitigation strategies), social and political networks, etc. An additional group that is recognized as vulnerable corresponds to immigrants and ethnic minorities. Nonetheless, few researchers have studied these groups within an emergency context (Repetto, 2016).

Finally, the theory of resilience emphasizes allows to visualize emergencies as opportunities to continuously review the management system and look for conditions that may contain lower risk levels after each emergency. Thus, humanitarian logistics and resilience management can be seen not only as a source of opportunities to be better prepared, adapted and be proactive, but also to innovate in emergency response, although this challenges powers of interest or alter the status quo (Aldunce *et al.*, 2014).

The social aspect is, therefore, a a relevant issue that has to be incorporated in the formulation of support models for humanitarian logistics decision making. Afterwards, there is a clear challenge in the integration of disaster psychology with the documents and experiences collected in the sites, which should enrich the humanitarian logistics formulations and strategies of aid (Holguín-Veras *et al.*, 2013b). In humanitarian situations, the operations conducted are in charge of the national and/or local government, which implies that political and ideological affairs would inevitably take part on the situation (Mora-ochomogo *et al.*, 2016).

1.2.3.2. Material convergence, network structures, planning and response coordination

A factor that has been identified as an eventual "second disasterïs convergence, since in post emergency logistics there might be hundreds or even thousands of formal or informal/improvised supply chains interacting, they overlap, cooperate or even compete for limited resources and try to help (Holguín-Veras *et al.*, 2013a). Within this context, convergence is referred to the "mass movement of people, messages and supplies to the area affected by the emergency", including staff convergence (movement of individuals), data convergence (movement or transmission of symbols, images and messages), and material convergence (actual movement of supplies and equipment), as well as the affluence of other observers and looters in zones affected in the aftermath of an emergency (Fritz y Mathewson, 1957). Material convergence is also issue due to the accumulation of emergency supply and equipment in an exorbitant amount destined for relief goals (Holguín-Veras *et al.*, 2014).

The nature of convergence, especially in the case of aid materials and supplies, requires an analysis of the underlying factors that influence the behaviour of donating, both at individual as organizational level (Holguín-Veras *et al.*, 2014, 2015), situation that makes difficult to quantify converging amounts. Destro y Holguín-Veras (2011) conducted a first quantitative analysis of the topic and estimated material convergence generated by hurricane Katrina, using data extracted from post-processing of media articles; they analysed reported donations after hurricane Katrina and estimated monetary and goods donations with econometric models.

As that catastrophic events are often characterized by an increase of non-requested donations and spontaneous volunteers that present a logistic problem to the officials, a set of obstacles in organization planning and coordination is observed, adding difficulties to the work by formal staff and specialized crews (Lodree y Carter, 2016). Very often the information about resources available and contributions from suppliers can be unpredictable (Kovács y Spens, 2007).

Traffic congestion, as well as other phenomena that are direct consequences of convergence, obstruct relief efforts organized by humanitarian agencies such as the Red Cross, including other professionals' organizations in emergency management, characterized by the police force, fire-fighters and emergency medical technicians, among others (Holguín-Veras *et al.* 2015, 2014; Lodree y Carter, 2016).

Generally, there is pressure by donors towards relief agencies, trying to show that promised aid and goods are quickly arriving to the affected population (Van Wassenhove, 2006). In relation to convergence, some proposals have come up in the literature aiming at a previous assessment of needs, and the corresponding communication with relief chains.

Balcik (2016) addressed the selection of sites and routing decisions by a team in charge of conducting an evaluation of the post-emergency conditions of diverse community groups with different characteristics (for instance, ethnicity, income level, etc.), for a specific period of time. This problem called Selective Assessment Routing Problem (SARP), determines the sites to be visited and the order of visits, ensuring enough coverage for a given set of features. Lodree y Carter (2016) presented the Donation Collections Routing Problem (DCP) for the management of the operations after a disaster, related to material convergence and volunteers, whose objective is to assist on traffic congestion after an emergency through the design of a process where donors deliver goods into collection centres located in safe places out of the affected areas. Within this context, DCP does not pretend to reduce or eliminate convergence, but to present an alternative set up to assist management of traffic stream resulting from the number of vehicles travelling to the affected areas.

Coordination and Cooperation

Another relevant aspect of convergence reduction or elimination is: coordination and cooperation. The actors involved in large-scale emergency management, very often involve many stakeholders such as non-governmental organizations (Red Cross), several local governmental agencies, state or federal (for instance, Federal Emergency Management Agency-FEMA in USA); faith-based organizations (churches and religious groups), and private sector companies (local stores close to the emergency site). Some organizations work autonomously, providing specialized products (food, water) or services (medical care, shelter), while some others work at a wider collaborative structure lead by either a governmental authority of the affected zone or by a coordinating entity (Davis *et al.*, 2013 ; Holguín-Veras *et al.*, 2014).

An example where coordination is important is in the last mile distribution problem, which is defined as the final stage of a humanitarian aid chain, where the main tasks are the allocation of relief supplies, vehicle delivery scheduling and routing of vehicles. Limitations can come up with transportation resources and emergency supplies, damaged transportation infrastructure and lack of coordination between relief agents (Balcik *et al.*, 2008a).

Nagurney (2016) pointed out that most of the studies have been focused on centralized decision making, not having enough knowledge regarding cooperation or competence related to service provisioning or critical supplies. The author defined an equilibrium model related to the provision network for emergency relief, formulated as a variational inequality problem, from which they finally build a collaborative system optimization model. Then, they studied the effect on a case analysis about personal protective equipment supply delivery, within the context of the Ebola humanitarian crisis in Eastern-Africa.

Davis *et al.* (2013) wrote up the first document in the field of preparedness that considers emergency coordination and planning through inventory management, in an area almost unexplored. A stochastic programming model is proposed to determine how supplies should be located and distributed in a network of collaborative stores (specific coordination structure characterized by provision of capacity or storage space and inventory associated with relief supplies); in the model, specific constraints imposing equity in service are incorporated. Also, they consider traffic congestion resulting from a possible evacuation behaviour and time constrains to provide an effective response. Within a post emergency context, Özdamar y Demir (2012) proposed a hierarchical clustering and routing procedures to facilitate vehicles coordination in distribution activities and large-scale evacuation after the emergencies.

Coordinated activities must come together with indicators that would allow computing network performance with multiple agents. Balcik *et al.* (2008b) pointed out that there are three main performance indicators in humanitarian supply chains: (i) resources and how to measure their effective use, through distribution costs, inventory obsolescence, number of employees per aid beneficiary, etc.; (ii) outlet performance, measured by the average response time, amount of supplies delivered, delivery rate of achieved aid, average level of pending orders, etc.; (iii) flexibility, in the sense of bein able to modify the capacity of response, quantified through minimum response time, combination of supplies per period, etc.

Mitsakis *et al.* (2016) defined criticality indicators of the network as a measure of its performance, in the context of emergency management, using as case study the highway network of the Peloponnese region, Greece. There is an open field for research in emergency distribution and evacuation that is related to graph theory and complex network analysis, to identify features of networks affected by emergencies along with proper indicators to assess network performance.

Multi-stakeholder models and game theory

A control mechanism for coordination would be more efficient using mathematical models considering the confluence of different stakeholders. This is a type of problem that can be presented as a two-level programming problem or a leader-follower Stackelberg game, where a leader (top decision-making level) is the planner of facilities and the follower (lower decision-making level) is the set of users of the network.

On the matter, Camacho-Vallejo *et al.* (2015) formulated a two-level mathematical programming model for humanitarian logistics with the objective of optimizing decisions related to international aid distribution after a catastrophic disaster. It must be considered that non-profit international organizations and foreign countries offer aid by shipping certain necessary items, such as bottled water, food, medicines, therefore shipping costs should be minimized. At the same time, the affected country looks for distribution of the aid received to deliver it in the most efficient and fastest way possible to the affected zones. In this study the bilevel model is reformulated and it is reduced to a single level non-linear mathematical model, and then to a mixed integer programming problem.

Rath y Gutjahr (2014) considered the problem of distribution and vehicle routing associated with storehouses where the external aid is received and kept. A multiobjective approach was proposed to minimize the cost of operating the centre and to maximize the satisfied demand. For this effect, they studied a three-objective problem, including medium and short terms economic components and a medium-term humanitarian component, which considers fixed costs for storehouses and vehicles, transportation cost from plants to storehouses and storage cost, as well as the non-monetary benefits of maximizing the met demand.

Gutjahr y Dzubur (2016) built a bi-objective model of bilevel optimization including coverage and cost, and modelling a user equilibrium resulting from the individual cost minimization (with respect to travel costs and unsatisfied demand). The authors assume that distribution centres are subject to possible congestion effects; the model is extended to an stochastic user equilibrium considering imperfect information. Regarding stakeholders, top-level decision maker (an aid supplying organization) selects locations for relief distribution centres, while at lower level, beneficiaries choose a centre according to distance and level of supply expected.

Fereiduni *et al.* (2016), proposed a robust two-level model to optimize decisions related to distribution and evacuation aid after an earthquake. In this problem, foreign countries try to minimize their shipping costs and the affected country tries to minimize total local costs, including inventory, operations and transportation. This situation is a game between different decision makers after an emergency; a two-level model is proposed, where the affected country is the leader and the suppliers are the followers.

Reverse logistics

Regarding another aspect of the problem, the concept of reverse logistics is necessary to understand the best way of releasing the flow of supplies in this specific context. Krapp *et al.* (2013) and Agrawal *et al.* (2015) recognize necessities related to study a better implementation of return of products, externalization and humanitarian aid networks from the secondary market perspective. In figure 1.3 we summarizes the design of networks with reverse logistics, considering product acquisition, recollection, inspection, classification and disposition.

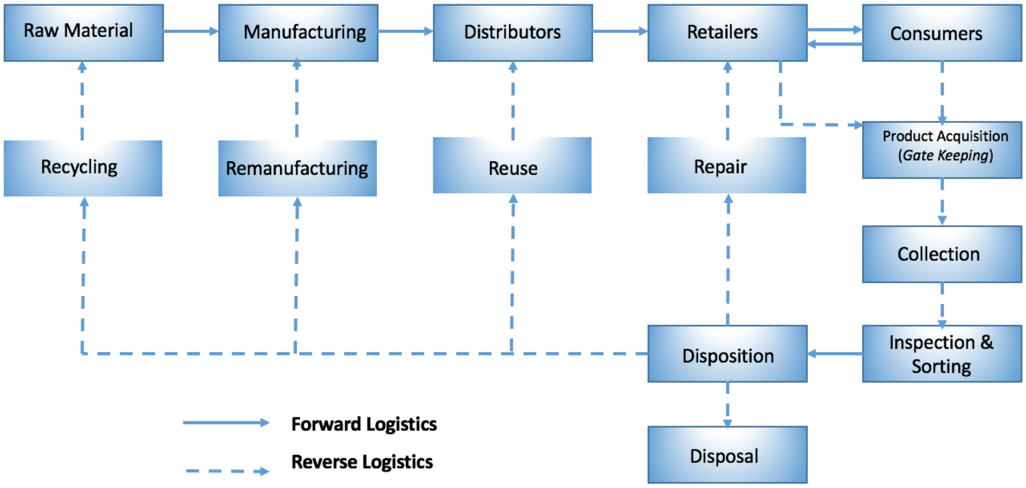


Figura 1.3: Traditional and reverse logistic flow and processes Agrawal *et al.*, 2015

Alshamsi y Diabat (2015) defined reverse logistics as a set of operations starting at consumer level with product recollection and ending up with the new processing of those products in re-manufacturing facilities. They built a mixed integer linear programming model to address the configuration of a humanitarian aid network system, where the decisions variables are the optimal locations of centres, capacity of inspection centres and re-manufacturing facilities, including transport considerations, offering the option to use internal fleet as well as the option of outsourcing.

Fetter y Rakes (2012) who studied waste reverse logistics after emergencies, focusing on the location of the facilities and logistic costs minimization. Hu y Sheu (2013) presented a waste reverse logistic system post emergency through the formulation of a multiobjective linear programming model in order to systematically minimize total reverse logistic costs, the corresponding environmental and operational risks, as well as the psychological trauma experienced by local residents.

1.2.3.3. INCLUSION OF UNCERTAINTY AND EXTENSIONS

Stochasticity can be present not only on the supply, as the existence of uncertainty on the number of available goods for distribution, but also on the demand. Uncertainty on supply can be the result of delays and losses of relief goods at multiple points of the relief supply chain. In case of the demand, that can unexpectedly fluctuate due to many sources. These sources include people who improved their situation and started being self-sufficient, beneficiaries moving around to find greater relief or unexpected challenges. Another variable of non-deterministic nature is the travel time of vehicles, which may also be subject to uncertainty (De la Torre *et al.*, 2012).

Typically, in these situations, two-stage stochastic programming models are used, integrating decisions of "here and now"type with later decisions of "wait and see"type. In order to model uncertainty of damage caused by disasters and its effect on supply and demand, the literature show different approaches such as multiobjective optimization, dynamic programming and sequential incorporation of events or scenarios, fuzzy programming, robust optimization.

Taskin y Lodree (2011) incorporated a hurricane forecast model within a Bayesian decision framework to address complex decisions made in response to a tropical cycle. The supply chain system is a single supplier and a set of demand points, where demand is a random variable affected by the trajectory of an observed hurricane. Ni y Zhao (2014) put forward a Markov decision model with the objective of maximizing life-saving through an emergency medical resource allocation problem considering injuries of diverse levels of priority for care, after a large-scale disaster.

Rawls y Turnquist (2012) consider pre-positioning of supplies to meet the demand of household at a short term (within 72hrs from the evacuation order). A stochastic programming model of several periods is presented, where first stage decisions determine where and how much relief supplies to provide, while second stage decisions deal with how supplies must be distributed during the 72 hrs after the emergency. The model incorporates constraints on the delivery of supplies due to: specific loading tariffs and vehicle dispatching, delivery delays based on distance between storage sites and demand locations, and reduction of transportation capacity as a result of damaged or destroyed transportation.

1.2.3.3.1. DYNAMIC PROGRAMMING .

An additional difficulty in emergency response planning is the fact that relevant logistic data can change during the response (Yi y Özdamar, 2007; Özdamar *et al.*, 2004).

Sheu (2010) improved relief demands in natural emergencies through a dynamic relief-demand management model, which includes imperfect data (which usually occurs in actual scenarios). His methodology is based on three steps: data aggregation to forecast relief demand in multiple areas, clustering (through a fuzzy clustering scheme) and multi-criteria decision making to classify the degree of urgency. Ben-Tal *et al.* (2011) used a robust optimization method and a cellular transmission model to formulate the traffic dynamic allocation issue with demand uncertainty depending on the emergency and rescue response time.

Liu y Zhao (2011) built a dynamic optimization model with time-variable demand, based on the epidemic spread rule SEIR - most of epidemics split people in four classes: susceptible people (S), exposed people (E), infected people (I), and recovered people (R) - on the small-world network. Ozguven and Ozbay (2012) proposed a comprehensive framework for the development of a humanitarian emergency inventory management based on real-time tracking of emergencies supplies and demands integrating emerging technologies such as RFID (Radio Frequency Identification Devices). The authors pointed out that this unified framework is robust with respect to transport system disruptions and unexpected increase consumption of vital products after an emergency.

Rottkemper *et al.* (2012) proposed an integrated approach of planning, relocation and distribution considering the current demand and possible future developments, through a mixed-integer programming model which has two objectives: to minimize unsatisfied demand and operational costs. Penalty costs for unsatisfied and uncertain demand are periodically increased. In order to include new information suggested during relief operations, the model is repetitively solved for each time period of the planning horizon (rolling horizon solution approach). The authors suggest to analyse a possible non-linear increase in penalty costs for uncertain unsatisfied demand, which concur with the ideas previously discussed in (Holguín-Veras *et al.*, 2013a).

Atasoy *et al.* (2012) consider the manufacture production/inventory issue (or a retailer) under a variable supply availability. Although supply availability is uncertain, the supplier may forecast shortages in the near future. It is considered the case of anticipated supply provided by the supplier. Customer's demand is deterministic but non-stationary, and system costs comprises orders fixed-costs, holding and pending orders. Therefore, a dynamic programming model is formulated, and an optimum inventory management policy is provided.

Peng *et al.* (2014) proposed a system dynamic model to analyse the behaviour of the relief supply chain through simulation. The authors also proposed a decision tree to assist decision makers to choose appropriate storage strategies.

Najafi *et al.* (2014), generated a dynamic version of the integrated last-mile transportation and distribution problem, with data updates through a dynamic model to dispatch and route of vehicles in response to earthquakes and transportation of basic items to the affected zones and hospitals. The model hierarchically minimizes total time up to hospital arrival for the wounded people, as well as total waiting time to meet basic demand needs. Kirac *et al.* (2015) formulated a routing problem with imperfect data updates (travelling salesman problem with imperfect information) obtained from social communication media.

Within the same simulation approach, Sahebjamnia *et al.* (2017) developed a Hybrid Decision Support System (HDSS) consisting on a simulator, a rule-based interference engine and a Knowledge-Based System (KBS) in order to configure three-level humanitarian aid chains, setting up locations for facilities, relief element allocation and distribution plan for previously generated scenarios.

Zhan *et al.* (2014) addressed the multiple suppliers relief allocation problem, where multiple stakeholders are involved in the aid, and multiple vehicles for emergency logistics. A multiobjective optimization model based on disasters' scenario data updates is proposed, attempting to coordinate efficiency and equity through timely and appropriate decisions about matters such as vehicle routing and relief allocation. The main contribution of this work is to solve the problem of relief allocation in a novel manner, correlating operational research and Bayesian sequential analysis.

Khayal *et al.* (2015) also considered a two-level supply chain in a network flow model for dynamic selection of temporary distribution facilities and resource allocation for emergency response planning. The model allows demand satisfaction delays when resources in a planning period are insufficient, and it allows transfer of resource surplus to a relief facility to another one within the forthcoming period with an objective function that minimizes the total social cost as the logistic costs and deprivation cost sum.

With regards transportation capacity loss at a network level, Maya Duque *et al.* (2016) considered the problem of programming emergency repair of a rural highway network that has been damaged by the occurrence of a natural disaster. Two approaches are developed for scheduling and routing the repair team that optimizes accessibility to cities and villages in need of humanitarian aid. A dynamic programming model was developed able to find optimal solutions to small and medium instances, and provides a fundamental structure outlook of the problem. Moreover, an Iterated Greedy-Randomized Constructive Procedure (IGRCP) was developed, which is able to solve medium to large-scale instances in very short computation time.

(Kirac *et al.*, 2015) proposed a formal method to quantitatively assess the impact of including non-verified information to the aid planning. There is a research field around communication detection and complex networks study that may be included in these models (Girvan y Newman, 2002; Clauset *et al.*, 2004).

1.2.3.3.2. USE OF SCENARIOS .

In many instances, scenarios are either designed by experts or based on limited historical data. These aspects make the model to completely depend on subjective judgement citepBozorgi-Amiri2013. In other studies, scenarios are generated by historical data and probability of occurrence. Activities prior to the event, are usually developed assuming future scenarios which must be characterized, decisions may be either common for all of them or could be defined for each one of them in case of occurrence, whereas decisions after the event usually include uncertainty coming from the lack of information or some ambiguity inherent to this uncertainty (Liberatore *et al.*, 2013). It is worth mentioning the existence of difficulties related to the estimation of supply and demand, the number of resources available and needed, as well as the exact demand location, supply and possible damaged infrastructure, among others (Hoyos *et al.*, 2015).

Rawls y Turnquist (2010) consider distribution, location and inventory decisions. The context for their work is based on hurricane scenarios faced in the USA gulf coast. A stochastic programming model was developed incorporating multiple raw materials, possibility of damage to highways and pre-positioned stores and supply.

Bozorgi-Amiri *et al.* (2013) developed a robust multiobjective stochastic programming for relief logistics in cases of uncertainty. Uncertainty is included in demand, supplies, acquisition and transportation costs. The objective function considers the total cost and met demand. A team of experts designed the scenarios, which needed subjective probabilities. A multiobjective model tries to minimize the relief chain expected value and total variance cost sum while it penalizes solution infeasibility due to parameters of uncertainty using compromise programming to reach into a solution.

Campbell y Jones (2011) assumed that each scenario consist of inventory losses or destroyed infrastructure for which historical data are not always available. The risk in this case would be reflected through a probability value related to each potential supply point, where any stored inventory will be destroyed or will be inaccessible during a period of time. These probabilities are estimated in different ways. For instance, they can be estimated using the distance to the ocean for hurricanes or the distance to the city center for possible terrorist attack. The model has two stages: In the first stage there is no decision about where to locate the inventory, but how much inventory should be stored in each retailer. In the second stage, the resource includes maintenance costs, shortages costs, redistribution costs and reordering costs.

Garrido *et al.* (2015) built a model that attempts to optimize inventory levels for emergency supply as well as vehicle availability to deliver enough supply to meet the demand with a determined probability. Emergency supply demand related to a disaster (in this case a flooding) is explicitly incorporated as a stochastic random variable with a proportional magnitude to the event intensity. Flooding occurrences are simulated through a stochastic process that incorporates the most prominent characteristic of a flooding: spatial and simultaneous temporal correlations, as well as flooding intensity, following the concept of exceedance probability (EP). The solution provides a strategic plan to be implemented before the flooding occurrence, as well as a tactical plan to deliver emergency supplies after the occurrence of the emergency.

1.2.3.3.3. Fuzzy programming .

There are other theoretical notions and models addressing imprecision, uncertainty, ambiguity, and partial knowledge in addition to the concept of probability. It is possible to process objects that belong to a category using fuzzy logic. It is not necessary to generalize the reality to classify it in classes; rather, a degree of membership for each category is given.

Due to the special features of disasters, there is not enough historical data, in most cases, to model uncertain parameters within each scenario as random data. Also, there is no repetition of disaster occurrence, and as such, it is difficult or even impossible to estimate probabilistic distributions for uncertain parameters. Therefore, in those situations we are faced to imprecise parameters whose imprecision comes from lack of knowledge of its exact values, creating epistemic uncertainty about these data (Tofighi *et al.*, 2016, Kabak y Ülengin, 2011, Pishvaee y Torabi, 2010).

At stochastic programming, the occurrence of each disaster scenario follows a stochastic process where each scenario has its own probability. Moreover, scenario-dependant parameters, together with scenario-independent parameters can be formulated as triangular possibility distribution or through fuzzy trapezoidal numbers to reflect its inaccuracy, among others (Tofighi *et al.*, 2016).

Utilization of fuzzy logic in disasters relief and emergency logistics was introduced by Hu y Sheu (2003), within the context of clustering and classification of the demand prior to a vehicle routing and distribution.

Stochastic programming assumes that the occurrence of each scenario (disaster) follows a stochastic process where each scenario has its own probability. Moreover, scenario-dependant parameters, together with scenario-independent parameters can be formulated as triangular possibility distribution or through fuzzy trapezoidal numbers to reflect its inaccuracy (Tofighi *et al.* (2016)). These authors proposed a two-stage Scenario-Based Possibilistic-Stochastic Programming (SBPSP), a method that combines traditional stochastic programming with fuzzy numbers to represent different uncertainties involved in the problem, seeking a decision about previous emergency supply positioning and distribution considering conditions prior to and after the emergency, also including decisions on location and capacity.

Barzinpour *et al.* (2014) formulated a bi-objective model where the first objective is to minimize transportation costs, installation costs and penalty costs due to lack of supplies, and the second objective is to maximize the satisfied demand. The model simultaneously determines location and allocation of relief distribution centres. Facilities will be established, and relief goods will be distributed to the beneficiaries of the affected zones, as a function of transportation costs, installation costs, inventory and demand fuzzy numbers.

Previous contributions in fuzzy programming include Adivar y Mert (2010), who optimized a relief distribution system under uncertainty using a multiobjective fuzzy model. Unlike other studies where relief operations performance is measured in terms of total cost and satisfied demand levels, here credibility is introduced and quantified using a non-linear fuzzy function.

1.2.3.3.4. ROBUST OPTIMIZATION .

Robust optimization models a possible set of values, but it does not say anything about its probabilities. The decision maker builds a solution that is admissible in a certain sense (for instance, almost optimum) for any realization of the uncertainty in the given set (Liberatore *et al.*, 2013). Robust optimization may be very efficient to search for the adequate and stable solution for any possible uncertain parameter (Mulvey *et al.*, 1995), expanding the stochastic programming field, which can include both decisions regarding risk and system stability.

Many studies propose two-stage stochastic programming models based on expected values. Nevertheless, we need to consider that expected values may not be enough for emergency events that rarely occur. Incorporating the risk concept is crucial to model uncertain variability inherent to relief systems in emergency cases (Van Wassenhove, 2006; Hong *et al.* (2015) proposed a stochastic model risk averse for a relief network design prior to a disaster, under uncertain demand and transportation capacities, determining sizes and locations of response facilities and relief supply inventory levels in each facility, guaranteeing a certain level of network reliability.

Najafi *et al.* (2013) proposed a multiobjective, multimodal, multiproduct and multiperiod stochastic model to manage critical logistic supplies and wounded people in response to an earthquake. A robust approach is developed and used to guarantee that the distribution plan will appropriately work on diverse situations that might occur in the aftermath of an earthquake. The proposed stochastic model combines three functions which are: total waiting time minimization (weighted) of unattended injured people, total time minimization (weighted) to meet basic product needs and minimizing total vehicles used in the response.

Zhang y Jiang (2014) presented a bi-objective robust model to design an efficient emergency medical service system. Location of services, assignment to demand areas and number of vehicles are detected simultaneously to balance costs and response capacity. A robust counterpart approach is proposed, where uncertainty is not described through a function of probability density or scenarios, but it is considered rather deterministic belonging to a set of uncertainty, since the decision maker pursues an optimal decision for all possible realizations of the set of uncertainty.

Rezaei-Malek y Tavakkoli-Moghaddam (2014) proposed a bi-objective mathematical model for humanitarian aid logistic operations planning where the first objective is to minimize the average response time while the second one try to minimize total operational costs, including stores settlement, unused supplies and unsatisfied demand costs. Survival of pre-established supplies, the demand level and conditions of routes after an event are considered as uncertain in the model, which is tackled with a robust scenario-based approach, to reduce uncertain parameter fluctuation effects in all possible future scenarios. Its resolution includes the Reservation Level Tchebycheff Procedure (RLTP) as interactive decision-making method.

Hu *et al.* (2016) studied the problem of resource allocation in a phase after the emergency from a resource centre. The emergency resource allocation model is robust, with two objectives that try to maximize efficiency and equity under different uncertainty sources, Furthermore, the authors expanded the optimization framework of Mulvey *et al.* (1995) to represent some uncertain parameters based on sets of uncertainties, while others based on scenarios; they developed an heuristic procedure to find a Pareto border along with a constrained decision method constrained by coefficient of equity and based on decision makers' preferences.

Ni *et al.* (2017) simultaneously optimized facility location decisions, pre-positioning of emergency inventory and relief delivery operations in a single disaster relief network of basic items. For this, they proposed a robust min-max two-stage model (prior to and after the emergency) where the sum of the first stage cost and the second stage cost are minimized, for the worst-case scenario among all possible realizations of uncertain parameters falling in a set of uncertainty. This approach is robust as it applies the min-max criterion to protect against all realizations of the set of uncertainties, related to the demand of each affected area, the provision of a usable inventory in each facility and the capacity of every highway link in the disaster relief network.

Haghi *et al.* (2017) built a multiobjective programming model to locate distribution centres of relief products and health centres together with the distribution of relief items and transfer of victims to health centres, with budget constraints for the logistics of goods for wounded prior to and after the disaster. This model maximizes the response level of the victims' medical needs focusing on fair distribution of relief items, minimizing total costs of preparedness and response phases with an array of available options to decide based on dispersion of the Pareto points and preference of the objectives.

Finally, and in the context of including the traffic phenomenon and user equilibrium, we highlight the work by Kulshrestha *et al.* (2011), who developed a robust two-level programming formulation based on location, allocation and distribution model, where it is presumed that the network traffic is under user equilibrium conditions and where a logit model is used for selecting shelters. This robust model allows to determine optimal shelter locations and capacities, from a determined set of potential sites, under demand uncertainty. The problem has a two-level structure. At superior level, a planning authority determines the number and location of shelters together with their capacities, while at the lower level, the evacuated choose shelters and routes to evacuate.

1.2.3.3.5. MULTIOBJECTIVE APPROACH .

Three different methods are mostly used for obtaining optimal solutions in the context of a multiobjective optimization problem. These are: A priori method, where decision makers specify their preferences before the search process; posteriori method, where decision makers specify their references after the search process; interactive method, which implies that decision makers specify their preferences during the search process.

Li *et al.* (2012) studied a two-level stochastic programming problem, where the top level consists of a model to locate and assign shelters, while the lower level chooses routes that will allow to meet evacuation needs from an array of possible hurricane events. A key element of the model is the explicit inclusion of the behaviour of drivers in route selection under a dynamic user equilibrium approach. Additionally, shelter locations and route selection decisions are made by two different decision makers: a facility planner that manages shelter facilities and a set of network users that try to minimize their travel time.

Another work considering traffic and user equilibrium is Kulshrestha *et al.* (2011), who developed a robust two-level programming formulation based on location, allocation and distribution models, presuming that the network traffic is at user equilibrium and that a logit model is used for selecting shelters. At top level, a planning authority determines the number and location of shelters together with their capacities, while at lower level, the evacuated choose shelters and routes to evacuate. The robust model allows to determine optimum shelter locations and their capacities, from a determined set of potential sites, under demand uncertainty.

Irohara *et al.* (2013) proposed a three-level programming model to tackle decisions on inventory pre-positioning, evacuation centres location and the assignment of communities to planning and preparedness centres. The interdiction framework instead of a stochastic or chance-constrained model, used in the three-level model presented in this work allows to consider the "worst case"scenario of damage, instead of an expected value approach.

Liberatore *et al.* (2014) used a hierarchic model which, in first place, it plans the restoration of highways, structures, and network damaged by a natural disaster to better distribute the requested aid. At first instance, the maximization of reached demand is pursued; then, a mid and long-term distribution planning model is applied, including performance attributes such as cost, delivery time, safety and reliability. It is highlighted the importance of aid distribution coordination and cooperation through restored highways, since agencies in charge of recovery operations may not coincide with those in charge of distribution.

Rennemo *et al.* (2014) used a function of linear utility to capture humanitarian aid distribution equity in a three-stage stochastic programming model for disaster response planning, taking in consideration opening of local distribution facilities, initial supply allocation and aid distribution in the last mile. The stochastic model captures demand uncertainty, vehicle fleet capacity and status of infrastructure.

Noyan *et al.* (2016) studied the stochastic design problem of the last mile relief network which determines locations and capacities of distribution points that must be located in the last mile network, it allocates demand and available supplies location, while post-disaster relief uncertainty is considered, as well as the transportation network conditions. A two-stage stochastic programming model incorporates a hybrid allocation policy and simultaneously achieves high levels of accessibility and equity. Post-disaster uncertainty and transportation network conditions are captured through a set of finite scenarios.

Lin *et al.* (2011) addressed a relief distribution problem, representing equity minimizing the maximum gap of unmet demand. They proposed a multiple supply, multiple vehicles and multiple period model for delivery of items in aid operations on disaster cases. This model includes two objective functions which minimize total unmet demands and total travel time of all vehicles.

Nolz *et al.* (2011) developed a multiobjective model for humanitarian aid distribution in a post emergency situation. This model comprises three objective functions which includes risk minimization, maximizing coverage provided by the logistic system, and total travel time minimization. Zhan y Liu (2011), on the other hand, presented a multiobjective stochastic programming model to manage demand uncertainty, supply and transportation routes availability in an emergency logistic network. The model is focused on efficiency and equity, minimizing expected travel time and unmet demand proportion using chance constraints and scenario planning, looking for a solution through a goal programming approach.

Vitoriano *et al.* (2011) recognized the existence and importance of performance measures as response time, equity of distribution or reliability and safety of operation routes, proposing a model for vehicle routing and multiple distribution of products, to later build a comprehensive multicriteria optimization model for the problem of transportation and relief distribution. A case study of Haiti's earthquake is detailed (2010).

Rath *et al.* (2016) proposed a bi-objective stochastic optimization model and another humanitarian objective where decisions are related to determination of locations for intermediate storehouses and acquisition of vehicles, in pre and post emergency phases. Uncertainty in road network access is modelled through a discrete set of scenarios, and instead of adding the different objectives for a weighted sum, the authors determine a set of non-dominated Pareto solutions.

More recently, Manopiniwes e Irohara (2017) proposed a stochastic programming model for integrated decisions for preparedness and response stage operations prior to and after a disaster. This approach is based on costs and equity in an integrated multiobjective model for stock pre-positioning and transportation planning that uses a normalized weighted sum method to integrate metrics to be optimized. It is worth to highlight the use of flooding risk map to generate disaster scenarios with different probabilities of occurrence that closely match the actual problem of flooding in Thailand.

Finally, Burkart *et al.* (2017) assumed that allocating relief items demand in disaster cases to specific distribution centres by a central planner is unrealistic, if the beneficiaries had to go by themselves to developing countries. Based on that, a multiobjective location and routing model is proposed considering the beneficiaries selections with regards which support centre to use. This last information was provided through interviews conducted by the authors together with NGO members that have implemented emergency aid projects and development in Africa, Latin America and Eastern Europe. It is shown that beneficiaries can visit other developing countries different from the closest ones due to different reasons, from expectations of better relief items availability, or opportunity to see family members or closer familiarity with certain places.

1.2.3.4. SUMMARY

A summary of the reviewed works is presented next, including those articles that incorporate optimization models. In the table, a description of scientific journals, decision variables included in the models (related to location, inventory management, distribution, routing and other decisions), focused on previous stages and in the aftermath of the emergency, as well as considerations of the reviewed formulations, together with context where those studies were analysed and if those results were obtained through heuristic techniques or exact methods.

It is worth to mention that 15 % of reviewed articles do not specify a particular emergency at the moment of presenting outcomes and numeric analysis, while it is focused on earthquakes and hurricanes to a large extent.

Once the methodological analysis and context are presented, gap findings and future research opportunities are summarized in the next chapter.

		Variables & decisions					Emergency Phase		Considerations in formulation and objective function									
Journal	Authors/ year	Inventory	Location	Distribution	Routing	Others	Pre	Post	Social and behavioral aspect	Coordination between multiple agents	Convergence of material	Scenarios and uncertainty	Risk	Dynamic of systems	Multiobjective	Context, political and / or cultural issues	Type of disaster / Place	Resolution
Fuzzy Optimization and Decision Making	Adivar & Mert, 2010	✓		✓		x(fleet)	✓			✓		✓	✓		✓	✓	Floods/Algeria	Exact
International Transactions in Operational Research	Al Theeb & Murray, 2016			✓	✓	x(workers transferred, unsatisfied demand)		✓		✓							Doesn't specify	Heuristic
Dynamics of Disasters—Key Concepts, Models, Algorithms, and Insigh	Balcik 2016		✓		✓			✓	✓								Doesn't specify	Heuristic
The International Journal of Advanced Manufacturing Technology	Barzinpour & Esmaeili, 2014	✓	✓	✓		x(unsatisfied demand)	✓								✓	✓	Earthquake/Iran	Exact
Journal of Applied Mathematics	Barzinpour et al., 2014		✓	✓				✓				✓			✓		Earthquake/Iran	Exact
Transportation Research Part B journal	Ben-Tal et al., 2011			✓				✓				✓	✓		✓		Hurricanes/ USA	Exact
OR Spectrum	Bozorgi-Amiri et al., 2011	✓	✓	✓		x(unsatisfied demand)	✓	✓		✓		✓	✓		✓	✓	Earthquake/Iran	Exact
Annals of Operations Research	Burkart et al., 2016		✓	✓	✓	x(unsatisfied demand)		✓	✓	✓					✓	✓	Drought/ Mozambique	Heuristic
Journal of Cleaner Production	Camacho-Vallejo et al., 2014			✓		x(type of transport)		✓		✓					✓	✓	Earthquake/Chile	Exact
European Journal of Operational Research	Campbell et al., 2011	✓	✓				✓	✓				✓				✓	Hurricanes/ USA, MExico	Exact
International Journal of Production Economics	Davis et al., 2013	✓		✓		x (capacity, unsatisfied demand)	✓	✓		✓	✓	✓				✓	Hurricanes/ USA	Exact
Decision Science Letters	Fereiduni et al., 2016	✓		✓		x (unsatisfied demand)		✓		✓			✓		✓	✓	Earthquake/Iran	Exact
Socio-Economic Planning Sciences	Fetter & Rakes, 2012		✓	✓		x(assignment and technology)		✓		✓	✓					✓	Hurricanes/ USA	Exact
Transportation Research Part E journal	Garrido et al., 2015	✓		✓		x (fleet)		✓		✓		✓				✓	Floods/ Chile	Heuristic
Transportation Research Part E journal	Gutjahr & Dzubur, 2016		✓	✓	✓	x(unsatisfied demand)		✓	✓	✓					✓	✓	Doesn't specify/Senegal	Exact
Journal of Cleaner Production	Haghi et al., 2017	✓	✓	✓		x(transport of injured / evacuation)	✓	✓				✓	✓		✓		Earthquake/Iran	Exact
IIE Transactions	Hong et al., 2014	✓	✓	✓			✓	✓				✓	✓			✓	Hurricanes/ USA	Exact
Transportation Research Part B	Hu & Sheu, 2013	✓		✓				✓	✓		✓					✓	Earthquake/China	Exact
International Journal of Production Research	Hu et al., 2016		✓	✓		x(unused stock)		✓	✓		✓	✓	✓		✓		Earthquake/China	Heuristic
Lecture Notes in Computer Science ·	Irohara et al., 2013	✓	✓	✓		x(transport of injured / evacuation)	✓	✓				✓			✓		Hurricanes/ USA	Heuristic
International Journal of Production Economics	Kelle et al., 2014			✓		x (unsatisfied demand, unused stock, transport of injured / evacuation)	✓	✓			✓	✓	✓			✓	Hurricanes/ USA	Exact
Socio-Economic Planning Sciences	Khayal al., 2015	✓	✓	✓		x(unsatisfied demand)		✓	✓					✓			Hurricanes/ USA	Exact
IIE Transactions	Kirac et al., 2015			✓	✓			✓	✓					✓			Doesn't specify	Exact
Information Systems and Operational Research	Klibi et al., 2017	✓	✓	✓		x(capacity)	✓	✓				✓	✓		✓	✓	Doesn't specify	Exact
Journal of Transportation Safety & Security	Kulshrestha et al., 2011		✓	✓	✓	x (transport of injured / evacuation)		✓				✓	✓		✓		Doesn't specify	Exact
Transportation Research Part E	Li et al., 2012		✓	✓		x(transport of injured / evacuation)		✓				✓		✓	✓	✓	Hurricanes/ USA	Heuristic
Computers & Operations Research	Liberatore et al., 2014	✓		✓		x (unsatisfied demand, security, reliability)		✓				✓			✓	✓	Earthquake/Haiti	Exact
Socio-Economic Planning Sciences	Lin et al., 2011		✓		✓	x (backorder, unsatisfied demand)		✓		✓		✓			✓	✓	Hurricanes/ EEUU	Heuristic
International Journal of Systems Science	Liu & Zhao, 2012	✓		✓				✓				✓		✓		✓	Bioterrorism/ China	Heuristic
Dynamics of Disasters—Key Concepts, Models, Algorithms, and Insigh	Lodree et al., 2016				✓			✓									Doesn't specify	Heuristic
Production and Operations Management	Lorca et al., 2016	✓	✓	✓		x(collection, processing and sale debris)		✓		✓	✓					✓	Hurricanes/ USA	Exact
International Journal of Production Research	Manopiniwes & Irohara, 2016	✓	✓	✓		x(fleet, transport of injured / evacuation, type of transport)	✓	✓				✓			✓	✓	Floods/Thailand	Exact
European Journal of Operational Research	Maya et al., 2016			✓	✓	x(unsatisfied demand)		✓				✓		✓			Doesn't specify	Heuristic
International Journal of Operational Research	Nagurney et al., 2016			✓				✓		✓						✓	Doesn't specify	Exact
Transportation Research Part E	Najafi et al. 2013a			✓	✓	x(fleet, unsatisfied demand)		✓		✓		✓		✓	✓	✓	Earthquake/Iran	Exact
Transportation Research Part E	Najafi et al., 2013b			✓	✓	x(fleet, unsatisfied demand, transport of injured / evacuation, vehicles transference)		✓				✓	✓		✓	✓	Earthquake/Iran	Exact
OR Spectrum	Najafi et al., 2014			✓	✓	x(fleet availability, unsatisfied demand)		✓		✓		✓		✓	✓	✓	Earthquake/Iran	Exact
International Journal of Mathematics in Operational Research	Ni & Zhao, 2014	✓	✓					✓				✓		✓			Earthquake/ Doesn't specify	Exact
Production and Operations Management	Ni et al., 2017	✓	✓	✓		x(unsatisfied demand, unused stock)	✓	✓	✓		✓	✓	✓		✓	✓	Earthquake/China	Exact
European Journal of Operational Research	Noham & Tzur, 2017	✓	✓	✓			✓	✓	✓			✓				✓	Earthquake/Israel	Exact
OR Spectrum	Nolz et al., 2011			✓	✓	x (fleet, unsatisfied demand)		✓					✓		✓	✓	Doesn't specify	Heuristic
Transportation Science	Noyan et al., 2016	✓	✓	✓		x(capacity)		✓				✓		✓		✓	Earthquake/Turkey	Exact
Transportation Research Part E journal	Ozdamar & Demir, 2012			✓	✓	x(transport of injured / evacuation, fleet)		✓		✓						✓	Earthquake/Turkey	Exact
Transportation Research Part E	Ozdamar & Demir, 2012	✓		✓	✓	x(fleet, transport of injured / evacuation, unsatisfied demand)		✓				✓					Earthquake/Turkey	Exact
International IEEE Conference on Intelligent Transportation Systems	Ozguven & Ozbay, 2012	✓					✓	✓						✓		✓	Hurricanes/ USA	Exact
Computers & Operations Research	Peng et al., 2014	✓		✓				✓				✓		✓		✓	Earthquake/China	Exact
Transportation Science	Pérez-Rodríguez & Holguín-Veras, 2015	✓		✓	✓	x (fleet tracking, type of transport)		✓	✓							✓	Doesn't specify/USA	Heuristic
Computers & Industrial Engineering	Pradhananga et al., 2016	✓	✓	✓		x (pre & post disaster purchases)	✓	✓	✓			✓				✓	Hurricanes/ USA	Exact
International Journal of Production Research	Ransikarbum & Masona, 2016		✓	✓		x(restoration facilities, unsatisfied demand)		✓		✓		✓			✓	✓	Earthquake/ USA	Exact
Computers & Operations Research	Rath & Gutjahr, 2014		✓	✓	✓	x(unsatisfied demand, budget)		✓							✓	✓	Earthquake/ Ecuador	Heuristic
International Transactions in Operational Research	Rath et al., 2015		✓	✓		x(fleet)		✓							✓		Doesn't specify	Exact
Transportation Research Part B	Rawls & Turnquist, 2010	✓	✓	✓		x(unsatisfied demand, unused stock)	✓	✓			✓	✓				✓	Hurricanes/ USA	Heuristic
Socio-Economic Planning Sciences	Rawls & Turnquist, 2012	✓	✓	✓		x(unsatisfied demand)	✓	✓				✓		✓		✓	Hurricanes/ USA	Exact
Transportation Research Part E	Rennemo et al., 2014		✓	✓	✓	x(unsatisfied demand)	✓	✓				✓			✓		Doesn't specify	Exact
Uncertain Supply Chain Management	Rezaei-Malek & Tavakkoli-Moghaddam, 201	✓	✓	✓		x(fleet, unsatisfied demand, unused stock)	✓	✓			✓	✓	✓		✓	✓	Earthquake/ USA	Exact
Socio-Economic Planning Sciences	Rottkemper et al., 2012	✓		✓		x(fleet, unsatisfied demand)		✓				✓		✓	✓	✓	Malaria/Burundi	Exact
Decision Support Systems	Sahebjamnia et al., 2017	✓	✓	✓		x(type of transport)		✓				✓		✓	✓	✓	Earthquake/Iran	Exact
Production and Operations Management	Salmeron & Apte, 2010	✓		✓		x(capacity, fleet, staff, transport of injured / evacuation)		✓	✓			✓			✓		Hurricanes/ USA	Exact
Transportation Research Part E	Sheu, 2010			✓				✓				✓		✓	✓	✓	Earthquake/ Taiwan	Exact
Transportation Research Part B	Sheu, 2014	✓		✓				✓	✓	✓						✓	Earthquakes and Floods/ Taiwan	Exact
Journal of the Operational Research Society	Taskin & Lodree, 2011	✓	✓					✓				✓		✓		✓	Hurricanes/ USA	Exact
European Journal of Operational Research	Tofighi et al., 2016	✓	✓	✓		x(capacity, unsatisfied demand, unused stock, response time)	✓	✓			✓	✓	✓		✓	✓	Earthquake/Iran	Heuristic
Journal of Global Optimization	Vitoriano et al., 2011			✓	✓			✓	✓			✓			✓	✓	Earthquake/Haiti	Exact
Networks and Spatial Economics	Yushimito et al., 2012		✓					✓	✓							✓	Hurricanes/ USA	Heuristic
International Joint Conference on Computational Sciences and Optimiza	Zhan & Liu, 2011			✓	✓	x(fleet, unsatisfied demand)		✓				✓			✓		...	...
International Journal of Systems Science	Zhan et al., 2014	✓		✓		x(fleet, unsatisfied demand)	✓	✓				✓		✓	✓	✓	Floods/China	Exact
Applied Mathematical Modelling journal	Zhang & Jiang, 2013		✓	✓		x(fleet, unsatisfied demand)		✓				✓	✓		✓		Earthquake/ China	Exact
Expert Systems with Applications	Zhang et al., 2012			✓		x(unused stock)		✓			✓	✓		✓	✓		Earthquake/ Doesn't specify	Heuristic

Tabla 1.4: Summary of papers and humanitarian logistic optimization models

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1.3. GAP ANALYSIS AND FUTURE RESEARCH CHALLENGES

Table 1.4 shows a summary of the reviewed works, focusing on the incorporation of mathematical programming and optimization models. Criteria and considerations with which these works have been reviewed are summarized in the social scope and human behaviour incorporation, coordination between multiple agents, materials convergence and/or organization failures, scenarios and uncertainty, risk and robust analysis, system dynamics, multiple objectives and background, political and/or cultural affairs. This last factor is relevant at the moment of applying these models on realistic cases and benchmarking results with public policies or private initiatives.

1.3.1. SOCIAL ASPECT AND HUMAN/ORGANIZATIONAL BEHAVIOUR

Incorporating metrics related to human behaviour, the effect of privacy, vulnerability and resilience becomes necessary to tackle a sociotechnical phenomenon. This effort demands greater integration and knowledge of the disaster psychology and human behaviour, as it has been reviewed in this document. Empirical studies and experiments are diverse. Within this context, Sheu (2014) established a conceptual model of survival-perception-attitude-resilience, which underlies the emergency logistic operational model. Notice that deprivation costs and intertemporal effects can be incorporated to such an approach (Holguín-Veras *et al.*, 2013b). These models define specific attitudinal functions for the survivor, structured as hierarchies of cognitive levels and attitude affective, and resilience.

Including affective dimensions as attitude moderators in multiple attribute models, improves accuracy of forecasts and attitude and personal behaviour diagnosis. Survivors after the disaster can experience huge losses such as personal belongings, exhaustion, disconnection with their family and other adverse situations. This would probably originate negative affective responses (distress, anxiety, fear and stress), making them more vulnerable and sensitive to changes perceived afterwards (Freedy *et al.*, 1994; Boss, 2006; Mawson, 2005; Kolves *et al.*, 2013), together with the definitions and conceptualizations of resilience in front of a natural disaster (Aldunce *et al.* 2014, 2015). In addition, it has not been observed in the literature the incorporation of new dimensions, latent variables and hypothesis based on theoretical construction related to performance, prestige or trust level that institutional management provides to the affected population (Bronfman *et al.* (2016)).

With this regard, since further research must tackle the traditional logistic aspect with the social phenomenon of human and organizational behaviour, it is fundamental to include empiric evidence by incorporating key informants. At first instance, these informants allow to obtain qualitative and quantitative aspects linked to natural disasters, based on historical records of the affected individuals and impact according to type of emergency, predictive models, simulations and/or assistance in construction and characterization of scenarios for post emergency periods, data processes and response protocols, and institutional and industrial organization, network structure and collaboration with formal and informal national and international entities, past experiences or human (including sample framework for site surveying) and organizational behaviour studies before an emergency .

This in order to build models that will embody behaviour, vulnerability, attitude and response (resilience) based on actual data and in accordance with what has been stated in interviews or surveys to key informants (field work with primary sources), in order to validate analysis dimensions and relevant variables, theoretical models and performance indicators. It is fundamental to incorporate data collection from primary sources to the research process, through the application of qualitative and quantitative tools such as semi-structured interviews, focus groups and in field surveys.

1.3.2. Coordination and multiobjective models

Development of further research focused on types of cooperation, coordination and competence, considering different stakeholders' perspective of the decision-making process (centralized or decentralized), and interactions between stakeholders (including the role of social networks). Besides, it is needed specification of better performance indicators to measure effectiveness of the proposed models, using interdisciplinary techniques best-suited for emergency cases, establishing narrower relationships between the academia, humanitarian organizations and society as a whole.

Very often, most of the articles reporting multiple objectives use the weighted sum method to combine multiple objectives in a single goal to simplify the resolution procedure. With this regard, it is difficult to specify adequate weights between the different objectives to reach to the ideal solution. Several documents are focused on building a complex model but it is neglected how to assist decision makers to choose a solution in an interactive or hierarchical framework, since priorities incorporate multiple stakeholders, and the existing research does not always consider priorities and hierarchy of the response objectives.

1.3.3. Multiple stakeholders

More accurate frameworks are needed to study the relationship between complexities and proactive management practices in supply chain resilience and its stakeholders, together with a proper empirical validation. Regularly, local and international suppliers and the affected country have different goals, which generates problems involving multiple organizational structures and decision makers. This multi-organizational characteristic requires a good coordination and cooperation that must be taken to the mathematical modelling and numeric outcome discussion. Further research in topics such as disaster communication network is needed, as well as consideration of multiobjective or multi-criteria models to make better decisions.

Some challenges come up at incorporating multiple independent followers. Each country and/or aid agency that provides disaster relief have their own interests and separated budgets, although they share constraints related to demand or logistic performance in each link of the supply chain. At the inferior level, a Nash game is carried out, while the two-level problem can be seen as a Stackelberg game (Camacho-Vallejo *et al.*, 2015).

In addition, capacity of response must be considered as part of the decisions. It is also necessary to take over organizational failures such as convergence (materials, personnel and information), which generates difficulties in coordination, higher traffic and complex scheduling. There are gaps in the literature that would show donors behaviour and social networks, both at individual and organizational level that would allow to understand the nature of convergence, especially in the case of aid materials and supply (Holguín-Veras *et al.*, 2014, 2015), as to explicitly consider traffic congestion effects or traffic due to material convergence or damage in the network that might make this parameter a dynamic element or subjected to risk averse planning. The latter can give space to redesigns of supply network considering reverse logistic as treatment to potentially not demanded streams.

Finally, it has not been observed the inclusion of safety aspects in the decision-making support systems, which is essential if the application is not limited to "pure"natural disasters (Gutjahr y Nolz, 2016), but should also be expanded to man-made crisis, including loots and other types of crimes, administrative chaos, corruption and possible blockage that occurred in the aftermath of some events.

1.3.4. UNCERTAINTY, DYNAMIC AND RISK

As it has been reviewed in this paper, humanitarian logistics is not free from difficulties inherent to highly dynamic and highly uncertain environments. The logistic process starts from the emergency conception, and predictors that would show its onset, duration and impact are needed.

With this regard many models have considered different scenarios of simple occurrence instead of a more realistic situation that might be more complex if a simultaneous unexpected chain of events occurs, including those called second disasters due to organizational failure (as materials convergence, already analysed in this document). Since in some situations two or more disasters can occur, such as an earthquake followed by a tsunami, more research considering multiple disaster scenarios are needed (Boonmee *et al.*, 2017).

Furthermore, in most part of the models reviewed, scenario-dependant data are considered as sharp. As far as we know, there is a gap in the literature which considers the lack of sharpness/inaccuracy, for instance data randomness that are necessary for the design of humanitarian supply chains, a situation that can be tackled by enriching the uncertainty analysis with the use of, for instance, fuzzy logic or another method to capture this uncertainty. Nevertheless, in most cases there is not enough historical data to model uncertain parameters within random data scenarios. Also, there is no repetition of disaster occurrence, thus, it is very difficult to estimate probabilistic distributions for uncertain parameters.

Consequently, working with inaccurate parameters is required, whose imprecision comes from epistemic uncertainty on these data (Tofighi *et al.*, 2016, Kabak y Ülengin, 2011, Pishvaee y Torabi, 2010).

Taking in consideration the use of scenarios and the risk related to objective functions, as well as feasibility of different constraints within these scenarios, is that robust optimization has been a useful approach to tackle uncertain parameters. With this regard it is difficult to represent all uncertain parameters through a set of discrete scenarios with known probabilities, whereby scenarios planning for modelling uncertainty during a disaster response can be complemented with an adequate characterization of sets of uncertainties and the use of fuzzy programming

New technologies, such as geographical information systems and simulation software, have not been massively used in the reviewed literature. The use of simulation can help visualize data and outcomes comparing the model performance with the actual system, as well as predicting behaviours. Simulation research is focused on the development of models that assist to process and analyse input data for the response phase and they mainly consider development of spatial support decision systems using geographical information systems, with some models of Discrete Event Simulation type (Hoyos *et al.*, 2015).

It is clear the need to develop integrated decision support systems to support decision making in dynamic and uncertain environments in the aftermath of a disaster. We notice a gap to address these problems through an effective real-time decision-making framework, for better planning at different periods of time that would integrate feedback in a dynamic manner. There is a great challenge in the use of supporting models in dynamic humanitarian logistic decision making that would allow to incorporate uncertainty in periods of time, environments, risks and disruption events. Many models are not incorporated in the Decisions Support Systems to be used effectively by organizations involved. Systems that are already in use are focusing on data management, but they do not have optimization tools. Few works try to integrate their mathematical models to a decision support system equipped with maps, real-time data, and an easy-to-use interface, a fundamental situation so works can go beyond the academic border and can be taken to the application field, supporting humanitarian aid planners and decision-makers, providing relevant and accurate data (see examples, Gutjahr y Nolz, 2016; Liberatore *et al.*, 2013; Özdamar y Ertem, 2015).

In the real world, risk mapping is systematically applied for preparedness (emergency protocols usually developed by national or local civil protection entities) or imagery processing to obtain maps of the area affected by a disaster (captured by satellites or aircrafts, see Liberatore *et al.*, 2013), situation that must be integrated to the empirical validation of results and numerical studies of humanitarian logistic studies.

1.3.5. PRE AND POST EMERGENCY INTEGRATED DECISIONS.

As it has been discussed, much of the attention has been focused on mitigation, care and response, counting with studies in each one of these stages. Nevertheless, there is still a lack of integrated research along the phases of an emergency cycle. A challenge comes into this point, since it would be possible to combine aspects such as routing, evacuation, relief distribution, victim's transportation, inventory ,amagement, resource allocation, traffic control, debris management and community flow problems, with planning and mitigation. At a pre-disaster scope, there is a predominance of works focused on strategic decisions with a strong need of expanding the analysis to other decision levels (tactical and operational), because the reviewedliterature show that humanitarian logistic management efforts have a rather reactive nature, waiting for a disaster to occur before participating in aid efforts.

The experience in Haiti underscores the importance of conducting efficient recovery efforts; even after two years earthquake, the country was not able to recoverits regular functioning, debris removal, reconstruction of highways and buildings, and sustainable care to the affected population (Galindo y Batta, 2013). Another aspect is business continuity, regarding what it has been observed, there is lack of studies analysing the socioeconomic disruption of the families affected and functioning of the local economies after a disaster. Incorporating the concept of resilience in its multiple meanings may contribute to this point.

1.3.6. CONTEXT, POLITICAL AND/OR CULTURAL AFFAIRS

Regarding context and integration with political-cultural affairs application, it is observed that several authors and studies have tested their models and approaches on instances available in the literature, using actual data of disaster-prone regions, analysed in other researches. Nevertheless, literature lacks methodological proposals from a result and implementation assessment in actual operations. There are very little concrete applications in public policy context, humanitarian aid organizations, decision-making support systems, local data integration and community's response (public planning, risk education, social networks, among others).

In this sense, it is necessary that further research should reduce the gap between theory and application through case studies and site surveys development (Holguín-veras *et al.*, 2012, 2014, 2015, Gralla *et al.*, 2014). In addition, adequate contextualization with the local institutionalism and the political-social organization is necessary for implementation, tracking and measurement of humanitarian logistic initiatives success.

Regarding disasters involved in the application and numerical studies reviewed, literature is mainly focused on disasters so-called "sudden" (earthquakes, hurricanes, fires), with much less literature covering slow-onset disasters (such as droughts and floods), where usually it is possible to react with more time.

1.3.7. Resolution and scale methods

A critical aspect in humanitarian logistic models are the size and complexity of the numerical resolution. Very often, we observe large scale problems that require deep data analysis, strong computational efforts and/or training of final users. Metaheuristic approaches offer an interesting alternative to tackle these instances and support decision-making.

Regarding resolution mechanisms, several heuristics have been studied in those cases where the nature of the models does not allow to solve problems in an exact manner (see Korkou et al., 2016). Stochastic and dynamic models are even more difficult to solve and require a significant effort to efficiently find solutions for large scale problems (Anaya-Arenas *et al.*, 2014; De la Torre *et al.*, 2012; Alshamsi y Diabat, 2015).

1.3.8. Framework, modelling and future research development

Taking into consideration the revision and research gaps identified, it is necessary to structure and guide future humanitarian logistic research to harmonically integrate multiple dimensions analysed in this document. First, we need to locate each research around an emergency development cycle (see Figure 1.4), with this regard it is observed that few research proposals have integrated strategic and proactive decisions with tactical and operational responses once the disaster has occurred.

Within this line, it is necessary to integrate location and capacity decisions, inventory management, distribution, routing and fleet allocation, among other decisions, under an approach that would not be exclusive to mitigation or preparedness, response or restoration stages. For this, it is suggested to delve into studies that incorporate multi-stage structures, dynamic programming, simulation and optimization connecting these stages, trying to bring close the numeric experimentation and case studies to the practice. By the use of adequate indicators, a follow up of operations and decision-making induced by optimization model's outcome must be conducted.

Together with this temporal integration, there must be integration with stakeholders which cannot be foreign to the objectives pursued behind the formulations and constraints that would necessarily incorporate a multi-agent environment. Future research must incorporate an organizational, industrial and institutional analysis accounting for the social context where the occurrence of an emergency could involve a sociotechnical system. Tools inherent to disaster psychology, game theory and multi-level programming will be useful to model and analyse relationships, hierarchies and reactions in front of a multiobjective problem.

Hence, an opening research line shall be focused in multiobjective formulations, with adequate resolution that will allow the decision maker to interact with equilibrium inherent to balance and/or objective hierarchy, some of which come from the social aspect, given that it must also delve into the study of site surveying techniques and the incorporation

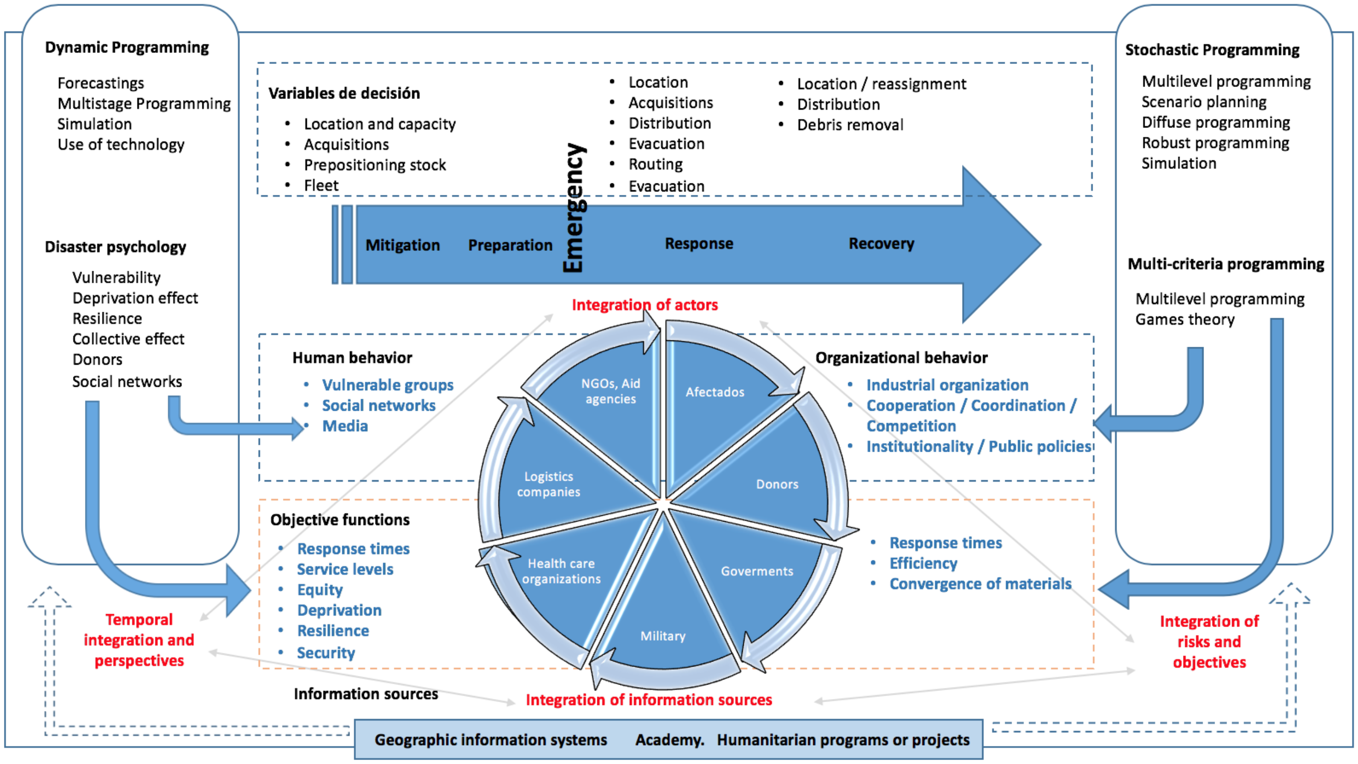


Figura 1.4: Modelling framework and future researches

of primary sources to build attitudinal and behaviour models. This integration of stakeholders must be introduced, therefore, in the multi-disciplinary research teams set up, from the economic and social point of view up to a more analytical view, predominant in the studies and models reviewed.

Since different objectives, times and stakeholders are integrated, it is relevant to have uncertainty and risk analysis in the modelling process, as well as sensitivity analysis (posteriori analysis) in stochastic programming, robust or multiobjective, every time that there is a hypothesis regarding outcomes or predominant objectives (a priori analysis). As it has been observed on this paper, one of the a priori techniques is the robust optimization, an integration of objectives programming with a data description of the problem based on possible scenarios, which can be the fruit of diverse sources of uncertainties, namely: changing environmental and operating conditions, production tolerances and actuator imprecision, uncertainty in system output, feasibility uncertainty.

With this regard, there are different possibilities to mathematically quantify the uncertainty sources quoted above. Basically, uncertainty can me modelled in a deterministic, probabilistic or possibilistic way, for instance: The deterministic type defines parameter domains in which the uncertainties can vary; the probabilistic type defines probability measures describing the likelihood by which a certain event occurs, and the possibilistic type defines fuzzy measures describing the possibility or membership grade by which a certain event can be plausible or believable (Beyer y Sendhoff (2007)).

Finally, integration of data sources is fundamental, both formal and informal, to tackle the definitions of uncertainties and inaccuracies before mentioned. Parameters acquisition from the social, industrial and institutional world must be facilitated, as well as integrating data collection technology and model dynamics update, which, at the same time, facilitates dissemination in environments where, given the criticality that the impact of emergencies transmits to society, they demand applied and relevant solutions to new hazards that nature gives us towards the future.

It is expected that this article will be used as guide for multi-disciplinary development of future research, considering the importance to develop harmonious solutions for humanitarian logistics, that can make responses much more efficient and effective to countless natural disasters that our planet faces, saving lives and improving communications of the stakeholders involved. We seek to improve the foundations for the creation of public policies with this and, of course, deepen and direct the scientific base of answers and papers of this field.

Capítulo 2

Modelo Integrado Multiobjetivo, Robusto y Posibilista de Logística Humanitaria con Costos Sociales y Convergencia de Materiales

Abstract

El presente estudio propone de un modelo integrado de planificación y respuesta a un desastre mediante decisiones de aprovisionamiento, compras, localización y distribución de un suministro crítico como es el agua potable. Se considera una función objetivo que incorpora la sensibilidad a los tiempos de respuesta y el componente social asociado al comportamiento humano y la privación, así como fenómenos de convergencia de materiales, además de los costos asociados a las deciciones logísticas. Se considera un entorno donde la incertidumbre se manifiesta de manera mixta, a través de escenarios con probabilidad conocida que describen localización, cobertura e impacto de los desastres, estado de la red, tiempos de respuesta e inventarios disponibles o dañados, así como información imperfecta o imprecisa respecto a parámetros asociados a la operación logística, los cuales no cuentan con leyes de probabilidad definidas y pueden variar dentro o entre cada escenario. Esta situación es trabajada con un modelo robusto y posibilista, que busca minimizar el riesgo en una función objetivo aversa a la variabilidad de los costos globales. Se incorporan medidas de credibilidad y lógica difusa para trabajar la incertidumbre epistémica en los parámetros. Finalmente, reconociendo la presencia de costos sociales y logísticos, se formulan modelos multiobjetivo, resueltos mediante programación por compromisos.

2.1. Introducción

Una crítica a los modelos de soporte para la toma de decisiones en logística humanitaria, debieran ser reformulados para tener en cuenta explícitamente los costos logísticos, así como los impactos sociales de las entregas de productos o servicios (Holguín-Veras *et al.*, 2013b). Lo anterior dado por el desafío de un proceso de modelamiento en logística humaniaria, donde es necesario incorporar métricas asociadas al comportamiento humano, dadas por el efecto de la privación, la vulnerabilidad y la resiliencia, conceptos que se tornan necesarios para enfrentar un fenómeno sociotécnico.

En este artículo, se propone incorporar, además de los costos logísticos, el *costo de privación* en la modelación, que conceptualmente se define como el valor económico del sufrimiento humano causado por la falta de acceso a un bien o servicio. Como tal, el costo de la privación es una función del tiempo de privación y las características socioeconómicas del individuo (por ejemplo, edad, género, condición física) (Holguín-Veras *et al.*, 2013a, Holguín-Veras *et al.*, 2013b, Holguín-Veras *et al.*, 2016). El *costo social* puede computarse como la suma de los costos de privación en las épocas en que se realizaron las entregas de ayuda, más la suma de los costos de privación para todas las demandas pendientes al final del horizonte de planificación. Para ello, es necesario entonces contar con estimaciones empíricas de las funciones de costo de privación, eliminando la necesidad de utilizar restriciones de equidad o indicadores proxy del sufrimiento humano, proporcionando una mejor manera de evaluar los impactos de las acciones de entrega. Al respecto, Holguín-Veras *et al.* (2016) utiliza técnicas de valoración contingente, aplicaciones econométricas y experimentos de preferencia declarada para obtener una función de privación para el agua potable como suministro crítico.

Junto a lo anterior, la logística humanitaria debe hacerse cargo de entornos donde predomina la incertidumbre, respecto a las demandas y privaciones, así como a los parámetros propios de la logística tradicional (tiempos de viaje y estado de la red, capacidades y stock utilizable, entre otros). Considerando estos puntos, esta investigación se construye a partir del trabajo de Pradhananga *et al.* (2016), quienes presentan un modelo estocástico basado en escenarios de red de tres escalones (proveedores, centros de acopio y demandas) para la planificación integrada de preparación y respuesta ante emergencias, respecto de la distribución de suministros de emergencia. Su modelo minimiza el costo social asociado a la privación y espera, basándose en la formulación de Holguín-Veras *et al.* (2016). En el modelo propuesto se identifican conjuntos de puntos de suministro potenciales, de consolidación de los flujos, desde los que se envían a las instalaciones de preposicionamiento, además de considerar las decisiones de compra o adquisiciones pre y post emergencia, permitiendo envíos directos desde los puntos de suministro y las instalaciones preposicionadas a los puntos de demanda (*aggregated demand points*).

Estudios como el anterior, proponen modelos de programación estocástica en dos etapas basados en valores esperados. Sin embargo, considerar los valores esperados puede no ser suficiente para eventos de emergencias que ocurren muy eventualmente. La incorporación del concepto de riesgo es crucial para modelar la variabilidad aleatoria inherente a los sistemas de socorro en casos de emergencia (Van Wassenhove, 2006; Noyan, 2012; Hong *et al.*, 2015). A partir de lo anterior, en nuestra investigación proponemos una versión aversa al riesgo del modelo integrado de localización, asignación y distribución, donde la función objetivo tiene funciones generales de penalización que robustecen el modelo y de su solución, ponderadas con un parámetro destinado a capturar las preferencias del modelador.

El modelo multiobjetivo propuesto intenta minimizar la suma del valor esperado y la varianza del costo total de la cadena de socorro (combinando el aspecto de la logística tradicional con el impacto social y la privación), penalizando además la infactibilidad de la solución debido a la incertidumbre de parámetros asociados a la convergencia de materiales. Este último fenómeno es propio de los fallos en la organización y coordinación, por lo cual su inclusión permite enriquecer el aspecto social en el modelo. La caracterización y optimización del riesgo se materializa mediante un proceso de planificación por escenarios, definiendo distintos contextos de emergencia en base a información histórica y proporcionada por expertos.

Bajo una mirada integradora con el modelo averso al riesgo, se incluye la protección ante la incertidumbre epistémica provocada por la impresiciónen el cálculo de los parámetros con que se caracterizan distintos escenarios, dado que en muchos casos no hay suficientes datos históricos para modelar los parámetros inciertos dentro de cada escenario. Así, se complementa el hecho de que en programación estocástica, la ocurrencia de cada escenario de emergencia sigue un proceso estocástico con cierta probabilidad. Junto a lo anterior, los parámetros dependientes del escenario junto con los parámetros independientes de los mismos se pueden formular como distribuciones de posibilidad.

Cabe descatar que la posibilidad, en nuestro contexto de modelación, es entendida como una circunstancia u ocasión de que una cosa exista, ocurra o pueda realizarse. Por lo tanto, lo posible es aquello que puede ser o existir, es decir, se trata de todo suceso que puede ocurrir y está basado en hipótesis o suposiciones que se pueden dar o no en una situación o caso, pero que no necesariamente sea probable. Así, que algún suceso sea posible no implica que éste sea probable (Tofighi *et al.*, 2016). La probabilidad, en tanto, es una situación que podría suceder o que existe mayor factibilidad de que suceda, basándose en pruebas, las cuales dan sustento a que tal situación suceda. Por ello, la posibilidad de que suceda algún hecho es mayor, y para que un evento sea probable primero debe ser posible, es decir, que pueda o no ejecutarse o suceder (Liu, 2009).

Finalmente, el modelo incluye la ocurrencia de fallos en la organización y presencia de convergencia de materiales. Este fenómeno ha sido caracterizado por diversos autores como un eventual "segundo desastre", fruto de que en la logística post emergencia puede haber cientos o incluso miles de cadenas de suministro formales o informales/improvisadas que interactúan, se superponen, cooperan o incluso compiten por recursos escasos y tratan de ayudar (Holguín-veras *et al.*, 2012). Comprender la naturaleza de la convergencia, especialmente en el caso de los materiales y suministros de ayuda, requiere un análisis de factores subyacentes que influyen en el comportamiento de la donación, tanto a nivel individual como organizacional (Holguín-Veras *et al.*, 2014, Destro y Holguín-Veras, 2011), lo cual hace muy difícil su cuantificación así como su incorporación en entornos estocásticos, como el estudiado en este artículo.

2.2. Revisión bibliográfica

Respecto del uso de optimización robusta, si nos enfocamos en decisiones propias de la logística humanitaria, que deben ser tomadas en situaciones concretas que no se volverán a repetir, al menos bajo las mismas condiciones probabilísticas, como evacuaciones y asistencia de servicios de emergencia, los criterios de decisión no necesariamente apuntan a valores esperados, como se ha indicado. Se hace necesario reforzar la toma de decisiones de forma que se proteja al tomador de decisiones contra eventualidades que pudiesen ocurrir. Por otro lado, la consecuencia de cualquier acción viene determinada, no sólo por la acción en sí misma, sino también por una variedad de factores externos. Estos factores están habitualmente fuera del control del tomador de decisiones y suelen ser desconocidos al momento de la toma de decisión. Si estos son conocidos o caracterizados adecuadamente en escenarios, es posible predecir las consecuencias de cada acción con mayor certeza.

Respecto a este enfoque destacan trabajos como el de Hu *et al.* (2016), quienes estudian el problema de asignación de recursos de emergencia al comienzo de la fase posterior a la emergencia en un centro de recursos y múltiples áreas afectadas. El modelo de optimización robusta permite la asignación de recursos de emergencia, con dos objetivos que intentan maximizar la eficiencia y la equidad bajo diferentes fuentes de incertidumbre. Además, ampliando el marco de optimización robusta de Mulvey *et al.* (1995) representan algunos de los parámetros inciertos con conjuntos de incertidumbre, y otros con el método basado en escenarios. Además de un diseño heurístico para la construcción de una frontera de Pareto, se establece un método de decisión restringido por coeficientes de equidad y basado en las preferencias de los tomadores de decisión.

Más recientemente, Ni *et al.* (2017) optimizan simultáneamente las decisiones de ubicación de las instalaciones, pre posicionamiento de inventario de emergencia y operaciones de entrega de socorro en una sola red de alivio de desastres de productos básicos. Para ello, los autores proponen un modelo min-max de dos etapas (previa y posterior a la emergencia), donde se minimiza la suma del costo de la primera etapa y el costo de la segunda etapa en el peor de los casos entre todas las posibles realizaciones de los parámetros inciertos que caen dentro de un conjunto de incertidumbre. Este enfoque de optimización robusta aplica el criterio min-max para protegerse contra todas las realizaciones en el conjunto de incertidumbre, asociadas con la demanda en cada área afectada, la proporción de inventario utilizable en cada instalación y la capacidad de cada arco en la red de alivio de desastres.

Por otro lado, e incorporando la modelación multinivel y la aplicación de teoría de juegos, Fereiduni *et al.* (2016), proponen un modelo de optimización robusta de dos niveles para optimizar las decisiones relacionadas con la distribución y la ayuda a la evacuación después de un terremoto. En este problema, los países extranjeros tratan de minimizar sus costos de envío y el país afectado trata de minimizar sus costos totales, donde se incluyen gastos de inventario, operación y transporte. Esta situación es un juego entre diferentes tomadores de decisiones después de una emergencia, proponiendo un modelo de dos niveles en el que el país afectado es el líder y los proveedores son los seguidores.

La implementación de la lógica difusa en el alivio de desastres y la logística de emergencia es introducida por Hu y Sheu (2003), en el contexto de la agrupación y clasificación de la demanda previa al ruteo de vehículos y distribución en operaciones logísticas. Respecto a lo anterior, Tofighi *et al.* (2016) proponen una mirada novedosa de programación posibilista-estocástica en dos etapas (SBPSP – scenario based possibilistic-stochastic programming), enfoque híbrido de programación de incertidumbre mixta mediante la incorporación de programación de posibilidades basada en la medida de credibilidad, en un marco de programación estocástica basada en escenarios. Este nuevo método combina la programación estocástica tradicional con números difusos para representar las diferentes incertidumbres involucradas en el problema, buscando decidir sobre el posicionamiento previo y la distribución de suministros de emergencia. Lo anterior, tomando en cuenta decisiones previas y posteriores a la emergencia, incluyendo además decisiones de localización y capacidad.

Otro trabajo que destaca en el uso de estas herramientas es el de Barzinpour *et al.* (2014), quienes formulan un modelo bi objetivo, donde el primer objetivo es minimizar los costos de transporte, los costos de instalación y los costos de penalización por falta de suministro. El segundo objetivo es maximizar la demanda satisfecha. El modelo determina simultáneamente la ubicación de los centros de distribución de socorro y la asignación de áreas afectadas a estos centros. Las instalaciones se establecerán y los bienes de socorro se distribuirán a los beneficiarios en las áreas dañadas, en función de los costos de transporte, el costo de instalación, el inventario y la demanda, representados por números difusos.

Contribuciones anteriores en la línea de la programación difusa incluyen a Adivar y Mert (2010), quienes optimizan un sistema de distribución de socorro bajo incertidumbre, utilizando un modelo difuso multiobjetivo. A diferencia de otros estudios, donde el rendimiento de las operaciones de socorro se mide en función en el costo total y niveles de satisfacción de la demanda, en este trabajo se introduce y cuantifica la credibilidad mediante el uso de una función difusa no lineal.

2.3. Contribuciones

En esta investigación se construye un modelo multiobjetivo de programación estocástica, averso al riesgo y posibilista, el cual permite enfrentar decisiones de localización, manejo de inventarios y distribución de manera previa y posterior a la ocurrencia de una emergencia, enfocándose en la mitigación y respuesta. Se trata de optimizar el riesgo asociado a la planificación de escenarios y la incertidumbre epistémica dada por el uso de parámetros imprecisos e información imperfecta o escasamente sistematizada, considerando en la función objetivo tanto los costos releventes y propios de la logística tradicional, así como el impacto social dado por el efecto en la privación de suministros críticos. Las contribuciones del modelo son las siguientes:

- Incorpora una función objetivo robusta y aversa al riesgo, la cual se descompone en dos objetivos: el primero asociado a la logística tradicional y el segundo al costo social vinculado a la privación.

- Incorpora la optimización de la robustez del modelo y sus soluciones, a través de la factibilidad de los resultados en distintos escenarios, así como variabilidad respecto a la robustez del modelo, incluyendo el efecto de la convergencia de materiales.

- En conjunto con la incertidumbre aleatoria asociada en la ocurrencia de los escenarios, reconoce e incluye la incertidumbre epistémica, mediante el uso de *fuzzy chance constrained programming*. Esta última surge de datos imprecisos, no sistematizados o parcialmente ocultos que, dentro de cada escenario o entre los mismos constituyen una nueva fuente de incertidumbre general en el sistema.

- En un marco de optimización multiobjetivo, permite construir la frontera Pareto óptima entre los objetivos de la logística tradicional y los costos sociales dados por las privaciones, utilizando modelos empíricos para el costo de privación de un suministro crítico específico.

En la siguiente sección, se detallan los componentes de problema a estudiar y el proceso de construcción del modelo propuesto en nuestra investigación. En primer lugar se presenta el modelo base de Pradhananga *et al.* (2016), luego una versión multiobjetivo aversa al riesgo, además de la incorporación de incertidumbre epistémica. Finamente, se presentan los resultados y análisis de sensibilidad en base a un estudio de caso.

2.4. Modelo estocástico de localización, asignación de inventarios y distribución de suministros críticos

2.4.1. Descripción del problema

Se considera una red de 3 escalones, en donde las decisiones de logistica humanitaria incluyen la localización, el manejo de inventarios y la distribución para fases previas y posteriores a la ocurrencia de un desastre natural. Los nodos de la red (conjunto V) cumplen distintos roles, a saber (ver figura 2.1): *Supply point* SP (conjunto M, con $j \in M$), donde se pueden tomar decisiones de preposicionamiento y abastecimiento post emergencia; *Aggregated demand point* ADP (conjunto N, con $i \in N$), que colaboran entre sí con flujos de suministros recibidos desde los nodos de suministro, así como disponibles en inventario. En estos nodos además es posible recibir donaciones, las cuales pueden generar convergencia de materiales.

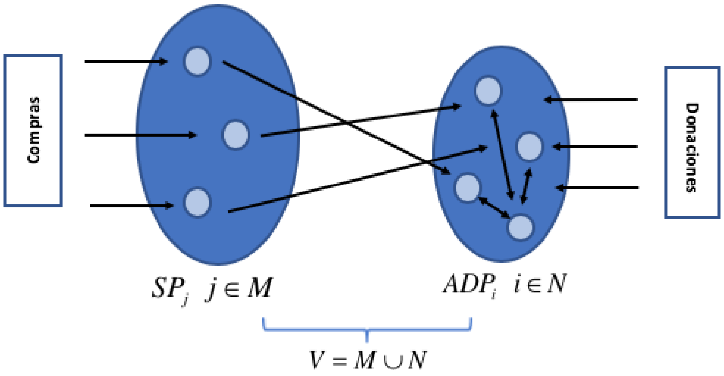


Figura 2.1: Red de suministro

Una vez ocurrida la emergencia, la demanda en un i-ésimo ADP puede satisfacerse de varias fuentes, en el siguiente orden de preferencia: (i) si los artículos están preposicionados en algún ADP i, los artículos supervivientes preposicionados en estos puntos se utilizan para satisfacer la demanda de ese ADP, y si hay un excedente, se usará para satisfacer las demandas de los ADP cercanos; (ii) si hay un déficit en un ADP i, los artículos almacenados en los SP se envían directamente hacia los ADP para satisfacer la demanda; (iii) si las dos fuentes de suministro no son capaces de satisfacer la demanda, se compran más artículos en los SP en la era posterior al desastre y se entregan directamente a los ADP; (iv) se reciben donaciones como un flujo independiente del proveniente de otros ADP o SP.

La incertidumbre se incluye en la demanda y el comportamiento de los donantes, costos de transporte y estado de la red, así como la privación asociada al tiempo que transcurre hasta que la demanda es satisfecha y el sufrimiento asociado con la demanda parcialmente satisfecha o insatisfecha. Frente a este contexto, el problema consiste en optimizar la localización y preposicionamiento de un suministro crítico en los nodos potencialmente habilitados para ser *supply points*, así como en los nodos seleccionados para funcionar como *aggregated demand points*. Estas decisiones son ejecutadas anteriormente a la ocurrencia de un desastre natural, las cuales se complementan con decisiones posteriores al desastre, tales como la distribución del stock preposicionado o fruto de la compra o recepción de donaciones en los nodos seleccionados como SP.

Como existen flujos posteriores al desastre y donaciones o compras ejecutadas una vez que el desastre ya ha ocurrido, también se incluye la existencia de convergencia de materiales, definida anteriormente, fenómeno que jugará un rol inportante en la formulación de una función objetivo aversa al riesgo.

2.4.2. DESCRIPCIÓN DEL MODELO

La formulación matemática considera varios escenarios de desastres predefinidos, cada uno denotado por $s \in S$, con una probabilidad de ocurrencia Θ_s (ver detalles de parámetros y variables de decisión en cuadros 2.1-2.2). Estos son determinados en base a registros históricos de eventos similares en un área específica), incluyendo posibles daños en la red, así como costos de privación Π^s_{ji}, calculados sobre la base de la distancia a recorrer o el tiempo de viaje para suministrar los recursos y la satisfacción total o parcial de la demanda (es decir, cada escenario permite calcular costos de privación para aquellas demandas asistidas, así como costos de oportunidad para aquellas demandas no asistidas a tiempo).

Los costos de privación aumentan con el tiempo de privación. El tiempo de privación para un individuo es el tiempo entre la ocurrencia del desastre y la satisfacción de su demanda, el cual suponemos proporcional a la distancia a recorrer para suministrar los bienes. Cuando la demanda de un ADP se cumple a través de cantidades preposicionadas en el mismo ADP, el tiempo de privación, y por lo tanto, el costo de privación, se vuelve insignificante. Los costos de privación son funciones no lineales de los tiempos diferidos y son parámetros específicos del modelo propuesto.

Utilizamos un modelo de costo de privación basado en Pérez-Rodríguez y Holguin-Veras (2015) como una función exponencialmente creciente del tiempo de privación.

La función objetivo incluye costos de localización, abastecimiento o preposicionamiento y transporte previo a la emergencia, así como costos de transporte, abastecimiento y mantenimiento de inventarios, además de costos de privación y oportunidad asociados a las ayudas percibidas (desde fuentes de suministro y stock existente o comprado, así como nodos de demanda cercanos), y el costo de la convergencia de materiales generada por donaciones, todo ello una vez ocurrida la emergencia y sujeta a escenarios previamente identificados.

La formulación robusta y aversa al riesgo se construye considerando el valor esperado y varianza del costo total, así como aquellos ítems de costo que de manera determinista se manifiestan en fases previas a la emergencia, tales como la activación o localización de nodos de suministro, compras o adquisiciones y transporte para el preposicionaminto. Estas decisiones son simbolizadas por un vector X asociado al período de planificación o preparación (en nuestro caso simboliza el período previo y posterior a la emergencia, considerando que el modelo es integrado), $\Omega(X)$ es la parte determinista de la función objetivo (ver en cuadro 2.3 parámetros del modelo robusto).

Los costos asociados a fases post emergencia, dependen de los distintos escenarios y se denotan por ξ_s para cada escenario $s \in S$. Se separan dos objetivos, a saber: $\xi_s^{(1)}, \xi_s^{(2)}$. Esta separación considera un primer término que incluye los costos de la logística humanitaria tradicional, cuyas decisiones están vinculadas al vector X: compras o adquisiciones, transporte y manejo de inventarios. El segundo término $\xi_s^{(2)}$ incluye los costos de oportunidad y efectos intertemporales del sufrimiento humano, los cuales están caracterizados por costos de privación (Holguín-Veras *et al.* (2016)) y son calculados paramétricamente según cada escenario, puesto que ellos dependen de los tiempos de privación o falta de suministros críticos, que a su vez dependen de las distancias recorridas para llegar con la ayuda a destino. Se incluye además en este término el costo de la convergencia de materiales dada por las donaciones que en cada escenario tienen lugar en los nodos ADP, las cuales serán proporcionales a la demanda de cada i-ésimo nodo ADP.

A continuación de detallan los componentes de la función objetivo:

$$\Omega(X) = \sum_{j \in M} (F_j y_j + P_j^0 p_j^0) + \sum_{i \in N} F_i x_i + \sum_{j \in M} \sum_{i \in N} TRC_{ji}^0 q_{ji}^0 \tag{2.1}$$

$$\xi_s^{(1)} = (\sum_{k \in V} \sum_{i \in N} TRC_{ki}^s q_{ki}^s + \sum_{j \in M} \sum_{i \in N} TRC_{ji}^s o_{ji}^s) + \sum_{k \in V} H_k I_k^s \tag{2.2}$$

$$\xi_s^{(2)} = (\sum_{j \in M} \sum_{i \in N} \pi_{ji}^s q_{ji}^s + \sum_{k \in N} \sum_{i \in N} \pi_{ki}^s q_{ki}^s + \sum_{j \in M} \sum_{i \in N} \pi_{ki}^{so} o_{ji}^s) + \sum_{i \in N} W_i^s u_i^s + \sum_{i \in N} Z_i^s \gamma_i \tag{2.3}$$

Previa presentación de la formulación robusta del modelo multiobjetivo, se presentan las restricciones del modelo estocástico basado en escenarios, tomando como referencia el trabajo formulado por Pradhananga *et al.* (2016) e incluyendo el fenómeno de convergencia de materiales. Esto es necesario para identificar aquellas restricciones que se deberán penalizar en el modelo cuando en algún escenario estas no son satisfechas (robustez del modelo). Estas restricciones son:

$$p_j^0 \le c_j Y_j, \forall j \in M \tag{2.4}$$

$$p_j^0 \ge v_j^0 = \sum_{i \in N} q_{ji}^0, \forall j \in M \tag{2.5}$$

$$q_i^0 = \sum_{j \in M} q_{ji}^0 \le c_i X_i, \forall i \in N \tag{2.6}$$

$$\varphi_i^s q_i^0 - a_i^s + b_i^s = D_i^s, \forall i \in N, s \in S \tag{2.7}$$

$$a_i^s \le |\varphi_i^s q_i^0 - D_i^s|, \forall i \in N, s \in S \tag{2.8}$$

$$b_i^s \le |D_i^s - \varphi_i^s q_i^0|, \forall i \in N, s \in S \tag{2.9}$$

$$q_{ik}^s \le a_i^s, \forall i, k \in N, s \in S \tag{2.10}$$

$$\sum_{i \in N} q_{ji}^s = p_j^0 - v_j^0 - I_j^s, \forall j \in M, s \in S \tag{2.11}$$

$$p_j^s \le o_j^s Y_j, \forall j \in M, s \in S \tag{2.12}$$

$$q_{ni}^s \le b_i^s, \forall n \in V, i \in N, s \in S \tag{2.13}$$

$$o_{ji}^s \le b_i^s, \forall j \in M, i \in N, s \in S \tag{2.14}$$

$$a_i^s - b_i^s - \sum_{n \in N} q_{in}^s + \sum_{n \in N} q_{ni}^s + \sum_{j \in M} (o_{ji}^s + q_{ji}^s) = I_i^s - \mu_i^s, \forall i \in N, s \in S \tag{2.15}$$

$$Y_j, X_i \in \{0, 1\}, \forall j \in M, i \in N \tag{2.16}$$

$$q_{ji}^0, q_i^0, v_j^0 \ge 0, \forall j \in M, i \in N \tag{2.17}$$

$$q_{ni}^s, I_n^s \ge 0, \forall n \in V, s \in S \tag{2.18}$$

$$a_i^s, b_i^s, u_i^s, o_{ji}^s \ge 0, \forall i \in N, j \in M, s \in S \tag{2.19}$$

la restricción (2.4) limita la adquisición previa a la emergencia para cada nodo SP_j, (2.5) y (2.6) restringuen el preposicionamiento de stock para SP_j, ADP_i. La restricción (2.7) corresponde a la ecuación de equilibrio en la demanda de ADP_i en los escenarios post-emergencia, en tanto que (2.8) y (2.9) determinan la cantidad disponible a_i^s o requerida b_i^s en cada nodo AD_i post- emergencia. La demanda restante en cada ADP_i puede ser satisfecha a través de otros ADP, a través de artículos disponibles los nodos de suministro SP, a través de adquisiciones post-emergencia desde los mismos SP o mediante donaciones. (2.10) limita la cantidad que se puede enviar de un ADP a otro para cada escenario post-emergencia. La ecuación (2.11) representa el equilibrio de flujo para cada SP_j, (2.12) limita la capacidad en los SP para la adquisisiones post-emergencia. (2.13) y (2.14) son restricciones de capacidad en los ADP que reciben las entregas desde cada SP o ADP. Finalmente, la restricción (2.15) define el equilibrio de flujo e inventario para cada ADP_i, donde u_i^s representa la escasez o falta de inventario en cada ADP_i para un escenario $s \in S$ y z_i^s la convergencia de materiales producida por donaciones. Las restricciones (2.16) a (2.19) indican la naturaleza de las variables.

2.4.3. FORMULACIÓN ROBUSTA Y MULTIOBJETIVO

A partir del modelo estocástico basado en escenarios, se construye un modelo averso al riesgo, considerando las ideas de Mulvey *et al.* (1995), quien presenta la definición de optimización robusta

Tabla 2.1: Parámetros y variables adicionales, modelo robusto

Simbolo	*Descripción:*
Parametros	
λ	Peso asignado a variabilidad de costos
γ	Peso asignado a penalidad por infactibilidad del modelo
Variables de decisión	
δ_s	Variables usadas para linealización de función objetivo, escenario $s \in S$

como un enfoque que integra formulaciones de programación por metas con una descripción de los datos basada en escenarios, para resolver problemas de programación estocástica (ver ejemplos de aplicaciones en Haghi *et al.*, 2017, Hu *et al.*, 2016, Rezaei-Malek y Tavakkoli-Moghaddam, 2014).

Fundamentalmente, y basados en lo anterior, nuestra visión de optimización robusta involucra dos tipos de robustez, a saber:

- Robustez de la Solución: Una solución es robusta con respecto a optimalidad si permanece cerca del óptimo para cualquier escenario $s \in S$
- Robustez del Modelo: Una solución es robusta con respecto a factibilidad si permanece factible para cualquier realización de escenarios $s \in S$.

Respecto de la robustez del modelo, en general se asume la existencia de un organismo coordinador entre la zona afectada y los proveedores locales y externos para evitar el envío de productos de socorro innecesarios, lo cual genera fallos de organización como la convergencia de materiales.

En este trabajo, como se ha mencionado, la convergencia de materiales es considerada y entendida como la acumulación de suministros de emergencia en cantidades exorbitantes destinadas a fines de socorro (Holguín-Veras *et al.*, 2014), lo cual para algunos escenarios podría representar una segunda emergencia, producto de que en la logística post emergencia puede haber cadenas de suministro formales o informales/improvisadas que interactúan, se superponen, cooperan o incluso compiten por recursos escasos. La incorporación de este fenómeno en la función objetivo se materializa como una penalización γ para la robustez del modelo frente a restricciones vinculadas al flujo de inventario en los nodos de demanda ADP en donde exista esta convergencia, que se denota $\rho(z)$, y que podría registrarse en algunos escenarios. En esta notación, $z = (z_i^s)_{i \in N, s \in S}$ corresponde al conjunto de parámetros asociados a la eventual convergencia de material presente en algunos escenarios, la cual es penalizada respecto a la restricción (2.15), resultando:

$$a_i^s - b_i^s - \sum_{n \in N} q_{in}^s + \sum_{n \in N} q_{ni}^s + \sum_{j \in M} (o_{ji}^s + q_{ji}^s) = I_i^s + z_i^s - \mu_i^s, \forall i \in N, s \in S \tag{2.20}$$

de esta forma $\gamma\rho(z) = \gamma \sum_{i \in N} \sum_{s \in S} \theta_s z_i^s$.

Junto a lo anterior, la robustez de las soluciones se considera mediante la minimización de la variabilidad en los ítems de costos post emergencia, denotada por $\sigma = \sum_{s\in S}\xi_s + \lambda\sum_{s\in S}\Theta_s|\xi_s - \sum_{s'\in S}\Theta_{s'}|$.

Recordando los objetivos en el modelo, las funciones objetivo se formulan de manera robusta y aversa al riesgo como sigue: En primer lugar, se tiene un objetivo asociado a los costos deterministas de las operaciones pre desastre, así como el riesgo asociado a la componente estocástica del costo para operaciones logísticas post emergencia:

$$F_1 : Min(\Omega(X) + \sigma_1) = Min(\Omega(X) + \sum_{s\in S}\xi_s^{(1)} + \lambda\sum_{s\in S}\Theta_s|\xi_s^{(1)} - \sum_{s'\in S}\theta_{s'}\xi_{s'}^{(1)}| + \gamma\rho(z)) \tag{2.21}$$

Por otro lado, se tiene el segundo objetivo del modelo, asociado a los costos de oportunidad y efectos intertemporales sobre la privación:

$$F2 : Min\ \sigma_2 = \sum_{s\in S}\xi_s^{(2)} + \lambda\sum_{s\in S}\theta_s|\xi_s^{(2)} - \sum_{s'\in S}\theta_{s'}\xi_{s'}^{(2)}| \tag{2.22}$$

A las restricciones del modelo estocástico, reemplazando (2.15) por (2.20) se suman:

$$\xi_s^{(1)} - \sum_{s\in S}\theta_s\xi_s^{(1)} + \delta_{s1} \geq 0, \forall s \in S \tag{2.23}$$

$$\xi_s^{(2)} - \sum_{s\in S}\theta_s\xi_s^{(2)} + \delta_{s2} \geq 0, \forall s \in S \tag{2.24}$$

$$\delta_{s1}, \delta_{s2} \geq 0, \forall s \in S \tag{2.25}$$

donde las restricciones (2.23), (2.24),(2.25) permiten linealizar y resolver $\lambda\sum_{s\in S}\theta_s|\xi_s^{(1)} - \sum_{s'\in S}\theta_{s'}\xi_{s'}^{(1)}|$ eficientemente (Bozorgi-Amiri *et al.*, 2013)

2.5. *Fuzzy chance constrained programming* (FCCP) E INCERTIDUMBRE MIXTA

Dado que la mayoría de los parámetros, en ambos objetivos del modelo robusto, están contaminados con alto grado de *incertidumbre epistémica*, el problema podría ser formulado efectivamente por distribuciones de posibilidades en forma de números difusos. Lo anterior con el fin de enfrentar incertidumbres mixtas en un modelo que conducirá a soluciones robustas al tomar en cuenta una cartera de eventos aleatorios y posibles con respecto a las diversas realizaciones de datos inciertos.

En nuestro modelo robusto, la mayoría de los parámetros están contaminados con algún grado de incertidumbre epistémica que podría ser formulada por *distribuciones de posibilidad* en forma de números difusos. Si se aplica el enfoque *fuzzy chance constrained programming*-FCCP, es posible satisfacer *possibilistic chance constraints* (Tofighi *et al.*, 2016) dentro de niveles de confianza seleccionados.

En términos generales, hay tres medidas borrosas prominentes en la literatura para hacerse cargo de las restricciones posibilistas, convirtiéndolas en sus contrapartes *crisp*, las cuales son: posibilidad, necesidad y credibilidad (ver Liu, 2009). *Posibilidad* definida como el nivel de posibilidad, es decir, el más optimista, de ocurrencia de un evento incierto, en tanto que la *necesidad* muestra el nivel de posibilidad mínimo correspondiente bajo la visión más pesimista. La principal ventaja de estas medidas es la especificación de un grado de ocurrencia para cada evento difuso con actitudes pesimistas u optimistas.

Un evento posible puede fallar incluso si su grado de posibilidad es uno, y mantenerlo así aunque su grado de necesidad sea cero. Sin embargo, un evento confuso se mantendrá si su grado de credibilidad es uno, y fallará si su grado de credibilidad es cero (ver Liu, 2009). Dado lo anterior, se utiliza la *medida de credibilidad*, definida como el grado de certeza de que se produzca un evento incierto, para convertir restricciones posibilistas en sus contrapartes nítidas en nuestra formulación, con resultados más confiables que los relacionados con las medidas de posibilidad y necesidad.

Se utilizará el enfoque *fuzzy chance constrained programming - FCCP* para tratar este tipo de incertidumbre, el cual permite satisfacer *possibilistic chance constraints* dentro de niveles de confianza seleccionados, a fin de proporcionar la confiabilidad adecuada para la satisfacción de estas restricciones. El modelo estándar de FCCP que se utiliza es (Liu, 2009; Pishvaee et al., 2012):

$$\text{mín}\,\overline{f}$$

s.t.

$$Cr(f(x,\xi) \leq \overline{f}) \geq \beta$$

$$Cr(g_j(x,\xi) \leq 0) \geq \alpha_j; \forall j \tag{2.26}$$

donde ξ es un vector de coeficientes difusos, $\overline{f}$ y g_j denotan la función objetivo posibilista y la j-ésima restricción posibilista, respectivamente. Además, β y α_j son los niveles mínimos de confianza para la satisfacción de la función objetivo posibilista y la j-ésima restricción posibilista, respectivamente. Cabe señalar que el uso de la medida de credibilidad garantiza la satisfacción de la función objetivo posibilista y limita al nivel de certeza en al menos β y α_j, permitiendo al tomar de deciciones sensibilizar los niveles de confianza de sus resultados y restricciones.

Con ello, si se trabaja con números difusos triangulares y simétricos, la versión equivalente *crisp* de la desigualdad difusa $Cr(\widetilde{a} \leq \widetilde{b}) \geq \alpha)$ se puede simplificar de la siguiente manera:

$$a^C + (2\alpha - 1)w_a \leq b^C + (1 - 2\alpha)w_b; \forall \alpha \tag{2.27}$$

donde a^C y w_a denotan el centro y el rango del número difuso simétrico $\widetilde{a}$, respectivamente (Tofighi *et al.*, 2016).

Con ello, es posible formular el modelo robusto considerando la incertidumbre epistémica de ciertos parámetros, junto a medidas de credibilidad y números difusos triangulares con δ de propagación o *spread* (medido como proporción) en ambos lados. Es decir, si $\widetilde{a} = \langle a^c, \delta a^c \rangle \equiv TFN((1-\delta)a^c, a^c, (1+\delta)a^c)$. Así, si para la restricción (2.4) del problema original, el parámetro c_j (capacidad pre-desastre para $SP_j, j \in M$) puede considerarse contaminado por este tipo de incertidumbre, resultando la siguiente transformación (ver anexo para mayor información):

$$p_j^0 \leq \widetilde{c_j} Y_j, \forall j \in M \to Cr(p_j^0 - c_j Y_j \leq 0), \forall j \in M \to p_j^0 \leq c_j^C[(1+\delta/100) - 2\alpha\delta/100]Y_j, \forall j \in M \tag{2.28}$$

Lo mismo puede hacerse con la restricción (2.7) donde los parámetros φ_i^s (proporción de recursos preposicionados en ADP_i $i \in N$ utilizables, escenario $s \in S$), D_i^s (demanda en ADP_i $i \in N$, escenario $s \in S$) pueden incluir imprecisión, luego:

$$\widetilde{\varphi_i^s} q_i^0 - a_i^s + b_i^s = \widetilde{D_i^s}, \forall i \in N, s \in S$$

$$\to \begin{cases} (\varphi_i^s)^C[(1-\delta) + 2\alpha\delta]q_i^0 - a_i^s + b_i^s \leq (D_i^s)^C[(1+\delta) - 2\alpha\delta] & \forall i \in N, s \in S \\ (\varphi_i^s)^C[(1+\delta) - 2\alpha\delta]q_i^0 - a_i^s + b_i^s \geq (D_i^s)^C[(1-\delta) + 2\alpha\delta] & \forall i \in N, s \in S \end{cases} \tag{2.29}$$

Otras restricciones a ser modificadas con parámetros imprecisos son (2.6),(2.8),(2.9),(2.12),(2.20) resultando:

$$q_i^0 = \sum_{j \in M} q_{ji}^0 \leq c_i^C[(1+\delta) - 2\alpha\delta]X_i, \forall i \in N \tag{2.30}$$

$$a_i^s \leq |[(1+\delta) - 2\alpha\delta]((\varphi_i^s)^C q_i^0 - (D_i^s)^C)|, \forall i \in N, s \in S \tag{2.31}$$

$$b_i^s \leq |[(1+\delta) - 2\alpha\delta]((D_i^s)^C - (\varphi_i^s)^C q_i^0)|, \forall i \in N, s \in S \tag{2.32}$$

$$p_j^s \leq (o_j^s)^C[(1+\delta) - 2\alpha\delta]Y_j, \forall j \in M, s \in S \tag{2.33}$$

La transformación de la restricción (2.20) es análoga a la mostrada para la restricción (2.7), donde el parámetro impreciso es la convergencia de materiales z_i^s. Las demás restriciones del modelo se mantienen sin cambios, por no considerar parámetros imprecisos (nos referimos a las restricciones (2.5),(2.10),(2.11),(2.13)), donde la versión robusta incorpora las restricciones (2.23)-(2.25) que no sufren cambios.

Respecto de las funciones objetivo del modelo robusto, se tiene que tanto sus componentes deterministas así como las estocásticas (dependientes de cada escenario) pueden incorporar parámetros imprecisos, los cuales para las componentes estocásticas son independientes de los escenarios, a saber:

$$\widetilde{\Omega}(X) = \sum_{j \in M}(\widetilde{F}_j Y_j + \widetilde{P}_j^0 p_j^0) + \sum_{i \in N} \widetilde{F}_i x_i + \sum_{j \in M}\sum_{i \in N} \widetilde{TRC}_{ji}^0 q_{ji}^0 \tag{2.34}$$

$$\widetilde{\xi}_s^{(1)} = (\sum_{s \in S}\sum_{k \in V}\sum_{i \in N} \Theta_s \widetilde{TRC}_{ki}^s q_{ki}^s + \sum_{s \in S}\sum_{j \in M}\sum_{i \in N} \Theta_s \widetilde{TRC}_{ji}^s o_{ji}^s) + \sum_{s \in S}\sum_{k \in V} \Theta_s \widetilde{H}_k I_k^s \tag{2.35}$$

$$\widetilde{\xi}_s^{(2)} = (\sum_{s\in S}\sum_{j\in M}\sum_{i\in N}\Theta_s\widetilde{\pi}_{ji}^s q_{ji}^s + \sum_{s\in S}\sum_{k\in N}\sum_{i\in N}\Theta_s\widetilde{\pi}_{ki}^s q_{ki}^s + \sum_{s\in S}\sum_{j\in M}\sum_{i\in N}\Theta_s\widetilde{\pi}_{ki}^{so} o_{ji}^s) + \sum_{s\in S}\sum_{i\in N}\Theta_s\widetilde{W}_i^s u_i^s \tag{2.36}$$

El tiempo de privación se supone proporcional a la distancia a recorrer para suministrar los bienes, donde los costos de privación son funciones no lineales de los tiempos diferidos, los cuales son parámetros específicos del modelo propuesto, los que al ser dependientes de datos de la red también pueden absorber incertidumbre epistémica e impresisión.

Tomando la formulación robusta basada en la minimización del riesgo asociado al utilizar planificación por escenarios, se reconoce además la convivencia de la incertidumbre subyacente a las probabilidades de ocurrencia de los escenarios con la imprecición de los parámetros utilizados en ellos. Definiendo $\overline{Cr} = [(1-\delta/100) + 2\beta\delta/100]$, $\underline{Cr} = [(1+\delta/100) - 2\beta\delta/100]$, se tienen las siguientes componentes para las funciones objetivo *defuzificadas*:

$$\Omega(X)^{DF} = \sum_{j\in M}\overline{Cr}(F_j^C Y_j + P_j^{0C} p_j^0) + \sum_{i\in N}\overline{Cr}F_i^C x_i + \sum_{j\in M}\sum_{i\in N}\overline{Cr}TC_{ji}^{0C}T_{ji}^{0C}q_{ji}^0 \tag{2.37}$$

$$\xi_s^{(1)DF} = (\sum_{s\in S}\sum_{k\in V}\sum_{i\in N}\Theta_s\overline{Cr}TC_{ki}^{sC}T_{ki}^{sC}q_{ki}^s + \sum_{s\in S}\sum_{j\in M}\sum_{i\in N}\Theta_s\overline{Cr}TC_{ji}^{sC}T_{ji}^{sC}o_{ji}^s)$$

$$+ \sum_{s\in S}\sum_{k\in V}\Theta_s\overline{Cr}H_k^C I_k^s \tag{2.38}$$

$$\xi_s^{(2)DF} = (\sum_{s\in S}\sum_{j\in M}\sum_{i\in N}\Theta_s\overline{Cr}\pi_{ji}^{sC}q_{ji}^s + \sum_{s\in S}\sum_{k\in N}\sum_{i\in N}\Theta_s\overline{Cr}\pi_{ki}^{sC}q_{ki}^s + \sum_{s\in S}\sum_{j\in M}\sum_{i\in N}\Theta_s\overline{Cr}\pi_{ki}^{soC}o_{ji}^s)$$

$$+ \sum_{s\in S}\sum_{i\in N}\Theta_s\overline{Cr}W_i^{sC}u_i^s \tag{2.39}$$

Volviendo a la formulación robusta y aversa al riesgo, junto a las componentes defuzificadas, el modelo propuesto resulta en dos objetivos que separan aquellas componentes de costo de la logística tradicional para un problema de localización, asignación y distribución de inventarios, con aquellas componentes del costo social.

$$F_1 : Min(\Omega(X)^{DF} + \sum_{s\in S}\xi_s^{(1)DF} + \lambda\sum_{s\in S}\theta_s|\xi_s^{(1)DF} - \sum_{s'\in S}\theta_{s'}\xi_{s'}^{(1)DF}| + \gamma\rho(z)^{DF}) \tag{2.40}$$

$$F_2 : Min\ \sigma_2() = \sum_{s\in S}\xi_s^{(2)DF} + \lambda\sum_{s\in S}\theta_s|\xi_s^{(2)DF} - \sum_{s'\in S}\theta_{s'}\xi_{s'}^{(2)DF}| \tag{2.41}$$

Con ello se protege a la formulación del modelo de aquellos parámetros imprecisos, se incorpora la robustez del modelo frente a infactibilidades en algunos escenarios y se permite que el modelo cumpla los niveles de confianza β y α_j mínimos para la satisfacción de la función objetivo posibilista y la j-ésima restricción de oportunidad posibilista (possibilistic chance constraints), respectivamente.

La figura 2.2 resume la idea subyacente a esta formulación, donde la planificación por escenarios reconoce la existencia de incertidumbre aleatoria asociada a ocurrencias con probabilidades conocidas, respecto de las cuales se desea que el modelo sea averso al riesgo. Por otro lado, el reconocimiento de la incertidumbre epistémica incorpora mediante *fuzzy chance contrained programming* aquella impresición propia de algunos parámetros dentro de cada escenario, obteniendo con ello un modelo robusto a una incertidumbre global del sistema, de tipo mixta y conformada por distintas fuentes de incertidumbre.

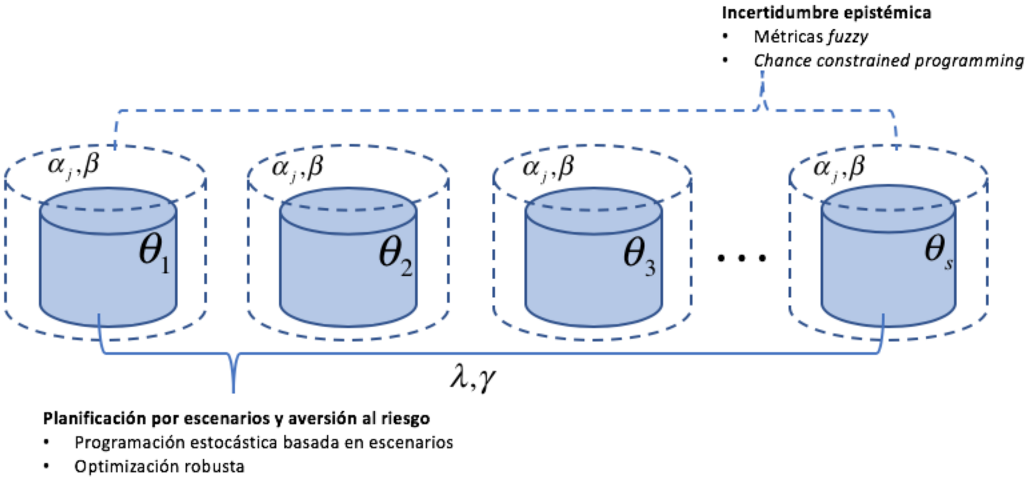


Figura 2.2: Modelo Robusto y posibilista

Así, la planificación por escenarios permite contar con un listado conocido de probabilidades de ocurrencia con parámetros asociados a cada instancia. Por otro lado, la optimización robusta optimiza el riesgo asociado a la variabilidad de los costos entre escenarios y factibilidad de restricciones dentro de los mismos (como la convergencia de materiales), usando los pesos λ y γ, respectivamente. Finamente, dentro de cada escenario y entre los mismos existe la incertidumbre epistémica que es considerada en el modelo mediante *fuzzy chance constrained programming* con números difusos y medidas de credibilidad.

2.5.1. MODELO MULTIOBJETIVO, ROBUSTO Y POSIBILISTA

Finalmente, la formulación multiobjetivo se trabaja mediante compromise programming, basada en el método L_p metrics (Romero *et al.*, 1998), donde cada objetivo se resuelve por separado, obteniendo soluciones F_1^*, F_2^* y luego formulando un tercer objetivo dado por:

$$\text{mín} \;\; F_3 = [wF_1 + (1-w)F_2] \tag{2.42}$$

donde $0 \leq w \leq 1$ es el peso relativo de los componentes de la función objetivo dados por el tomador de decisiones, a saber, el coeficiente L_p metrics (Romero *et al.*, 1998). Usando esta función objetivo y teniendo en cuenta las restricciones del modelo propuesto, se obtiene un modelo de programación con un solo objetivo, que se puede resolver de manera eficiente utilizando programación lineal. Esto permite que el modelo sea analizado de manera interactiva, proponiendo una frontera Pareto-óptima en virtud de los objetivos asociados a costos de la logística tradicional y costos sociales.

2.6. CASO DE ESTUDIO

En esta sección se presenta un análisis numérico del modelo en torno a un caso práctico basado en antecedentes reales y con evidencia empírica, con el objetivo de contrastar resultados, analizar el impacto de las contribuciones del modelo y analizar cómo las distintas formulaciones contribuyen a soliciones óptimas del problema. Finalmente, con estos resultados será posible probar la sensibilidad de la solución a los parámetros del modelo que resulten relevantes a la hora de tomar decisiones y evaluar la disponibilidad y exactitud de la información con que el modelo pueda ser aplicado.

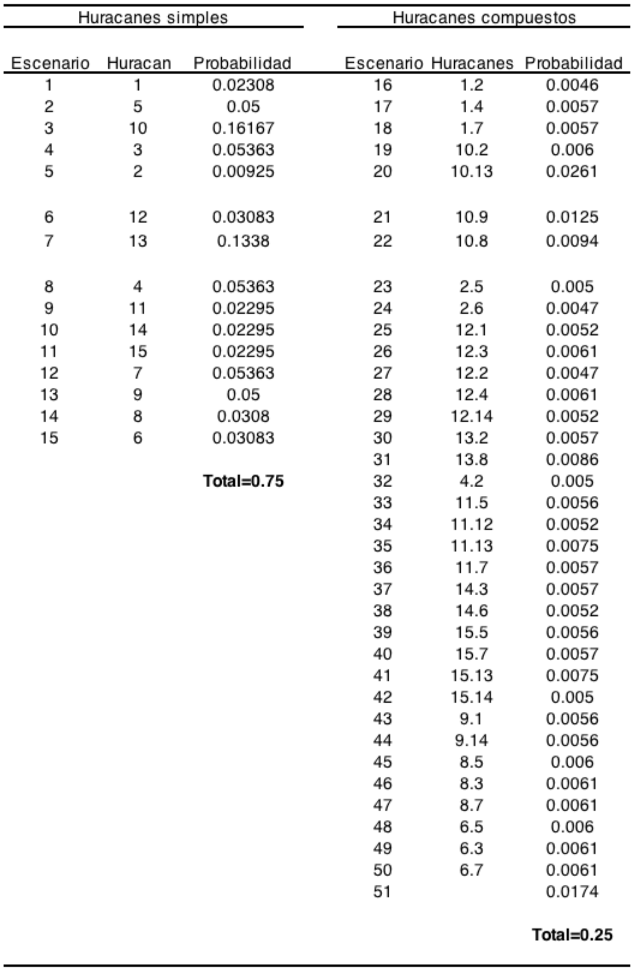
Para ello se utiliza una instancia adaptada del caso expuesto por Rawls y Turnquist (2012) y utilizadado por Pradhananga *et al.* (2016) para el modelo estocástico basado en escenarios. La instancia probada consta de: una red afectada por un desastre natural respecto del cual se tiene registro histórico de ocurrencia, localización o cobertura, e impacto; un conjunto de escenarios en donde se materializa la incertidumbre de parámetros como la demanda, el estado de la red, conectividad y tiempos de respuesta, disponibilidad de inventarios, así como aspectos del comportamiento humano que han sido introducidos en la función objetivo, tales como la privación y la sensibilidad a los tiempos de respuesta.

En esta instancia, la red está compuesta por 30 nodos y 55 arcos que abarcan las regiones del sureste de los Estados Unidos, como se muestra en la figura 3. Arbitrariamente, cinco de los 30 nodos se seleccionan al azar como posibles ubicaciones de SP, y demás nodos de la red se designan como ADP.

Los escenarios de demanda y los datos de confiabilidad de la red consisten en un conjunto de 51 escenarios de huracanes construidos a partir de una muestra de 15 huracanes (10 mayores - categoría 3-5 y cinco menores - categoría 1 y 2). La definición de categorías de huracanes puede obtenerse de Rawls y Turnquist (2012). Los registros históricos de una muestra de quince huracanes forman la base para construir escenarios que representan demandas potenciales y daños en la red (ver tabla 2.2).

Figura 2.3: ADPs y potenciales SPs en instancia de estudio (fuente: Rawls y Turnquist (2012))

En las definiciones de escenarios, se considera que se han destruido todas las instalaciones (y todos los suministros almacenados en el nodo respectivo) ubicados en los puntos de impacto para huracanes mayores (ver tabla 2.3). En el caso de los huracanes menores, se supone que las instalaciones y los suministros disponibles (en caso de haberlos) en el punto de impacto están dañados (con un 50 % de pérdida). Por lo anterior, se observa que la proporción de los recursos preposicionados en cada ADP, que siguen siendo utilizables en el escenario $s \in S$, definida por q_{si} para cada ADP i-ésimo, se asume igual a 0 para todos los nodos afectados por huracanes mayores, y 0.5 para todos afectados por huracanes menores.

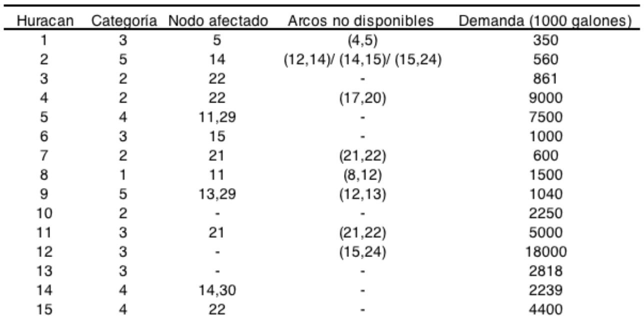


Huracanes simples			Huracanes compuestos		
Escenario	Huracan	Probabilidad	Escenario	Huracanes	Probabilidad
1	1	0.02308	16	1.2	0.0046
2	5	0.05	17	1.4	0.0057
3	10	0.16167	18	1.7	0.0057
4	3	0.05363	19	10.2	0.006
5	2	0.00925	20	10.13	0.0261
6	12	0.03083	21	10.9	0.0125
7	13	0.1338	22	10.8	0.0094
8	4	0.05363	23	2.5	0.005
9	11	0.02295	24	2.6	0.0047
10	14	0.02295	25	12.1	0.0052
11	15	0.02295	26	12.3	0.0061
12	7	0.05363	27	12.2	0.0047
13	9	0.05	28	12.4	0.0061
14	8	0.0308	29	12.14	0.0052
15	6	0.03083	30	13.2	0.0057
			31	13.8	0.0086
		Total=0.75	32	4.2	0.005
			33	11.5	0.0056
			34	11.12	0.0052
			35	11.13	0.0075
			36	11.7	0.0057
			37	14.3	0.0057
			38	14.6	0.0052
			39	15.5	0.0056
			40	15.7	0.0057
			41	15.13	0.0075
			42	15.14	0.005
			43	9.1	0.0056
			44	9.14	0.0056
			45	8.5	0.006
			46	8.3	0.0061
			47	8.7	0.0061
			48	6.5	0.006
			49	6.3	0.0061
			50	6.7	0.0061
			51		0.0174
					Total=0.25

Tabla 2.2: Definición de escenarios y probabilidad de ocurrencia (Rawls y Turnquist (2012))

Respecto de la incorporación del comportamiento humano y los costos de privación, en este experimento se considera un producto de emergencia, a saber, agua potable, puesto que se cuenta con funciones de privación calibradas para este insumo en Pérez-Rodríguez y Holguin-Veras (2015). Se supone que los costos de penalización por demanda insatisfecha para cada producto son diez veces superiores al precio de compra del recurso, y se supone que los costos de mantenimiento representan el 25 % del precio de compra.

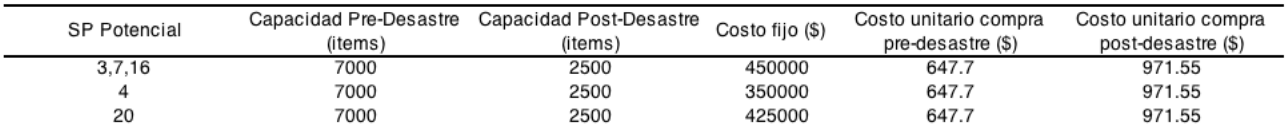
Los costos de transporte se asumen proporcionales a las distancias entre las ubicaciones y la cantidad enviada. Los parámetros TC_{ji}^{0} y TC_{ji}^{s} son los costos de transporte unitario entre los



Huracan	Categoría	Nodo afectado	Arcos no disponibles	Demanda (1000 galones)
1	3	5	(4,5)	350
2	5	14	(12,14)/ (14,15)/ (15,24)	560
3	2	22	-	861
4	2	22	(17,20)	9000
5	4	11,29	-	7500
6	3	15	-	1000
7	2	21	(21,22)	600
8	1	11	(8,12)	1500
9	5	13,29	(12,13)	1040
10	2	-	-	2250
11	3	21	(21,22)	5000
12	3	-	(15,24)	18000
13	3	-	-	2818
14	4	14,30	-	2239
15	4	22	-	4400

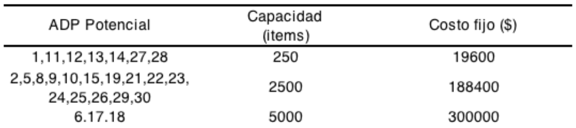
Tabla 2.3: Características de huracanes (Rawls y Turnquist (2012))

nodos definidos como SP $j \in M$ y ADP $i \in N$, en la etapa anterior al desastre y en los escenarios posteriores al desastre, respectivamente. Recordar que no hay envíos entre los ADP en la etapa previa al desastre, y no hay envíos entre los SP en ninguna fase de la emergencia. Los costos unitarios, por tanto, no están definidos para tales pares de nodos.



SP Potencial	Capacidad Pre-Desastre (items)	Capacidad Post-Desastre (items)	Costo fijo ($)	Costo unitario compra pre-desastre ($)	Costo unitario compra post-desastre ($)
3,7,16	7000	2500	450000	647.7	971.55
4	7000	2500	350000	647.7	971.55
20	7000	2500	425000	647.7	971.55

Tabla 2.4: Datos para SPs potenciales (Rawls y Turnquist (2012))



ADP Potencial	Capacidad (items)	Costo fijo ($)
1,11,12,13,14,27,28	250	19600
2,5,8,9,10,15,19,21,22,23, 24,25,26,29,30	2500	188400
6.17.18	5000	300000

Tabla 2.5: Datos para ADPs potenciales (Rawls y Turnquist (2012))

Los costos unitarios pueden diferir entre dos puntos dependiendo del tipo de modo de transporte disponible (en nuestro caso es un único modo), y también son diferentes para las etapas previa y posterior al desastre, dado que la red puede sufrir cambios que alteran las distancias a recorrer para el suministro de productos de emergencia. En relación con lo anterior, las distancias entre dos puntos pueden cambiar después del desastre, ya que el desastre puede afectar la red de transporte, inhabilitando algunos arcos de la red. Para un escenario dado s, la distancia entre dos nodos, que se denota por T_{ji}^{s}, es computada ejecutando un algoritmo *Floyd Warshall* (Floyd, 1962) para cada red definida por el set de escenarios disponibles.

El tiempo de privación para un individuo es el tiempo entre la ocurrencia del desastre y la satisfacción de su demanda. El tiempo de privación se supone proporcional a la distancia a recorrer para suministrar los bienes en cada escenario $s \in S$. Cuando la demanda de un ADP se cumple a través de cantidades preposicionadas en el mismo ADP, el tiempo de privación, y por lo tanto, el costo de privación, se vuelve insignificante. Para las otras situaciones de entrega, los costos de privación son funciones no lineales de los tiempos de viaje y son parámetros específicos del modelo propuesto.

El costo de privación es exponencialmente creciente con el tiempo de privación y por lo tanto la distancia a recorrer, sigue la estructura sugerida por Pérez-Rodríguez y Holguin-Veras (2015). Esto es, para cada escenario $s \in S$ se define el costo de privación dependiente del tiempo de privación t como: $\pi^s(t) = e^{a+bt} - e^a$, con parámetros a y b adecuadamente calibrados (Acorde al estudio de Pérez-Rodríguez y Holguin-Veras (2015), los parámetros son a=1.5031, b=0.1172, valores que se complementan utilizando dicha expresión a partir de las distancias conocidas para cada escenario y una velocidad promedio a recorrer por los vehículos que distribuyen agua potable como suministro crítico) y contando con las distancias entre nodos pertenecientes al conjunto de ADP y SP, para cada escenario $s \in S$, donde la cantidad de demanda por persona es fija, y las condiciones para el tiempo de privación son las siguientes (Pradhananga *et al.* (2016)):

i) $t = 0$, si una persona es provista desde el ADP i designado.

ii) $t = f$ (distancia desde un ADP i' y el ADP i designado), si una persona es suministrada desde otro ADP.

iii) $t = f$ (distancia entre SP j y ADP i designado) $+ T_1$, si una persona se abastece directamente de existencias en SP.

iv) $t = f$ (distancia entre SP j y ADP i designado) $+ T_2$, si SP suministra a una persona a través de compras directas, donde $T_2 > T_1$.

2.6.1. ANALISIS DE RESULTADOS

En primer lugar se toma el modelo base como un modelo estocástico basado en escenarios, luego de lo cual se introduce la programación robusta y multiobjetivo con el fin de minimizar el riesgo e incorporar la convergencia de materiales como parte de la robustez del modelo. Finalmente, reconociendo la presencia de incertidumbre epistémica se plantea un modelo multiobjetivo posibilístico aplicando *fuzzy chance constrained programming.*

Con ello, se obtienen los resultados que serán analizados en términos de: costos globales en la respuesta de la logística humanitaria, análisis de Pareto para el modelo robusto y mutiobjetivo, análisis de robustez del modelo y sus soluciones, sensibilidad de parámetros difusos y efecto de la incorporación de la incertidumbre epistémica. Los modelos son codificados utilizando Python y se resuelven con el optimizador Gurobi V12.5.1 en un computador portátil de 2.6 GHz con 8 GB de RAM.

Análisis de costos globales y sensibilización

En el primer gráfico (figura 2.4), se comparan los valores de los costos logísticos para las fases pre y post desastre, así como los costos sociales cuando la estructura robusta y posibilista se incorpora a la función objetivo y las restricciones con parámetros imprecisos, respectivamente.

En términos globales, se observa la contribución de incorporar el análisis robusto y posibilista en un modelo bi-objetivo, el cual, como se ha indicado anteriormente, separa el costo de la logística tradicional dada por decisiones de localización, compra, almacenamiento y distribución de suministros críticos en las fases previas y posteriores al desastre, de aquellos costos sociales dados por el impacto en la privación de los tiempos de respuesta y la sensibilidad respecto de la demanda. Como se aprecia en el gráfico, los ítems de costo social (privación y fallo organizacional por convergencia

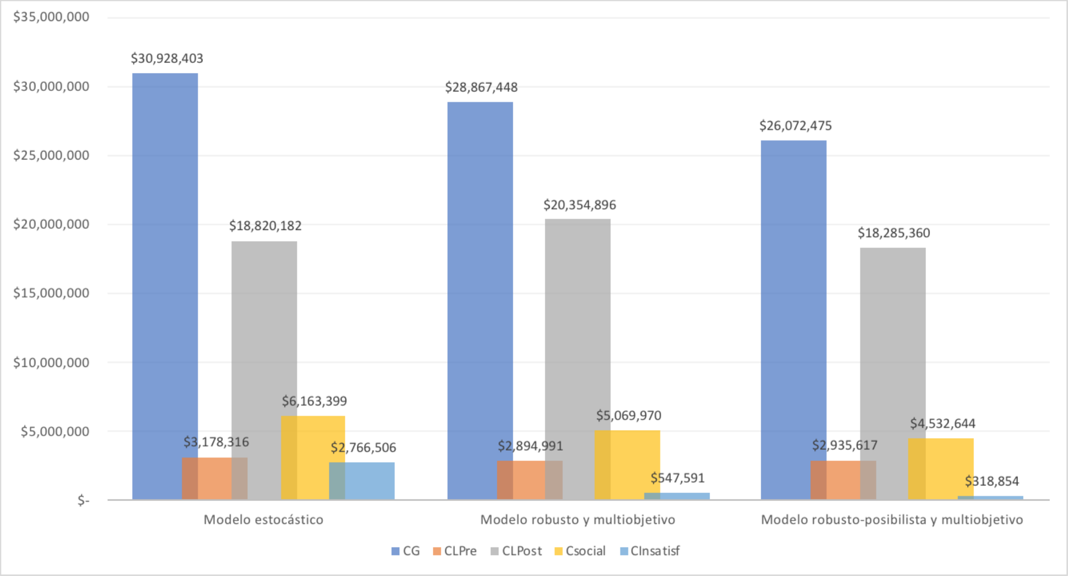


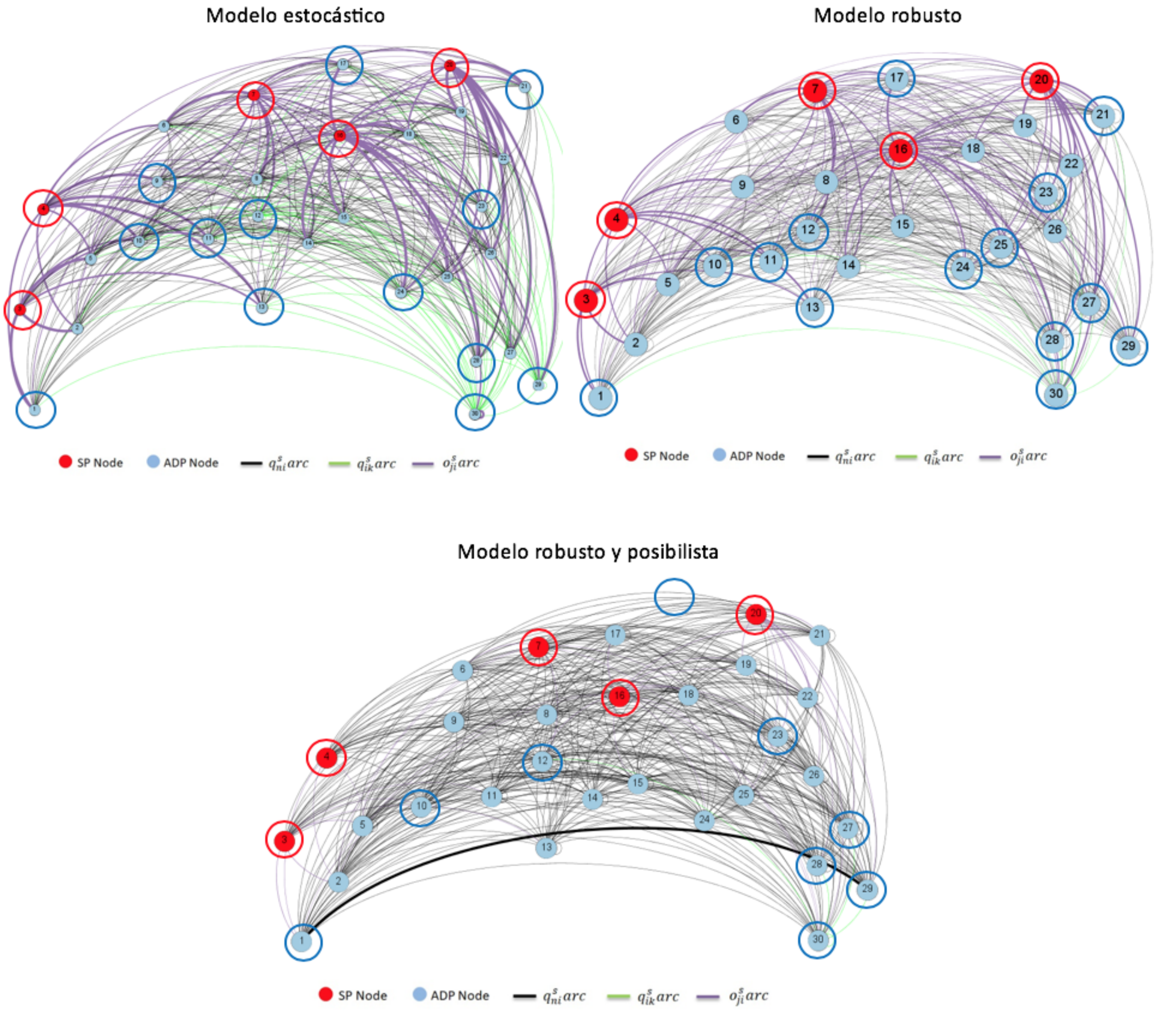
Figura 2.4: Resultados globales - Comparación de estructura de costos

de materiales) disminuyen a medida que el modelo base se formula como un modelo bi-objetivo robusto y averso al riesgo, y luego reconociendo la incertidumbre epistémica mediante el uso de *fuzzy chance constrained programming.*

En este sentido, las decisiones se toman de manera tal que no sólo se busque minimizar un valor esperado para los costos de la logística humanitaria, sino más bien tratando que el riesgo sea el mínimo posible, donde la variabilidad y optimalidad de los resultados para distintos escenarios (robustez de las soluciones), así como la factibilidad de restricciones que incorporan fenómenos no deseados como la convergencia de materiales (robustez del modelo) permiten satisfacer el conjunto de restricciones originales con resultados donde los costos globales disminuyen, haciendo más eficiente la operación, más aún cuando se incluye además la posibilidad de contar con parámetros imprecisos dentro de cada escenario. Las decisiones asociadas a patrones de localización y elección de nodos como SP, ADP, así como los flujos enviados entre nodos de la red pueden observarse en las siguientes figuras (estas representan los flujos de las redes una vez resueltos los modelos, destacando los nodos seleccionados como SP, ADP respectivamente):

Se observa que, cuando la función objetivo se cambia desde un valor esperado de los costos globales a una función objetivo aversa al riesgo, las decisiones privilegian flujos vinculados a inventarios en nodos ADP o desde los SP en la fase post desastre, disminuyendo decisiones asociadas a compras de suministro en la fase post desastre. Este efecto se acentúa cuando además se reconoce la convergencia de materiales y la variabilidad de parámetros con incertidumbre epistémica. Por otro lado, en términos generales, las redes se vuelven menos densas, observándose menos arcos con flujo para satisfacer las mismas necesidades, cuando el modelo es robusto y/o posibilista.

Finalmente, este costo global es aún menor si además del riesgo en la función objetivo, que reconoce la presencia de parámetros imprecisos (los cuales proporcionan variabilidad dentro y entre distintos escenarios), se introducen niveles de confianza para la satisfacción de una función ojetivo y restricciones posibilistas, usando medidas de credibilidad para convertir las restricciones y funciones objetivo posibilistas en sus contrapartes defuzificadas. Esta medida, como se ha indicado,


Modelo estocástico

Modelo robusto

Modelo robusto y posibilista

Figura 2.5: Resultados y estructura de red: Modelo Estocástico - modelo robusto - modelo posibilista

representa el grado de certeza de ocurrencia de un evento incierto, mientras que los niveles de confianza representan parámetros que el tomador de decisión puede discutir previa resolución del modelo. En nuestro caso se ha trabajado con un criterio del 95 % de confianza para credibilidad en la función objetivo y en las restricciones.

Convergencia de materiales

Respecto al comportamiento de los donantes, existen estudios que dan cuenta de flujos de ayuda enviados directamente al área afectada o a los receptores finales, incluyendo donaciones realizadas a través organizaciones caritativas y agencias gubernamentale que distribuyen las donaciones a las víctimas del desastre en forma no coordinada (Holguín-Veras *et al.*, 2014, Destro y Holguín-Veras, 2011). Estas donaciones a menudo incluyen donaciones monetarias, esfuerzos de reconstrucción del transporte, suministros médicos, equipos y servicios de telecomunicaciones, así como comida y agua.

Al respecto, existen mediciones y estadísticas que sin duda están lejos de ser completas porque incluyen solo las donaciones que se informan en los medios, datos que sin duda proporcionan una mirada útil en los patrones estadísticos de la convergencia de materiales. Para ver este efecto, tal como se muestra en el gráfico de la figura 2.6, se sensibilizan los modelos incrementando el porcentaje de la demanda que llega a los nodos ADP como flujo que produce convergencia de materiales, el cual genera costos asociados a mantenimiento de inventarios y transporte.

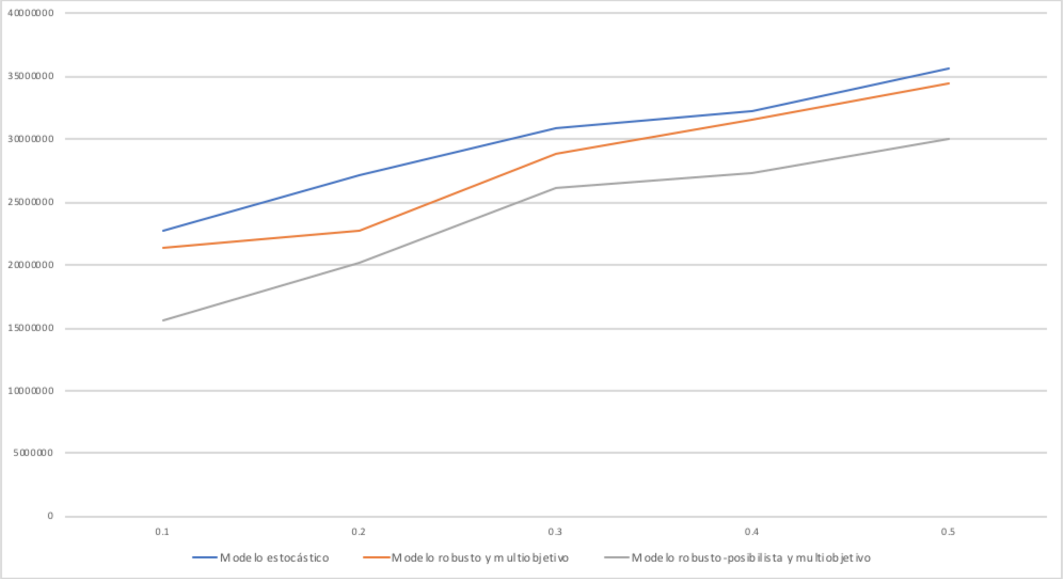


Figura 2.6: Convergencia de materiales y costos globales

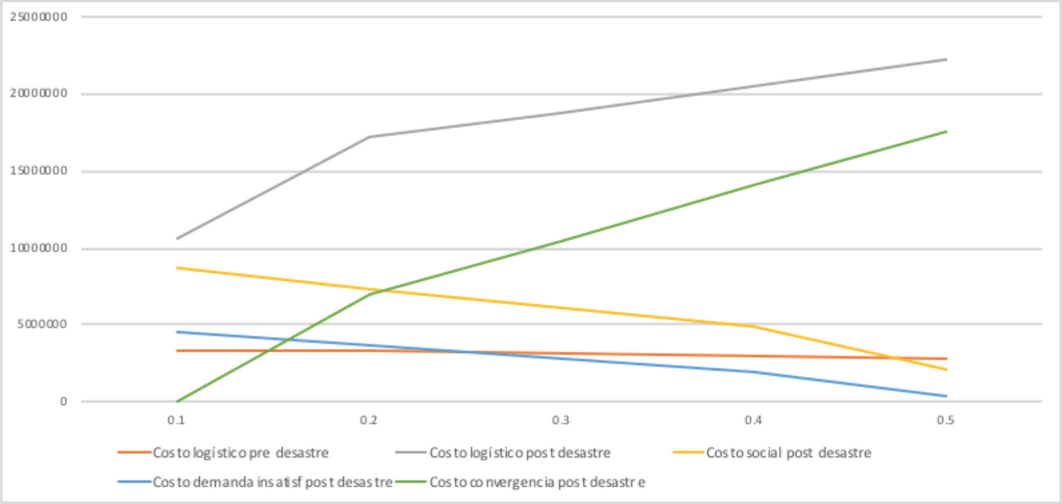


Figura 2.7: Convergencia de materiales y costos globales: Detalle modelo estocástico

Como se aprecia en el gráfico, los costos globales aumentan a medida que el flujo de convergencia es mayor, resultando en cualquier caso menor cuando en el modelo se incorporan la aversión al riesgo y la imprecisión de parámetros por incertidumbre epistémica, respectivamente. Este aumento afecta la logística post desastre, en la medida que se incrementan los flujos de suministros por sobre la demanda y se generan necesidades de almacenamiento y tranporte adicionales, por otro lado, si bien disminuye la privación y el quiebre potencial, en términos globales el efecto es negativo, como se ha dicho (ver ejemplo modelo estocástico - figura 2.7)

Respecto del modelo robusto, podemos decir que los costos de convergencia de materiales se reducirán con un aumento en el valor de γ (penalidad o peso asignado a la robustez de la solución equivalente al costo de convergencia de materiales). Por otro lado, el costo esperado aumenta al aumentar su valor, lo cual indica que la incorporación de este fenómeno a los costos de logística humanitaria representa un aporte a la toma de decisiones, y plantea un desafío para mejorar su medición y registro. Para efectos de cálculo, en la instancia de prueba se utiliza un valor gamma equivalente al 50 % del costo de almacenamiento de suministros críticos.

Modelo multiobjetivo y análisis de robustez

Respecto de las formulaciones multiobjetivo, para llegar a una solución adecuada que permita al tomador de decisiones hacer concesiones de un criterio contra otro, basándose en los resultados, el problema se resuelve varias veces mientras se varía el coeficiente w. La disminución del peso para los costos logísticos hace que los costos sociales disminuyan. Por lo tanto, al aumentar la meta para cualquiera de los objetivos (figura 2.8), se genera más espacio para mejorar otros objetivos, entregando versatilidad a la formulación al momento de ponderar prioridades y buscar resultados, siendo muy sensible el aspecto social. Esto se puede observar en la curva de pareto:

Finalmente, en nuestro trabajo, todos los parámetros difusos se consideran simplemente como números borrosos (*fuzzy numbers*) triangulares simétricos con un 10 % de propagación (*spread*) en ambos lados. Cuando esta propagación aumenta, observamos que los costos en general se reducen, dado que los parámetros imprecisos pueden tener una mayor variabilidad. Esto, sumado a los niveles de confianza para restricciones posibilistas entrega una versatilidad a la planificación que el tomador de decisiones puede aprovechar como mecanismo de sensibilización y discusión de impacto

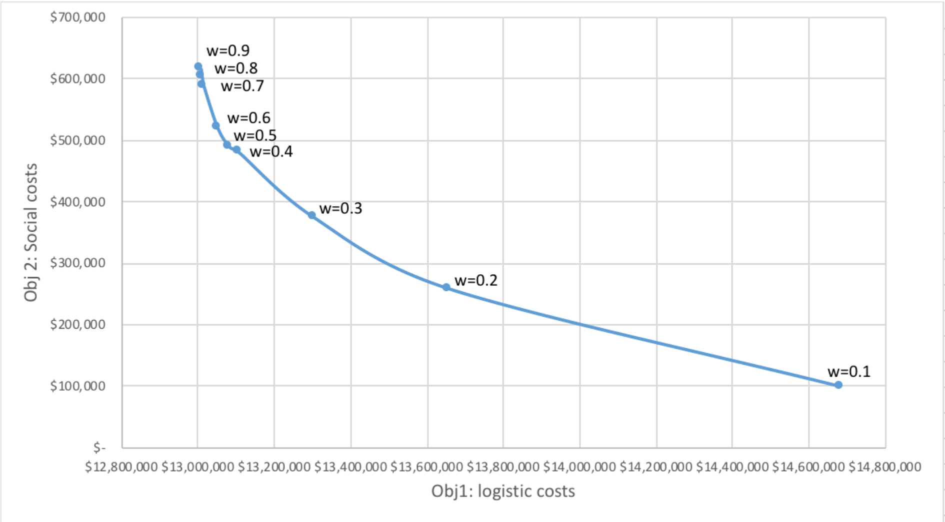


Figura 2.8: Analsis Pareto - Modelo Robusto y Posibilista (variación de peso w)

de políticas o procedimientos elaborados a partir de resultados de los modelos presentados.

2.6.2. CONCLUSIONES

En esta investigación se propone un modelo para el problema del diseño de la red de logística humanitaria, donde se incorpora la incertidumbre y los objetivos múltiples del problema de decisión para las etapas previas y posteriores al desastre, de manera integrada. El modelo se hace cargo de la planificación de la preparación y la respuesta e incorpora la planificación de la distribución de los artículos de socorro durante la preposición del stock, incluyendo el fenómeno no deseado de convergencia de materiales que ocurre en fases posteriores a la emergencia.

Las incertidumbres se tratan teniendo en cuenta la naturaleza difusa y aleatoria inherente a los datos disponibles, de manera que el modelo reconoce la existencia de probabilidades para fenómenos en donde se cuenta con registros históricos de ocurrencia y escenarios enumerados, así como también incorpora la incertidumbre epistemica propia de datos imprecisos donde estas leyes de probabilidad no se encuentran disponibles, por lo cual es conveniente trabajar con lógica difusa y grados de pertenencia o credibilidad en torno a niveles de incertidumbre o confianza esperados y predefinidos.

Cabe destacar que la incertidumbre es incorporada mediante una función objetivo aversa al riesgo, donde la penalidad por no cumplimiento de restricciones de balance de flujo es interpretada con la presencia de la convergencia de materiales, lo cual permite evaluar la robustez del modelo y complementarla con la robustez de las soluciones, toda vez que al trabajar con distintos escenarios se ha buscado minimizar la variabilidad de los costos globales y no tan sólo trabajar con valores esperados, como es muy común en el ámbito de la optimización estocástica.

Finalmente, la gestión de la incertidumbre y la incorporación de múltiples objetivos están sujetos a los criterios del tomador de decisiones, que pueden utilizar el modelo y sensibilizar los resultados. Con esto, se está entregando una herramienta de suma utilidad en un entorno donde no existen muchas aplicaciones concretas en contextos de políticas públicas, organizaciones de ayuda humanitaria, sistemas de apoyo a la toma de decisiones, integración de información local y respuesta de las comunidades (planificación pública, educación de riesgo, redes sociales, entre otros). En este sentido, es necesario que como parte de la investigación futura reduzca la brecha entre la teoría y la aplicación a través del desarrollo de estudios de casos y levantamiento de campo (Holguín-veras *et al.*, 2012, 2014, 2015, Gralla *et al.*, 2014). Además, se requiere una contextualización adecuada con la institucionalidad local y la organización política-social para la implementación, seguimiento y medición del éxito de iniciativas de logística humanitaria.

2.6.3. Futuras Investigaciones

De este trabajo, se pueden identificar oportunidades de investigación futura que debieran hacerse relevantes en la toma de decisiones respecto de logística humanitaria, tales como: Costos de privación y modelo multiproducto, con sensibilidades diferenciadas por demanda, donde se cuente con costos de privación dependientes del sentido de urgencia y disposición a pagar que diferentes suministros críticos suponen para la demanda; incorporación psicología del desastre y resiliencia (relacionada con la psicología del desastre, incluida la angustia, la ansiedad, el miedo, el estrés, la satisfacción y el contagio emocional), conceptos para los cuales resulta interesante ver estudios como los de Aldunce *et al.* (2015) y Sheu (2014); programación dinámica, red expandida en el tiempo y ruteo de vehículos, incluyendio a nuestro modelo decisiones de ruteo de vehículos, convergencia de materiales y congestión generada por el comportamiento de los donantes; formulación multiobjetivo y modelos jerárquicos, incorporando diferentes formas de organización y coordinación entre múltiples agentes involucrados en la logística humanitaria.

Finalmente, resulta interesante experimentar los modelos propuestos con distintos tipos de desastres naturales, por cuanto la naturaleza estocástica de los mismos difiere en información disponible y capacidad de predecir en el corto plazo los efectos o la propagación de los mismos. En nuestro caso hemos utilizado un estudio de caso basado en huracanes, pero ciertamente existen otros desastres donde la organización y respuesta incrementa su complejidad ante la escasa posibilidad de anticipar su ocurrencia, propagación o tipificación de escenarios, como en el caso de terremotos o erupciones volcánicas. Sin duda este punto requiere una mayor integración con sistemas de información integrada y desarrollo de métodos predictivos en el ámbito geológico.

CONCLUSIÓN

El presente trabajo establece una linea de investigación definida y estructurada en torno a la logística humanitaria, puesto que en primer término ofrece una revisión bibliográfica acuciosa de los trabajos publicados en los últimos 10 años. Esta revisión no tiene por objeto ser un análisis bibliométrico, sino más bien un análisis metodológico y contextual del proceso de modelamiento matemático para la optimización de decisiones de logística humanitaria.

Los criterios y consideraciones con los cuales se ha revisado la literatura toman en cuenta análisis de las diferencias fundamentales entre la logística tradicional y la logística humanitaria, por cuanto la primera se ocupa principalmente de la optimización de las diferentes características de la fabricación y distribución de bienes, cubriendo una amplia gama de actividades que requieren modelos analíticos específicos. El caso de la logística humanitaria, en tanto, abarca una amplia gama de actividades que ocurren en cualquiera de las fases de la gestión de emergencias, desde la mitigación, preparación, respuesta y recuperación.

Lo anterior conlleva a una mirada amplia del concepto de desastre natural y la logística, desde la perspectiva del comportamiento y objetivos perseguidos por las comunidades, organizaciones e individuos involucrados; la información disponible y la dinámica con que las decisiones son tomadas bajo escenarios dominados por la incertidumbre; el proceso de modelación matemática, la optimización e integración multidisciplinaria, así como los desafíos tecnológicos para enfrentar soluciones útiles para la gestión de la logística humanitaria, en todas sus fases.

Así es como la presente tesis doctoral parte con un análisis de la literatura enfocado en criterios como: La incorporación de aspectos sociales y de comportamiento humano; coordinación entre múltiples agentes, convergencia de materiales y/o fallos de organización; escenarios e incertidumbre, riesgo y análisis robusto; dinámica de sistemas, objetivos múltiples y contexto; asuntos políticos y/o culturales. Este último factor se hace relevante al momento de aplicar estos modelos sobre casos realistas y contrastar resultados con políticas públicas o iniciativas privadas.

Considerando las brechas y oportunidades de investigación en estas materias, se descatan ideas como:

- La incorporación de métricas asociadas al comportamiento humano, el efecto de la privación, la vulnerabilidad y resiliencia se tornan necesarias para enfrentar un fenómeno indudablemente sociotécnico. Este esfuerzo demanda mayor integración y conocimiento de la psicología del desastre y comportamiento humano.
- El desarrollo de investigación multiobjetivo enfocada en los tipos de cooperación, coordinación y competencia, teniendo en cuenta distintas perspectivas de las partes interesadas en

el proceso de toma de deciciones (centralizada o descentralizada), e interacciones entre los interesados (incluyendo el rol de las redes sociales). Se necesita profundizar en temas como redes de comunicación en desastres, así como la consideración de modelos multiobjetivos o multicriterio para tomar mejores decisiones.

- La logística humanitaria no está exenta de las dificultades propias de entornos altamente dinámicos y con mucha incertidumbre. El proceso logístico comienza desde la propia concepción de la emergencia, y se requiere contar con predicciones que den cuenta de su inicio, duración e impacto, así como modelos matemáticos que permitan gestionar distintas fuentes de incertidumbre.
- En períodos previos a la ocurrencia de un desastre natural, existe un predominio de trabajos centrados en decisiones estratégicas, con una fuerte necesidad de extender e integrar el análisis a otros niveles de decisión (táctico y operativo), con una mirada pre y post desastre.
- Son escasas las aplicaciones concretas en contextos de políticas públicas, organizaciones de ayuda humanitaria, sistemas de apoyo a la toma de decisiones, integración de información local y respuesta de las comunidades (planificación pública, educación de riesgo, redes sociales, entre otros).

Con ello, es que se propone un segundo trabajo que toma en consideración varios de los aspectos antes mencionados. Este segundo artículo consta de la construcción y resolución de un modelo de optimización robusta y posibilista, que considera objetivos vinculados a costos de decisiones de logística tradicional así como aspectos sociales.

Estos últimos incluyen la privación y sufrimiento humano dado por el tiempo de entrega de suministros críticos, mediante una aproximación económica y cálculo de funciones de costo de privación basadas en disposición a pagar (Pérez-Rodríguez y Holguin-Veras, 2015, Holguín-Veras *et al.*, 2016). Por otro lado, el modelo incluye la ocurrencia de fallos en la organización y presencia de convergencia de materiales, la cual ha sido caracterizada por diversos autores como un eventual “segundo desastre”, fruto de que en la logística post emergencia puede haber cientos o incluso miles de cadenas de suministro formales o informales/improvisadas que interactúan, se superponen, cooperan o incluso compiten por recursos escasos y tratan de ayudar (Holguín-veras *et al.*, 2012).

En términos específicos la contribución a la literatura del modelo se resume en lo siguiente:

- Incluye decisiones previas y posteriores a la ocurrencia de un desastre natural, tales como localización, asignación de inventarios y distribución de suministros críticos.
- Incorpora una función objetivo robusta y aversa al riesgo, la cual se descompone en dos objetivos: el primero asociado a la logística tradicional y el segundo al costo social vinculado a la privación.
- Incluye la incertidumbre aletoria en la ocurrencia de desastres mediante programación estocástica basada en escenarios.
- Incorpora la optimización de la robustez del modelo y sus soluciones, a través de la factibilidad de los resultados en distintos escenarios, así como variabilidad. Respecto a la robustez del modelo, se incluye el efecto de la convergencia de materiales.

- En conjunto con la incertidumbre aleatoria asociada en la ocurrencia de los escenarios, reconoce e incluye la incertidumbre epistémica, mediante el uso de *fuzzy chance constrained programming*. Esta última surge de datos imprecisos, no sistematizados o parcialmente ocultos que, dentro de cada escenario o entre los mismos constituyen una nueva fuente de incertidumbre general en el sistema.
- En un marco de optimización multiobjetivo, permite construir la frontera Pareto óptima entre los objetivos de la logística tradicional y los costos sociales dados por las privaciones, utilizando modelos empíricos para el costo de privación de un suministro cítico específico.

Tomando casos de estudio de la literatura (Rawls y Turnquist, 2012), en primer lugar se toma un modelo base como un modelo estocástico basado en escenarios (Pradhananga *et al.*, 2016), luego de lo cual se introduce la programación robusta y multiobjetivo con el fin de minimizar el riesgo e incorporar la convergencia de materiales como parte de la robustez del modelo. Finalmente, reconociendo la presencia de incertidumbre epistémica se plantea un modelo multiobjetivo posibilístico aplicando *fuzzy chance constrained programming.*

En términos globales, se observa la contribución de incorporar el análisis robusto y posibilista en un modelo bi-objetivo, el cual se separa el costo de la logística tradicional dada por decisiones de localización, compra, almacenamiento y distribución de suministros críticos en las fases previas y posteriores al desastre, de aquellos costos sociales dados por el impacto en la privación de los tiempos de respuesta y la sensibilidad respecto de la demanda. Por otro lado, las decisiones asociadas a patrones de localización y elección de nodos como suministros (*supply points*) o puntos de demanda agregada (*aggregated demand points*), así como los flujos enviados entre nodos de la red, muestran que las redes se vuelven menos "densas", observándose menos arcos con flujo para satisfacer las mismas necesidades, cuando el modelo es robusto y/o posibilista, con lo cual la operación logística es en general más eficiente.

Lo anterior, dado que cuando la función objetivo se cambia desde un valor esperado de los costos globales a una función objetivo aversa al riesgo, las decisiones privilegian flujos vinculados a inventarios preposicionados en puntos de demanda agregada o desde los nodos e suministro en la fase post desastre, disminuyendo decisiones asociadas a compras de suministro en la fase post desastre. Este efecto se acentúa cuando además se reconoce la convergencia de materiales y la variabilidad de parámetros con incertidumbre epistémica. Respecto de la formulación multiobjetivo, para llegar a una solución adecuada que permita al tomador de decisiones hacer concesiones de un criterio contra otro, basándose en los resultados, el problema se resuelve varias veces mientras se varía el peso de cada objetivo. La disminución del peso para los costos logísticos hace que los costos sociales disminuyan. Por lo tanto, al aumentar la meta para cualquiera de los objetivos, se genera más espacio para mejorar otros objetivos, entregando versatilidad a la formulación al momento de ponderar prioridades y buscar resultados óptimos, siendo muy sensible el aspecto social.

Con esto, se está entregando una herramienta de utilidad para la toma de decisiones, en un entorno donde no existen muchas aplicaciones concretas en contextos de políticas públicas, organizaciones de ayuda humanitaria, sistemas de apoyo a la toma de decisiones, integración de información local y respuesta de las comunidades (planificación pública, educación de riesgo, redes sociales, entre otros).

Por otro lado, se delinean desafíos para ser abordados en futuros artículos, dados por: costos de privación y modelos multiproducto; incorporación de resiliencia (relacionada con la psicología del desastre, incluida la angustia, la ansiedad, el miedo, el estrés, la satisfacción y el contagio emocional) y vulnerabilidad social heterogénea; uso de programación dinámica, redes expandidas en el tiempo y ruteo de vehículos; convergencia de materiales y modelos de equilibrio que incorporen la congestión generada por el comportamiento de los donantes; formulación multiobjetivo y modelos jerárquicos.

Anexo

Números difusos y medidas de credibilidad

Tomando la notación de Das *et al.* (2007) y Liu e Iwamura (1998), sean $\widetilde{a}$ y $\widetilde{b}$ dos parámetros posibilistas formulados por las siguientes distribuciones posibilistas triangulares (es decir, números difusos, como se muestra en la figura 2): $\widetilde{a} = TFN(a_1, a_2, a_3)$, $\widetilde{b} = TFN(b_1, b_2, b_3)$. El grado de posibilidad de que $\widetilde{a} \leq \widetilde{b}$ se pueda calcular de la siguiente manera:

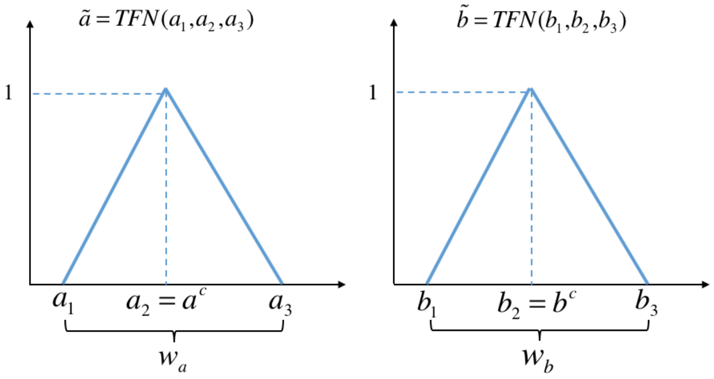


Figura 2.9: Números difusos triangulares

$$Pos(\widetilde{a} \leq \widetilde{b}) = \begin{cases} 0 & a_1 \geq b_3 \\ \frac{b_3 - a_1}{b_3 - b_2 + a_2 - a_1} & a_2 \geq b_2, a_1 \leq b_3 \\ 1 & a_2 \leq b_2 \end{cases} \tag{2.43}$$

$$Cr(\widetilde{a} \leq \widetilde{b}) = \begin{cases} 0 & a_1 \geq b_3 \\ \frac{b_3 - a_1}{2(b_3 - b_2 + a_2 - a_1)} & a_2 \geq b_2, a_1 \leq b_3 \\ \frac{a_3 - b_1 + 2b_2 - 2a_2}{2(b_2 - b_1 + a_3 - a_2)} & a_2 \leq b_2, a_3 \geq b_1 \\ 1 & a_3 \leq b_1 \end{cases} \tag{2.44}$$

Lo anterior se produce, dadas las relaciones entre posibilidad, necesidad y medidas de credibilidad que se establecen a continuación (Liu, 2009):

$$Nec(\widetilde{a} \leq \widetilde{b}) = 1 - Pos(\widetilde{a} \geq \widetilde{b}) \tag{2.45}$$

$$Cr(\widetilde{a} \leq \widetilde{b}) = \frac{1}{2}(Pos(\widetilde{a} \leq \widetilde{b}) + Nec(\widetilde{a} \leq \widetilde{b})) \tag{2.46}$$

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