On the Dynamic Inventory Routing problem in Humanitarian Logistics: a Simulation-Optimization approach using Agent-Based modeling

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Abstract

In the immediate aftermath of any disaster event, operational decisions are made to relieve the affected population and minimize casualties and human suffering. To do so, humanitarian logistics planners should be supported by strong decision-making tools to better respond to disaster events. One of the most important decisions is the delivery of the correct amount of humanitarian aid in the right moment to the right place. This decision should be made considering the dynamism of the disaster response operations where the information is not known beforehand and vary over time. For instance, the effect of the Word-of-Mouth and shortages in distribution points' demand can impact the operational decisions. Therefore, the inventory and transportation decisions should be made constantly to better serve the affected people. This work presents a simulation-optimization approach to make disaster relief distribution decisions dynamically. An agent-based simulation model solves the inventory routing problem dynamically, considering changes in the humanitarian supply chain over the planning horizon. Additionally, the inventory routing schemes are made using a proposed mathematical model that aims to minimize the level of shortage and inventory at risk (associated to the risk of losing it). The computational proposal is implemented in the ANYLOGIC and CPLEX software. Finally, a case study motivated by the 2017 Mocoa-Colombia landslide is developed using real data and is presented to be used in conjunction with the proposed framework. Computational experimentations show the impact of the word-of-mouth and the frequency in decision making in distribution points' shortages and service levels. Therefore, considering changes in demand over the planning horizon contributes to lowering the shortages and contributes to making better distributions plans in the response phase of a disaster.

Key words: Humanitarian Logistics, Word-of-mouth, Agent-based modeling and simulation, Mixed integer linear program, Inventory routing problem.

Resumen

Después de la ocurrencia de cualquier desastre se deben tomar decisiones para aliviar a la población afectada minimizando las pérdidas humanas y el sufrimiento. Para ello, los responsables de la logística humanitaria deben contar con robustas herramientas para tomar decisiones acertadas que respondan adecuadamente ante esos eventos. Una de las decisiones más importantes es la entrega de ayuda humanitaria en el lugar, las cantidades y en el momento correcto. La anterior decisión debe ser tomada teniendo en cuenta el dinamismo de las operaciones de respuesta humanitaria en donde la información no es conocida de antemano y varía en el tiempo. Por ejemplo, el efecto del Voz a Voz y la escasez en los puntos de distribución de ayuda humanitaira pueden impactar las decisiones operacionales. Es por lo anterior, que las decisiones de transporte de ayuda humanitaria deben ser realizadas constantemente para servir de una mejor forma a la población afectada. Este trabajo presenta una propuesta de simulación-optimización para tomar las decisiones de ruteo de inventario de ayuda humanitaria de forma dinámica. A través de un modelo de simulación basado en agentes se resuelve dinámicamente el problema de ruteo de inventario considerando cambios en la cadena de suministro humanitaria. Adicionalmente, las decisiones de ruteo de inventario son tomadas mediante un modelo matemático propuesto que busca minimizar el nivel de inventario en riesgo y el nivel de escases simultáneamente. La propuesta computacional es implementada en los programas ANYLOGIC y CPLEX. Finalmente mediante un caso de estudio basado en la catastrofe de Mocoa-Colombia en 2017 se evaluará la propuesta. Experimentos computacionales muestran el impacto del voz-a-voz y frecuencia de toma de decisiones en la escasez y el nivel de servicio en los puntos de distribución. Por lo tanto, considerar cambios en la demanda contribuye a disminuir la escasez y hacer mejores esquemas de distribución de ayuda humanitaria.

Key words: Logística Humanitaria, Voz a voz, Modelamiento y simulación basada en agentes, Programación lineal entera mixta, Problema de ruteo de inventarios.

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Chapter 1

PRELIMINARIES

1.1 Introduction

Over the last years, several disasters have drawn the world attention because of the great number of casualties and significant economic losses. Disasters such as the earthquake in Haiti in 2010, the earthquake and the subsequent tsunami in Japan in 2011 and more recently the Mexico and Ecuador earthquakes in 2016 and 2017 have claimed thousands of lives and have left millions of people homeless. These events have some factors in common such as the lack of preparation, lack of coordination and not knowing how to respond properly to the magnitude of the event. Additionally, during a disaster event, several circumstances must be considered: uncertainty in demand and supply, disrupted roads, no reliable and updated information, several stakeholders acting uncoordinated and the pressure of time difficult an accurate decision-making process in disasters [1]–[3].

To deal with these challenges, humanitarian logistics (HL) represents an opportunity to better prepare and respond to these events. One of its main objectives is to minimize casualties and human suffering by providing supplies to the affected population while making an efficient and effective allocation of scarce resources [1]. Moreover, it has been estimated that the impact of disasters can be reduced by enhancing logistics operations [2]. Finally, the sector is affronting difficult conditions such as the increasing number of aid requests and the funding gap they face to perform their operations [4].

To cope with the previous conditions, HL planners should rely on strong methodologies which allow them to optimize their operations and make better decisions despite budget constraints. One of the crucial decisions HL practitioners should face is the distribution of the collected humanitarian aid. To do so, the routes of the available vehicles (i.e. trucks) should be planned while considering the quantity to deliver to the humanitarian aid distribution points. Additionally, practitioners have to deal with the dynamic nature of humanitarian operations. For example, the victims can move between distribution points or leave them considering its own needs[1]. Finally, and unlike commercial logistics, the information in HL is not known beforehand. The demand (number of affected people being served in a distribution point) may vary, as well as the supply or even the fleet used to deliver humanitarian aid. The purpose of this work is to develop an agent-based simulation model which allows to solve dynamically the inventory routing problem of humanitarian aid. On the one hand, using the agent- based approach the dynamic nature of the humanitarian operations is tackled. On the other hand, using mathematical modelling, the inventory and routing decisions are made. The contributions of this thesis are the following:

1. We propose a new mixed-integer linear programming (MILP) formulation of the distribution of the humanitarian aid problem. Apart from the classical IRP constraints, our formulation considers the inventory at risk level and minimize it along with the shortage level simultaneously. The formulation can be implemented and solved in any commercial solver. Moreover, the model was implemented and tested in IBM CPLEX. Numerical results show that our model can find optimal inventory-routing schemes for small instances in a reasonable computational time.

2. We propose a agent-based simulation model for the the dynamic disaster relief distribution. In the model we represent the entities (e.g. victims or distribution points), their interactions, communication and decisions. We implemented the simulation model in ANYLOGIC. Preliminary results show that the simulation model captures the dynamism in the system when shortages and word of mouth are present.

3. We combined the agent-based model and the optimization model on a simulation-optimization approach. It is particularly useful when some decisions in the simulation model provide poor estimations or are complex. This is the case of the inventory routing decisions in the disaster relief distribution. Therefore, in the simulation model, an agent makes decisions using the optimization model.

4. We tested the simulation-based optimization approach using a real-world setting inspired by the Mocoa-2017 Landslide in Colombia. Numerical results show that better distribution plans are obtained considering demand changes.

5. We performed a brief documental analysis of the Colombian disaster risk management. We analyzed the roles and responsibilities of the entities which take part in the disaster response in the country, obtaining some suggestions for future response plans.

[1] In this document, we refer to victims as persons or families who suffered a disaster but managed to survive it and are in a vulnerable condition. Thus, they seek and receive humanitarian relief.

This document is organized as follows. Chapter 2 presents the research proposal methodology. In chapter 3 a brief literature review on the inventory routing problem (IRP) in HL is presented. Chapter 4 presents the documental analysis of Colombian protocols in humanitarian operations. Chapter 5 develops a multi objective mixed integer linear programming model to make the inventory and routing decisions in humanitarian aid distribution. Chapter 6 presents the agent-based model used to handle the dynamic components of the humanitarian supply chain. Also, in chapter 6 the hybridization with the optimization model is presented. Chapter 7 presents the case-study inspired in the 2017 Mocoa-Colombia Landslide. Lastly, in chapter 8, conclusions and perspectives for future works in the field are presented. The previous structure is shown as a flow diagram in Figure 1.1.

1.2 Theoretical Framework

1.2.1 Humanitarian Logistics (HL)

The humanitarian logistics (HL) concept falls into the logistics field. There are several definitions of logistics over the last decades since it is a term widely used in multiple fields. One simple and complete concept of logistics is the "Seven R's of Logistics" in [5]. There, the authors define logistics as ensuring the availability of the right product, in the right quantity, in the right condition, at the right time, at the right place, for the right costumer and at the right cost. To do so, decisions regarding transportation, inventory and location must be made [6]. The previous decisions are presented in the logistics triangle presented in Figure 1.2.

Furthermore, during a disaster there is a high level of unpredictability, time pressure, destroyed infrastructure, multiple actors trying to help uncoordinated and an urgent need to made accurate decisions[7]. The previous conditions led to the creation of a new research field in logistics, which is frequently referred as humanitarian logistics [8]. A formal and accepted definition of this relatively new field is: 'the process of planning, implementing and controlling the efficient, cost-effective flow of and storage of goods and materials as well as related information, from point of origin to point of consumption for the purpose of meeting the end beneficiary's requirements [9].

The decisions HL practitioners should make depend on the phase of the disaster. Altay & Green classify the phases in mitigation, preparation, immediate response and rehabilitation [10]. Furthermore, in [11] the main decisions concerning the phases and the status of information involved in humanitarian logistics planning are presented. The previous information is summarized and depicted in Table 1.1.

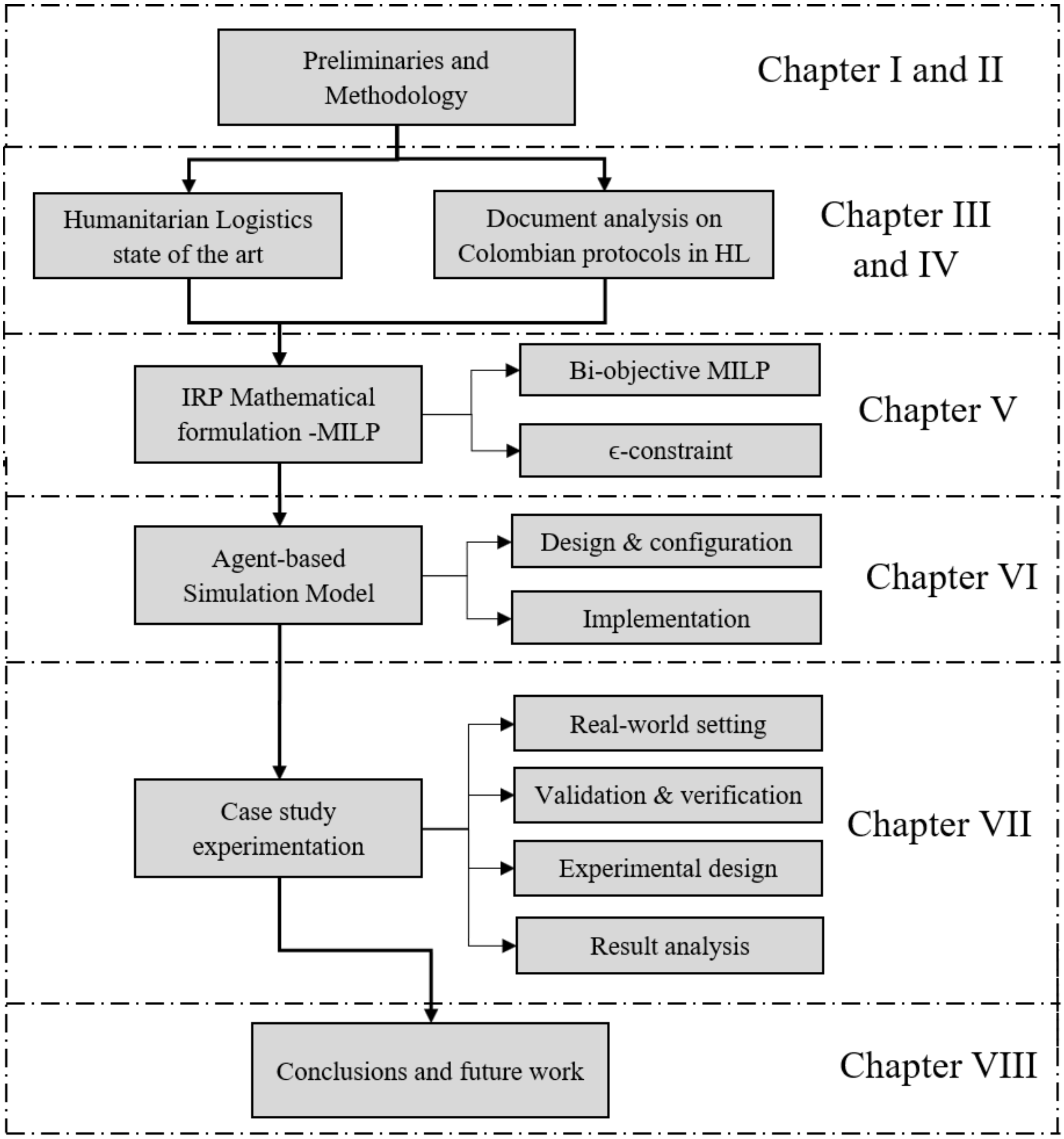

Fig. 1.1 Flow diagram of the research proposal

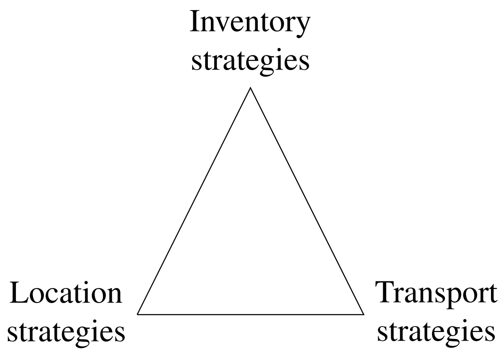

Fig. 1.2 Logistics Triangle adapted from [6]

The first phase in the humanitarian logistics timeline is the mitigation. In this phase decisions about evacuation plans, specification on building construction codes and prone-risks zones for constructions are made [3], [12]. These decisions have long-term impact in communities and are made to prevent and reduce the effects of disasters [13].

The next phase is preparation. In this part, governments and societies realize that a disaster could strike in any moment and several measures are taken. Strategic decisions such as number and ubication of distribution points and its initial inventory level are made [13]. It is worth mentioning that every village or city is unique and know in advance its potential distribution points which can be at schools, universities or churches. This prepositioning allows a fast response, although it requires additional investment and there is the chance of being destroyed by the disaster itself [14]. Another decision which is made during the preparation phase is to set an early warning system [3]. The warning system allows to know beforehand when a disaster strikes and the possible magnitude of it. However, this sophisticated technology is not always available, specially to villages located away from urban centers and villages without enough resources to acquire it.

The following phase in the timeline of a disaster is the immediate-response. In this moment the calamity has occurred and there is time pressure for rescuing people as well as the relieving the affected population. One of the most crucial decisions in this stage is the correct distribution of humanitarian aid in terms of quantities and delivery times. This humanitarian aid may be in form of kits, water, hygienic products and others. Unlike the commercial logistics where the pressure is mainly due to costs, in HL there is time pressure which is not just a matter of money but also a matter of life and death [7]. Furthermore, decisions concerning allocation and scheduling of emergency units must be made as a key part of a response-phase of a disaster [15].

The last phase of a disaster is the rehabilitation. In this part the efforts are directed to fully rehabilitate the affected area and stabilizing the affected persons life [16]. Therefore,

Table 1.1 Humanitarian Logistics information flow in its phases

	Information		
Phase	Known	Unknown	Decisions
Mitigation	Prone-risk zones Evacuation plans	Disaster location Disaster ocurrence	Building zones Building codes
Preparation	Possible DP Evacuation plans Inventory available	Location of disaster Disaster moment	Warning systems Inventory pre-positioning DP pre-allocation
Immediate response	Disaster location Central Warehouses Distribution centers Stakeholders	Demand Supply Vehicle availability Disrupted roads	Emergency services Aid distribution plan Psychological support Facility location
Rehabilitation	Infrastructure status Total investment		Roads reconstruction Buildings reconstruction Population rehabilitation

DP= Distribution points

governments and donors invest in people re-employment, reconstruction of roads, bridges, buildings and the infrastructure damaged by the catastrophe to bring back to normality in the area struck by the catastrophe. One key concept after a disaster event is the community resiliency. This term in a society context is defined in [17] as the process of using the information and knowledge generated from the past response, to enhance the ability of the community to withstand or resist better the next catastrophe. In this manner the disaster phases are completed, and the disaster cycle is ended.

To achieve the definition of HL and like every logistics operation, decisions regarding location, transportation and inventory should be made. This work presents an adaptation of the inventory routing problem for the distribution of humanitarian aid, which is solved dynamically over a planning horizon. In this manner the logistical decisions regarding inventory and transportation in a disaster context are faced.

1.2.2 Inventory Routing Problem (IRP)

The IRP in its basic version consists in finding the optimal set of lot sizes to deliver to a set of customers while minimizing the distribution costs [18]. In other words, IRP consists in finding the optimum routes (with the lowest cost) which serve a set of customers, delivering the adequate amount of materials. Following the logistics triangle of Figure 1.2, IRP is located between inventory and transport strategies as seen in Figure 1.3

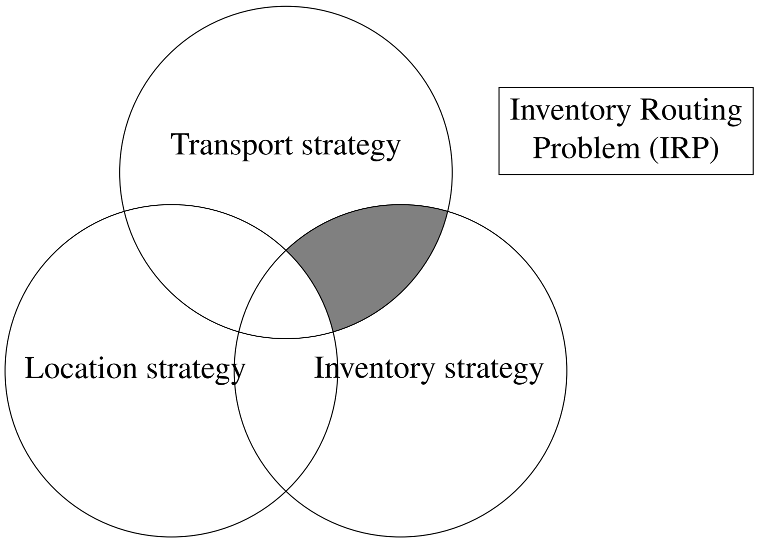

Fig. 1.3 IRP in Logistics decisions

Coelho et al. [19] established that in the IRP exists different orders specified by a set of customers and the supplier has the objective of satisfy the costumer while minimizing the distribution costs. While the VRP aims to find the delivery routes, in the IRP the quantity delivered and the time of the delivery are considered along with the routes [20]. A graphical representation of IRP is presented in Figure 1.4. There, five customers have to be served with the right amount of materials considering their inventory levels (in grey) from one depot and using two vehicles.

Over the last decades, there have been multiple variants of the basic IRP which are more elaborated and operate under different situations [19]. The variants increase the complexity of the problem by adding multiple objectives and conditions such as multiple depots, multiple periods, time windows, heterogeneous vehicle feet etc. A complete review with the objectives, variants and its solution methodologies of the IRP are presented in [19] and in [21].

1.2.3 Agent based modeling and simulation (ABMS)

Agent based modeling and simulation (ABMS) has been defined by the known authors in the field Macal & North in [22] as an approach to modeling systems comprised of individual, autonomous an interacting actors. This technique has been used successfully in multiple fields such as economics, marketing, transportation, health-care, energy analysis, epidemiology,

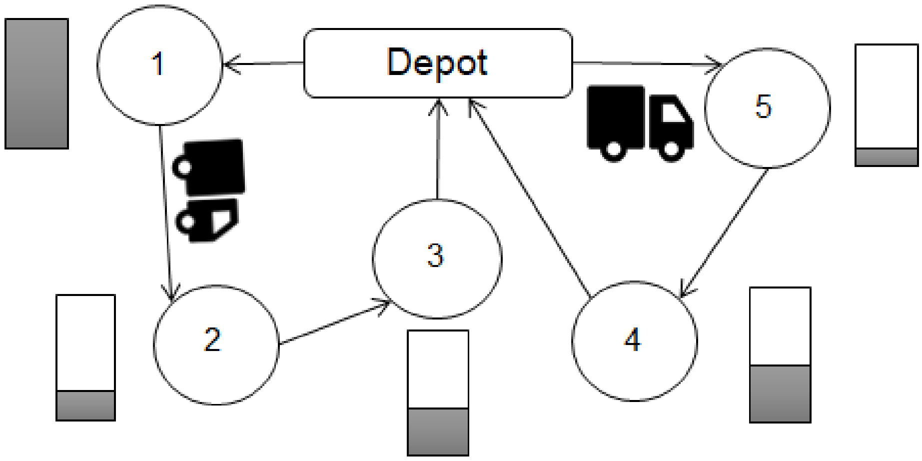

Fig. 1.4 IRP representation

air traffic control, etc. [23], [24]. The growing interest in this simulation technique is mostly because it allows to incorporate the complexity of the system regarding behaviors, interactions, and communications which occurs in the real world. These advantages are not offered by another simulation techniques such as system dynamics or discrete event-simulation [25].

In the agent based modelling simulation several intelligent agents interact and communicate in the same environment, each agent has their own motivations and aspirations but all work towards achieving the global objective of the system [23]. Inside every agent-based model there are communication, interactions and decision-making process. To model successfully a system using this approach the next structure has to be followed: **(i)** Identify the agents their attributes and behaviors,**(ii)** define the environment where the agents will interact, **(iii)** specify the agent methods which update the agent status, **(iv)** add the methods for agent interactions and **(v)** implement the model in a software [22].

Finally, to model a system as an agent-based model there are multiple specialized software like Anylogic, Netlogo, Java libraries (i.e. JADE), etc. A review on agent based modeling software is presented in [26] where the authors describe and compare the advantages and disadvantages of the principal agent development software.

1.3 Problem Statement and Justification

The scope of this research project lies in the distribution of humanitarian aid in the immediate-response phase of a disaster. It is motivated by the urgent need of developing robust tools which supports the decision-making process in the aftermath of catastrophes [4]. Besiou & Wassenhove in [27] stated that the research efforts and its results have to match with the real problems humanitarian practitioners face. They compared the challenges of humanitarian logistics practitioners with the frequent focus of HL academics. They find that the research in HL must be re-directed to address the humanitarian operations real challenges. Among the challenges they identified which are presented in Figure 1.5 are safety and the local aspect of response. This research project studies the safety from an inventory perspective by aiming to reduce the level of inventory at prone-risk distribution points or inventory considering facility failure scenarios. On the other hand, the local aspect of response is addressed by studying the Word of Mouth (WoM) concept. The WoM concept, can determine the victims movements between distribution points. In our opinion, with the objective of achieving realistic and useful tools for HL practitioners, it is important to incorporate human behaviour factors such as the WoM.

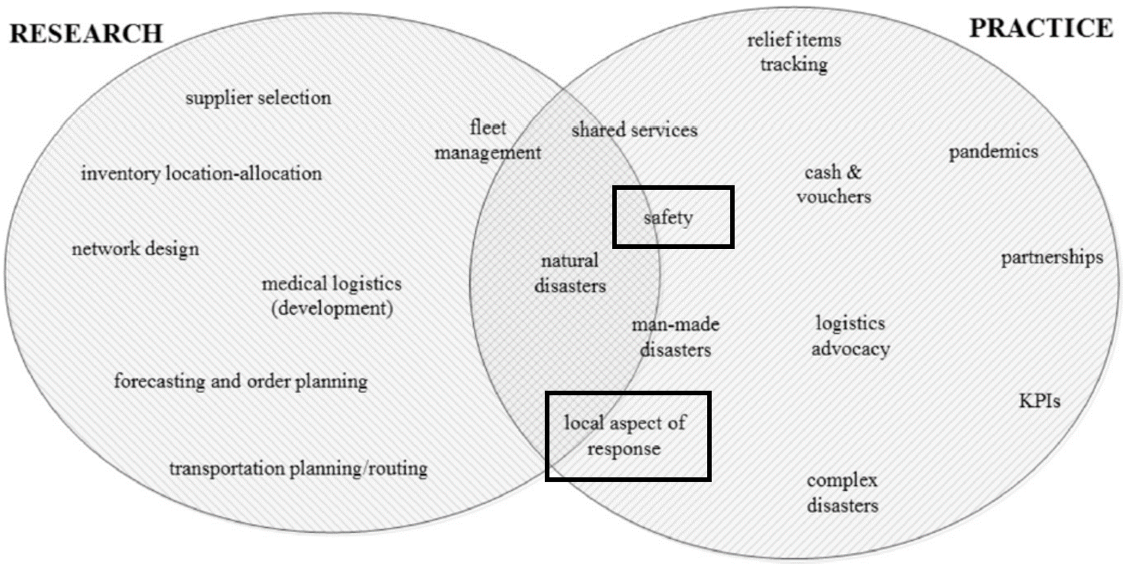

Fig. 1.5 Matching Research and Practice in HL. Adapted from [27]

One paradigm which until recently has been introduced to study humanitarian supply chains is the agent-based models. One related work is presented in [28]. In this work, the authors use agent-based simulation to model the impact of the word of mouth and transport disruptions on disaster relief distribution. Moreover, in [29] the authors developed a simulation and optimization-based decision-support system to evaluate transfer points and the last mile distribution of humanitarian aid. The main differences between these previous works and our research is that on the one hand, we consider the risk of facility failures in the humanitarian aid distribution decisions. Facility failures may have a significant impact when considering economic benefit and covering the demand and these failures should be considered in the location of an emergency facility [30]. On the other hand, within the agent-based simulation framework, we consider the victims decision of staying in a distribution point or leaving if shortage appears. On the other hand, another significant difference is that we consider the victims' choice of leaving or not a distribution point when, in a certain period, it is not handing-out humanitarian aid (shortages). It is worth noting that this decision is influenced by the number of accumulated periods in shortage in that distribution point. The more periods in consecutive shortage, the higher the probability of the victim leaving the distribution point. This consideration is important in cases when transporting to another distribution point is costly for the victim (it has to travel long distances), and there is no guarantee that the latter distribution point is handing-out humanitarian aid.

Given the characteristics of the problem, this paradigm results promising for capturing the dynamic nature of humanitarian supply chain and allows to study its reactions to various changes such as re-routing decisions as a result of shortages or word of mouth in distribution points [28]. Based on the previous information, the following research question is formulated: How should the structure of a simulation-optimization approach be when solving the inventory routing problem of humanitarian aid using agent-based simulation?

1.4 Objectives

1.4.1 General Objective

To propose a simulation-optimization approach for solving dynamically the inventory routing problem of humanitarian kits in a disaster situation using agent-based simulation.

1.4.2 Specific Objectives

1. Define the theoretical and technical characteristics of the disaster relief distribution problem.

2. Develop a mathematical model to optimize the inventory routing problem in a humanitarian logistics context.

3. Design an agent-based simulation model for the humanitarian logistics supply chain in the aftermath of a disaster and implement it in a specialized software.

4. Evaluate the performance of the agent-based simulation model in a real case study based on the Landslide that happened in 2017 in Mocoa-Colombia.

Chapter 2

METHODOLOGY

With the purpose of answering the research question and reaching the main objective, we propose the activities presented in Table 2.1.

The methodology section is organized as follows. In section 2.1 and 2.2 the definition of theoretical and technical characteristics of the problem (specific objective 1) are made. In section 2.3 the methodology for activities 3 to 5 is presented by explaining the construction of the mathematical models for re-optimization routes in disaster relief distribution problem (specific objective 2). The methodology for the agent-based model design (specific objective 3) is presented in the section 2.4 and this covers activities 6 to 9. Finally, in section 2.5 the method to evaluate and analyse the real case of the Mocoa-Colombia Landslide of 2017 (specific objective 4) is presented.

2.1 Literature review methodology

In this research project, a literature review is presented with the objective of contextualize the inventory routing problem (IRP) in the HL supply chain. We identify its technical and theoretical characteristics, identify the main related work, recognize research trends and we position the research project highlighting the novelty of the proposal. To do so, and given the fact that the IRP in general can be seen as a combination of decisions regarding vehicle routing problem (VRP) and inventory management (IM), the review is focused in the VRP and IM characteristics applied to a HL supply chain.

The literature review is restricted to papers from academic journals that are found in the Scopus, Web of Science and IEEE databases. In these databases the search strings are on one hand for VRP: "dynamic vehicle routing" AND "humanitarian logistics", "dynamic vehicle routing" AND "humanitarian", "vehicle routing" AND "disasters" in the years 2013 to 2019. On the other hand, for the IM component of the problem the search strings are “Inventory

Table 2.1 Research project activities

Specific Objectives	Activities	
Define the theoretical and technical characteristics of the dynamic disaster relief distribution problem	1	Review and classification of academic articles related to the IRP in HL
	2	Analyse the Protocols and responsibilities in Risk Management for Natural Disasters in Colombia
Develop a mathematical model to solve the inventory routing problem in a HL context	3	Define the problem characteristics: its variables, parameters, constraints, objective functions and solution methodologies
	4	Implement the mathematical model in a specialized software
	5	Test the model with literature instances to validate its performance.
Design an agent-based simulation model for the HL supply chain in the aftermath of a disaster and implement it in a software.	6	Define agent types, methods, and interaction processes of the agent-based model
	7	Integrate the mathematical model in the agent-based model simulation framework
	8	Implement the model in a specialized software and test the simulation model
Evaluate the performance of the agent-based simulation model in a real case study based on the Landslide that happened in 2017 in Mocoa-Colombia.	9	Collect and parametrize information related to the distribution of humanitarian aid in Mocoa 2017 landslide
	10	Run the simulation model elaborate and evaluating possible scenarios
	11	Analyse the results, conclude and provide recommendations for the humanitarian aid distribution problem

management” AND “humanitarian logistics”, "inventory management" AND "disasters" and as well as the VRP component the search is limited to the years 2013 to 2019. Next, a selection process is conducted for choosing papers based on their quality, relevance and relation to the research project. This review is presented in section 3.

2.2 Document analysis on Colombian Protocols in HL methodology

In the last years, Colombia has been affected by several natural and man-made disasters leading to important economic, environmental and social losses. Most of the Colombian population is located on risk-prone zones. For this reason, it is crucial to analyse how the decisions regarding risk management are taken nowadays in Colombia. Additionally, we study how the Colombian entity which is in charge of the disaster risk management system (UNGRD) establishes the responsible authorities which act when a disaster occurs, along with its roles and protocols. Also, a document analysis on how these aspects are addressed by the different territories and its strategy disaster response ("Estrategia de respuesta a emergencias" ERE) is presented. The "ERE" documents are studied for different Colombian cities and departments for wildfires, floods, earthquakes and landslides with the purpose of answering the following questions:

1. Which are the entities and their responsibilities in Colombian disaster emergency management?
2. Which are the roles and protocols in Colombian emergency disaster management?
3. How the characterization of natural disaster high-risk areas is made in Colombia?
4. How it is defined the resources used to attend victims?
5. How to define the number of victims and the level of damage (people and infrastructure)?
6. How humanitarian aid needs are estimated by victims and how they are managed?
7. How shelters are managed and how victims mobilize between them?

The answer of the previous questions and its analysis is presented in section 4.

2.3 Mathematical programming methodology

Mathematical programming is one technique of the operations research field. This branch studies the theory and methods to find the extreme values of functions on sets defined by linear and non-linear constraints in a finite-dimensional vector space [31]. In other words, mathematical programming aims to find optimal or near-optimal solutions given an input information and one or multiple problem restrictions and its applied into multiple knowledge fields. This specific branch has its own divisions which depends on the nature of the problem to solve and the input data characteristics. The main categories of mathematical programming are the following:

- Linear programming: The objective function and the constraints are linear expressions.

- Integer programming: One or multiple variables take integer or binary values $\{0,1\}$. It can be sub-divided into pure integer programming when all decision variables are integer or mixed integer programming when integer variables are present with another kind of variables.
- Stochastic programming: The data contains elements of indeterminacy that can be seen as a probability function.
- Non-linear programming: Constraints or at least one of them have non-linear expressions. Another case is when the objective function(s) are non-linear.

We tackled the IRP in HL problem with a mixed integer lineal programming model (MILP). We choose this particular category because there are binary decision variables (i.e. sending humanitarian aid to a specific distribution point in a time period) and integer variables (i.e. inventory levels). The proposed MILP is presented in section 5.

2.4 Agent-based modelling and simulation

As seen in the theoretical framework, in the agent based modelling simulation several intelligent agents interact and communicate in the same environment. Each agent has their own motivations and aspirations but all work towards achieving the system global objective. Macal & North proposed an agent-based methodology in [23] and is depicted in Figure 2.1. This methodology is used to design and implement the proposed agent based simulation model.

In our approach, five agent classes that interact with each other through the generation of multiple events are modelled. These agents interact in a specific geographical space in a simulation framework. The agent classes with its roles and relations are presented in Table 2.2.

Table 2.2 Agent types, main roles and interactions

Agent Type	**Main Rol**	**Interacts With**
Victims	To search and receive humanitarian aid	DP, Victims (WoM)
DP	To storage and distribute humanitarian aid	Depot, vehicles & victims
Vehicles	To transport humanitarian aid	Coord., depot & DP
Depot	To consolidate and distribute humanitarian aid	Vehicles,coord & DP
Crisis Room	To manage the humanitarian aid distribution	Vehicles & depot

DP= Distribution points

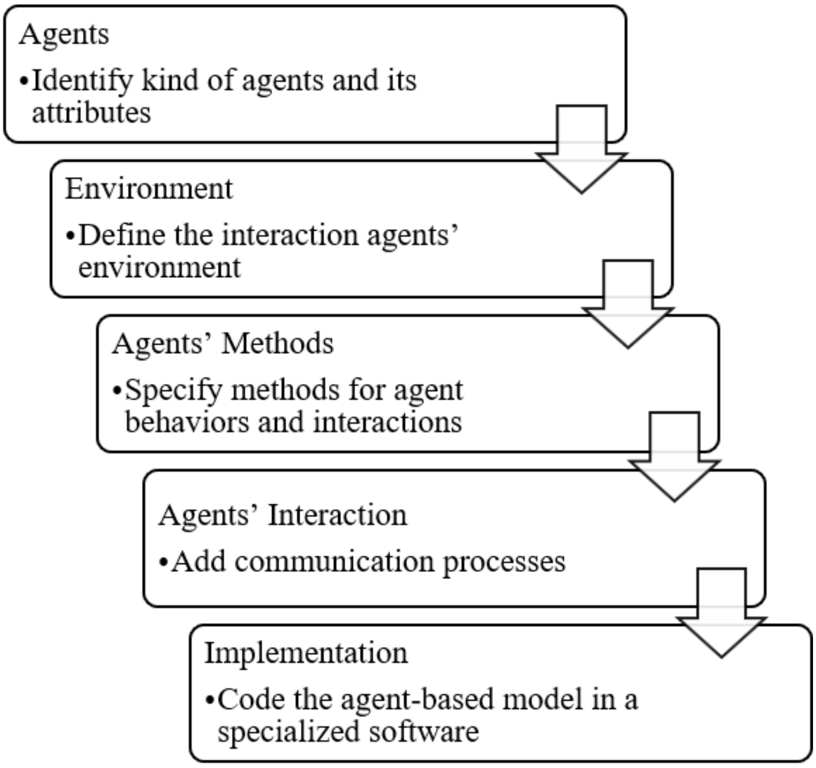

Fig. 2.1 Agent-Based simulation Methodology source [23]

The design and implementation of the agent-based simulation model is presented in section 6.

2.5 Case study and proposal implementation

In the last stage of the project, real data collected from the Mocoa-Putumayo-Colombia 2017 Landslide are studied. The outcome of this catastrophe was 333 deaths, 398 injured and 76 missing people with a response phase of 28 days [32]. This event is one of the deadliest disasters of Colombian recent history. This information must be parametrized to run the simulations and validate the model with real world information.

Output analysis will be made resulting in recommendations and conclusions for the specific real case study. By using the previous information in conjunction with the mathematical algorithms proposed in sections 5 and 6 multiple scenarios will be tested. In the scenarios, the most relevant models' parameters will be modified to get conclusions about the study case. The proposed framework is implemented in in IBM ILOG CPLEX Version 12.8.0.0 and in the Anylogic software Version 8.3.3.

The simulation-optimization approach implementation functions as follows. First, we build the simulation by modeling the different agents with their interactions and communication processes. Then the IRP model is developed upon a specific agent who takes the inventory routing decisions in the model. Last, the simulation model and the optimization algorithm are integrated in the following way. The simulation model collects the optimization algorithm parameters; it solves the IRP problem and then returns the routes and quantities to deliver to the distribution points. The simulation model implements this information in the system and recreate the victims' movements between distribution points given by shortages and the WoM. In this way, the demand varies for the next run of the optimization algorithm. Figure 2.2 presents the simulation based optimization methodology previously described. The case-study analysis is presented in section 7.

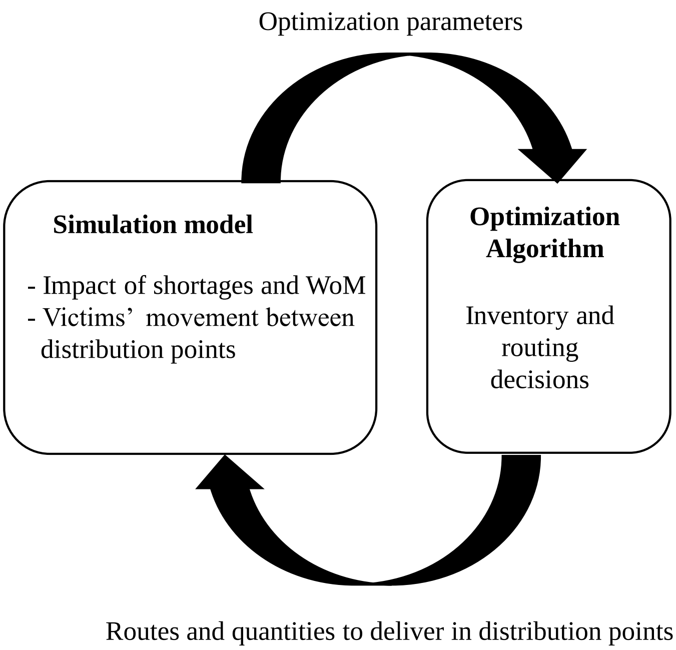

Fig. 2.2 Simulation based optimization methodology

Chapter 3

LITERATURE REVIEW

In this section we present a brief literature review on the related works. Since 2005 there has been an increasing attention from the academy in the field of humanitarian logistics. Before, high quality researches in the area were barely published and the field did not have the same recognition as it have nowadays [7], [33]. It is worth nothing even a dedicated journal was launched in the year 2011 (Journal of Humanitarian Logistics and Supply Chain Man agent) [34]. Early and decisive contributions in humanitarian logistics were given by recognized authors like Wassenhove in 2006 [3] or Kovacs & Spens in 2007 [8]. These works provide the bases, importance and common understanding of logistics during relief operations [7]. Specifically, the delivery of humanitarian aid problem is frequently modeled as multi-depot location-routing model, travelling salesman problem (TSP), vehicle routing problem(VRP) or multi-objective open location-routing model [35]. In this section a brief literature review in dynamic disaster relief of humanitarian aid is presented. We consider the main and relevant contributions of the last years and highlighting its principal characteristics of papers studied. These characteristics are classified as follows.

- **Phase:** There are four phases in the cycle of a disaster: Mitigation, preparation, immediate response and rehabilitation [10]. Section 1.2.1. presents a detailed description of these phases. However, preparation and intimidate response phases are the ones related to the IRP problem in HL and that is why this review only considers them. On the one hand, preparation concerns the LDC location. Frequently this location is established in existing facilities such as coliseums, schools or univerities [36]. On the other hand, the immediate response phase comprises decisions regarding distribution and scheduling of rescue units and humanitarian aid delivery [14].

- **Demand characteristics:** The requests of relief aid can be observed as deterministic, stochastic or dynamic. In the deterministic version the requested quantity is known, in the stochastic version depend on a probability function and in its dynamic version vary over time [29], [36].

- **Inventory:** Inventory decisions can be classified as Lost-sales and Back-order. In Lost-sales the unsatisfied demands are not considered further in the planning horizon unlike Back-order in which this unmet demand is contemplated ahead [1], [29].

- **Fleet homogeneity:** The vehicles which makes the routes and deliver the humanitarian aid can be categorized as heterogeneous where the vehicle characteristics vary as presented in [11]. Also, the fleet can be classified as homogeneous where vehicles share the same features [13].

- **Time horizon:** The distribution of humanitarian aid can be planned for multiple periods as in [29] or for a single period like in [37].

- **Number of depots:** After a disaster, donations arrive to warehouses (depots) and then are delivered by vehicles to the available LDCs. This can be modelled with a single depot [38] or multiple depots [36] consolidating and distributing the humanitarian aid.

- **Solution methodologies:** Methodologies can be classified in exact and approximate. Exact methodologies are able to find the optimal solution and usually works for small instances. Approximate methodologies are used to tackle big problems, where finding a optimal solution using and exact approach would cost huge amount of computational time and effort. That is why this approach sacrifice the optimality finding quality solutions with less and achievable computational times.

- **Nature of the data used:** To test the methodologies and the performance of the model it can be used real data or synthetic data. The real come from previous disasters where data is available, and the synthetic data is from literature instances or from data created from the authors.

The previous characteristics are classified and presented for the selected relevant articles in Table 3.1. Additionally, in the table our proposal characteristics are presented.

Table 3.1 Related literature in dynamic humanitarian logistics aid distribution

			Phase		Demand			Inventory		Fleet		Time H.		Depots		Solution		Data	
Ref	Year	Objective	P	I-R	DET	STO	DYN	L-S	B-O	HOM	HET	SP	MP	SD	MD	EX	AP	REAL	SYN
[39]	2013	Min Waiting time Min lead time		✓		✓		✓			✓		✓		✓	✓			✓
[37]	2014	Min fixed costs Min operational costs Max covered dem	✓	✓	✓			✓		✓		✓			✓	✓	✓	✓	✓
[11]	2014	Max distr. Fairness Max distr. Efectivity		✓		✓		✓			✓	✓			✓	✓		✓	✓
[13]	2015	Min Dist. Time Min Unmet dem. Min fixed costs	✓	✓	✓			✓		✓		✓			✓	✓	✓	✓	
[1]	2016	Min Dist. Costs Min Unused inv. Min Unmet dem.	✓	✓		✓		✓				✓			✓		✓	✓	
[29]	2016	Min lead time Coordination		✓			✓		✓		✓		✓		✓	✓	✓	✓	
[40]	2016	Min fixed costs Min Dist. Costs Min Unmet dem.	✓	✓		✓					✓		✓		✓	✓	✓	✓	✓
[41]	2017	Min Waiting time Min Unmet dem.		✓	✓			✓		✓		✓			✓	✓	✓		✓
[38]	2018	Min Unmet dem. Min Routing cost		✓	✓			✓			✓		✓	✓		✓		✓	
[36]	2018	Min operational costs Min social costs	✓	✓		✓	✓		✓		✓		✓		✓	✓	✓		✓
This approach		Min inventory at risk and shortage - MOO		✓			✓	✓		✓			✓	✓		✓	✓	✓	✓

EX: Exact AP: Approximate P: Preparation I-R: Immediate response L-S: Lost Sales B-O: Back Order
DET: Deterministic STO: Stochastic DYN: Dynamic SP: Single-period MP: Multiple-period
SD: Single depot MD: Multiple depot Hom: Homogeneous Het: Heterogenous Synt: Synthetic data

In addition to the classification presented in Table 2.2, next we describe some relevant works and then, we highlight our proposal identifying the research gaps and the novelty of it.

A practical application of an inventory routing model is found in [38] where the authors applied and adapted an IRP model to a real case scenario in Marikina City, Philippines. The model aims to minimize the routing cost while minimizing unsatisfied demands through penalties. Another recent relevant contribution is in [42]. In this work, the authors proposed a mixed integer problem to find the optimal route for drones to deliver packages to certain nodes and solved the model by column generation. Additionally, a related work which considers multiple objectives in its approach is presented in [39] where the authors introduced a mathematical model for tackling the distribution of materials and injured people and proposed a bi-objective stochastic model to solve the problem. In [29] a decision-support system (DSS) with simulation and optimization is proposed to determine potential transfer points in a disaster event. The approach introduced agent-based modelling, search heuristics and tabu search for better choosing transfer points. The authors considered the demand as dynamic, thus, they model the humanitarian supply chain of delivery of humanitarian aid as an agent based model with the aim of allocating LDC and select optimal vehicles.

According to the literature review , most of the previous work tackles the humanitarian delivery aid problem with inventory routing models which considers transportation costs, social costs, operational costs, location decisions, uncertainties in the supply or demand. These works do not consider the risks of inventory losses associated with the likelihood of the locations being struck by a natural or man-made disaster or security issues. To the best of our knowledge, the related works which consider inventory losses risk do no make inventory routing decisions, the consideration was only made at facility location level. This risk level is associated to the persistence of the thread regarding localization of distribution points. Some of them may be in risky zones with geological hazards (e.g., landslide points or flood areas), near dangerous facilities (e.g. gas stations, chemical ware-houses), in unsafe zones with probability of riots or located in facilities with no evacuation plans [43]. The previous factors in the worst-case scenario would cause entire distribution points to become useless or being destroyed. Consequently, large amounts of humanitarian aid would be unusable causing even more shortages increasing the suffering of the affected population.

This work addresses the distribution of humanitarian aid considering simultaneously distribution points shortage and the risk of inventory losses given by the persistence of the threat (aftershocks or new disaster events). These two objectives are opposites or are in conflict. For example, a distribution point with high inventory levels has less shortages, but, there would be more risk of humanitarian aid being destroyed. On the other hand, if there is less inventory the shortages would be more significant. Finally, it is worth noting that most of the previous work related to this research project consider the demand as deterministic or stochastic. Seeing the demand as dynamic is closer to reality due to the total affected population is not known in advance and vary over time.

As seen in in Table 2.2, the novelty of this research project lies mainly in the minimizing the inventory at risk and shortage levels while considering a varying demand (victims moving between distribution points). Therefore, the decisions of transportation and inventory (how much humanitarian aid the vehicle routes should deliver) should be re-optimized to better serve the affected people. To the best of knowledge, this is an approach who has not been studied yet and is relevant in decision-making process in real catastrophes. To validate the overall performance of the proposal a case study in Mocoa-Colombia 2017 landslide will be presented.

Chapter 4

DOCUMENT ANALYSIS ON COLOMBIAN PROTOCOLS IN HL

In this section, we present a brief document analysis of the main aspects of the Colombian protocols and responsibilities in humanitarian logistics. This analysis is made to get a better understanding of the disaster response phase in a local context. It also allows us to identify the main stakeholders in the response phase of humanitarian operations and their interactions. The primary sources for this document analysis correspond to the emergency operations plan or "Estrategia de respuesta a emergencia (ERE)" in Spanish. We reviewed EREs at departmental and municipal jurisdictions. Additionally, we examined the damage assessment and needs analysis formats (EDAN by its spanish acronim). The document analysis is organized as follows.

First, we describe the main entities in charge of responding to natural disasters. Next, we analyze such entities' responsibilities, which can be identified in the form of role matrices. In these matrices, the territorial jurisdictions define the leading and support entities when responding to a disaster in response services such as search and rescue or setting-up shelters. Then, we review how the victims' number and damage level definition is made when a disaster occurs. Last, we study how humanitarian aid needs are estimated and how shelters are managed in the Colombian disaster response. It is important to mention that the scope of this review corresponds to the representative natural disasters in Colombia which are earthquakes, landslides, wildfires, and floods. In this way, we can understand how the Colombian regulation works towards responding to a disaster. Finally, we make some recommendations for future policymaking in the field. [1]

[1]The document analysis of this section is based on the work made in collaboration with the industrial engineering students Paula Valentina Camacho-Perdomo, Laura Cárdenas-Vargas y Jessica Lorena Martínez-Guanga and under the supervision of this thesis author and advisor. The students are part of the Research Group Logistics Systems seedbed.

Entities in Colombian disaster risk management

According to the 1523/2012 law, the "Unidad Nacional para la Gestión del Riesgo de Desastres" (UNGRD) is the Colombian entity in charge of management and handling the disasters that occur in the country. It is responsible for controlling the main entities that must attend when an emergency occurs, like the national planning department, the national army, the armed forces, the police, the civil defense, the red cross, and the fire-fighters. The functions of some of these entities are described below.

- **National planning department**: The DNP (for its Spanish acronym), is a technical organization in charge of designing and giving guidelines for Colombian public policies. Regarding humanitarian operations, the DNP in its environmental branch, which manages the policies in disaster risk management.
- **National police**: This civil army institution is in charge of public security in the country. Among its different units, the Unidad de Operaciones Especiales en Emergencias y Desastres de la Policía Nacional - PONALSAR, has the mission of developing procedures to reduce the emergency risk and disasters to contribute to the well-being of people.
- **Civil defense**: This entity is in charge of the immediate response when a disaster occurs. Furthermore, it is responsible for implementing plans, programs, projects, and actions to prevent disasters. In this way, its principal function is developed activities to prepare for the response through training in the natural risk management area, search and rescue, social action and environmental management.
- **Colombian Red Cross**: The main objective of this entity is providing humanitarian aid when occasional contingencies occur.

Emergency management roles and protocols

The UNGRD created a guide for the elaborating of the strategy for the answer to emergencies (ERE, by its Spanish acronym). It establishes the guidelines to develop departmental and municipal EREs. The ERE collects information about territory description, response protocols to emergences, responsibilities, and complementary activities to act effectively in disaster situations. The responsibilities are frequently identified from a role matrix. It establishes the principal and support entities for each activity during and after an emergency. The territorial entities must have a role matrix for each disaster that affects their territory.

This matrix allows the identification of entities' roles with their responsibility level. In other words, the role matrix dictates which entities are involved in the response services as a responsible or providing support. In this work, we analyzed various activity matrixes at municipal and departmental levels. Next, we present the findings of the comparison between the EREs of Ocaña (Santander), Puerres (Nariño) and Olaya (Antioquía). These three matrixes are from territorial entities which are at the same level (municipalities) in different departments in Colombia.

Significant differences between the matrices roles of these municipalities are found. For instance, the number of entities and the number of roles for response services varies drastically. As an example, in Ocaña (Santander), 25 entities provide their services when a natural disaster occurs and there are 12 response services. In Puerres (Nariño), 12 entities are responsible for responding to the emergency and the response services are 14. Moreover, in Olaya (Antioquia), there are just nine entities and 11 response services.

Another critical difference is the presence and absence of some principal entities. For example, in the municipality of Ocaña, the police, civil defense, firefighters, red cross, and the national army play essential roles. In contrast, in the role matrix of Puerres, the firefighters, police, and the army are present, while in Olaya's role matrix there are only the police and the firefighters among other local entities.

Regarding the response services, most of them are common in the different role matrices. For instance, the damage assessment and needs analysis (EDAN) appears all role matrices. Another standard response services are accessibility and transportation, accommodation and feeding, search and rescue, firefighting, public information, handling of hazardous materials, health and basic services. From these role matrices, it is also possible to identify that the police and firefighters are two common entities in the three municipalities. However, they provide different response services. For example, in search and rescue, the police act in Olaya an Ocaña, but in Puerres this activity is carried out by firefighters.

The previous analysis was made at a departamental level with Santander, Antioquia, Casanare, and Meta. The behavior of the role matrices is the same as at municipal levels. There is a lack of standardization in the response services between them. It has a negative impact in cases where the affected territory alone cannot respond to a disaster and requires the presence or assistance of neighboring territories. For example, if a catastrophe strikes Santander and needs support from neighboring departments such as Antioquia, there would be a conflict between entities and their roles. It can delay emergency response services. The same fact occurs in the nearby departments like Casanare and Meta.

Resources destined to victims attention in emergency response

To quantify the resources that are available for a future disaster, each entity gives an equipment, kits and personal inventory to support disaster response operations. This information is established on the territory ERE. Nonetheless, it was found that the majority of the ERE does not have this information or is not updated. It is worth noting that there are different types of resources defined such as human resources and machinery resources.

Disaster data collection and analysis

When a natural disaster occurs, it is necessary to have updated and reliable information with the objective of providing assistance to victims. To do so, it is necessary first to gather the data, then analyse it and lastly generate technical reports. The collection of information must be clear and timely. There are methodologies and tools to carry out this task. Primary sources are entities whose roles and protocols are related to health and secondary sources refer to other sectors and local actors. Each source should make use of instruments such as health epidemiological surveillance forms, EDAN forms, field missions, databases, among others. Damage assessment and needs analysis (known for its acronym in Spanish as EDAN) is one of the most commonly used tools for data collection. The forms and user instructions can be found in [44]. The EDAN is also considered a process for planning the intervention of the territorial entity and requesting resources necessary for an effective response. EDAN should be applied mainly in three areas, health, habitat, and food.

Number of victims and estimation of humanitarian aid needs

After a disaster, it is important to make an estimation of the number of victims and their status. Thus, the EDAN health section is analysed. In the first case, in the EDAN format, the number of deaths, missing people, and injuries are collected. In the second case, changes in the environment are studied. Damage to the health service network must also be considered. All this information must be recorded in the EDAN form corresponding to a rapid assessment of the health situation.

Aspects related to water supply, basic sanitation, and housing are contemplated in the EDAN habitat section. It analyses the quality and availability of water sources and identifies critical points that may interfere with this process. Another factor analysed is the population's risk of poor basic sanitation in sewage and waste-water systems. The impact on housing is also studied to determine the availability of shelters or temporary housing, and the personnel required to provide such accommodation. Concerning the food victims needs, it is studied the food access limitation in the affected population. The study identifies the requirements for providing balanced diets, nutritional assessments and adequate support for food preparation.

An EDAN form regarding food status verification must be completed to carry out humanitarian assistance. Subsequently, with the collected information, the requirements for assistance and humanitarian aid are established and a distribution plan is developed. Finally, aid is sent to the affected areas and lastly distributed among the victims. It is important to explain that humanitarian aid must be immediate, that means, its management must begin within the first 48 hours after the EDAN is carried out.

Shelters and temporary housing

The shelter opening process is managed from the EDAN habitat section. Shelters must be located far from the emergency site. The number of shelters is defined after having made a census or applying one of EDAN forms and after consolidating the number of homes and people affected. The people who are entitled to temporary accommodation are people who do not have housing as it is destroyed by the natural disaster. It should be clarified that these shelters must have public services such as water, electricity, garbage collection, and a latrine system for excreta management.

Discussion

The main results of the review show that the Colombian disaster response activities are not standardized, yet the roles and responsibilities depend mainly on the territory where the natural disaster occurs. This lack of standardization creates disorder in disaster response, while some entities are responsible for a set of activities in a specific territory, in other territories the same activities are made by different entities. Efforts must be directed to tackle this problem with the aim of successfully respond in the response phase of disasters in the Country. In this manner, entities such as the Civil Defense, police, etc., would have the same responsibilities regardless the location or territory of the disaster. It is worth noting that this document analysis is still in process. More role matrices will be included to confirm the previous results.

Chapter 5

MATHEMATICAL FORMULATION

In this chapter, we present a multi-objective mixed-integer linear model for solving the inventory routing problem in the response phase of a disaster. It is worth noting that this model considers the problem as static. In other words, the models' parameters are known in advance and do not vary over time. This is a strong assumption and is not valid in real life due to the uncertainty and volatility of humanitarian supply chains. For instance, shortages may cause victims to move between distribution points looking for humanitarian aid or better service levels. However, this is the first step towards tackling the problem in its dynamic version, as presented in the next chapters.

This model is based on the MILP formulation presented in [45]. We extended the problem to a humanitarian logistics setting, including the risk of inventory losses due to facility failures and shortages as objective functions. These objective functions are considered simultaneously using an ε-constraint solution methodology. It is worth noting that the real-case setting will be introduced in the Chapter 7.

5.1 Problem definitinon

Making inventory and routing decisions in the aftermath of a catastrophe is a complex activity mostly made manually in which multiple criteria and factors must be considered. The purpose of this activity is to establish the quantities and the routes the available vehicles must follow to deliver humanitarian aid to the opened distribution points. To do so, we propose a multi-objective multi vehicle inventory routing problem for the delivery of humanitarian aid. The mathematical model is formally stated as follows.

It is considered a set of distribution points of humanitarian aid $N = \{1, 2, ..., m\}$ which are geographically distributed over an affected area and must be served in multiple $T = \{1, 2, ..., t\}$ periods with different quantities of humanitarian aid from a single depot. Thus, the inventory routing problem for delivering humanitarian aid can be defined in a non-directed graph $G = (V,A)$ with a set of nodes $V = N \cup \{0\}$, where N are the distribution points' locations and $\{0\}$ the depot. The set of arcs is defined by $A = \{(i, j) : i \in V, i \neq j\}$ and each arc (i, j) has associated a non-negative value c_{ij} which represents the travel cost between nodes i and j. The total cost of the routes should not be higher that an established budget P. Each distribution point $i \in N$ has a demand D_{nt} which must be fulfilled in the period $t \in T$. Each distribution point $i \in N$ has a maximum capacity U_n for receiving humanitarian aid and has an initial inventory level II_n. The depot has an initial inventory level ID. Additionally, the distribution points have a level of risk associated with the probability of being destroyed or its inventory being lost. This risk R_n is parametrized in a scale from 1 to 5 being 5 the higher risk level. Finally, to deliver the humanitarian aid from the depot to the different distribution points a fleet of vehicles $K = \{1,2,...,k\}$ are available which have a maximum load capacity Q_k. Lastly, it is worth noting that shortages do not accumulate between periods (lost sales policy). Next sub-section shows the mathematical model for the problem presented before.

5.2 Bi-objective mixed integer linear model

In this sub-section, the mathematical formulation for the problem is presented. First, the sets, parameters and variables are defined and finally equations 5.1- 5.22 presents the objective functions, and constraints of the model.

Sets

M distribution points set $N = \{1,2,...,m\}$.

K vehicles set $K = \{1,2,...,k\}$.

V vertex set (distribution points and depot) $V = N \cup \{0\}$.

A arcs set $A = (i, j) \in V, i \neq j$.

T time set $T = \{1,2,...,t\}$.

T' auxiliary time set $T' = T \cup \{t+1\}$.

Parameters

Q_k capacity of vehicle k.

C_{ij} transportation cost from node i to j.

D_{nt} demand from distribution point n in period t.

U_n maximum inventory level at distribution point n.

ID initial inventory level at depot.

II_n initial inventory level at distribution point n.

R_n risk level at distribution point n. [1 Lowest risk, 5 higher].

HD_t humanitarian aid donations available at depot in period t.

P total budget for transportation cost.

Variables

Y_{ijkt} 1 if vehicle k uses the arc $(i-j)$ in period t, 0 otherwise.
X_{nkt} quantity of humanitarian aid delivered to distribution point n in vehicle k in the period t
Z_{nkt} 1 if distribution point n is served by vehicle k in the period t, 0 otherwise.
B_t inventory Level at the depot in period t.
I_{nt} inventory level at distribution point n in period t.
S_{nt} shortage level at distribution point n in period t.

The two objectives in our model are indicated by equations 5.1 and 5.2 and described as follows: Objective function 1 minimizes the total shortage or stock-out at distribution points and objective function 2 minimizes the level of inventory at risk in distribution points.

$$Min\ OF1 \sum_{n\in M}\sum_{t\in T} S_{nt} \tag{5.1}$$

$$Min\ OF2 \sum_{n\in M}\sum_{t\in T'} I_{nt} R_n \tag{5.2}$$

Subject to:

$$B_t = B_{t-1} + HD_{t-1} - \sum_{n\in M}\sum_{k\in K} X_{nkt-1} \qquad \forall t \in T' | t > 1 \tag{5.3}$$

$$B_1 = ID \tag{5.4}$$

$$B_t \geq \sum_{n\in M}\sum_{k\in K} X_{nkt} \qquad \forall t \in T \tag{5.5}$$

$$I_{nt} = I_{nt-1} + \sum_{k\in K} X_{nkt} - D_{nt-1} + S_{nt-1} \qquad \forall t \in T', n \in M | t > 1 \tag{5.6}$$

$$I_{n1} = II_n \qquad \forall n \in M \tag{5.7}$$

$$I_{nt} \leq U_n \qquad \forall t \in T, n \in M \tag{5.8}$$

$$\sum_{k\in K} X_{nkt} \leq U_n - I_{nt} \qquad \forall t \in T, n \in M, k \in K \tag{5.9}$$

$$\sum_{k\in K} X_{nkt} \leq U_n Z_{nt} \qquad \forall t \in T, n \in M \tag{5.10}$$

$$X_{nkt} \geq Z_{nt} \qquad \forall t \in T, n \in M \tag{5.11}$$

$$\sum_{n \in M} X_{nkt} \leq Q_k \qquad \forall t \in T, k \in K \tag{5.12}$$

$$\sum_{(0,i) \in A} Y_{0ikt} \geq Z_{0kt} \qquad \forall t \in T, k \in K \tag{5.13}$$

$$\sum_{(0,i) \in A} Y_{0ikt} \leq 1 \qquad \forall t \in T, k \in K \tag{5.14}$$

$$\sum_{n \in M} X_{nkt} \leq Q_k Z_{0kt} \qquad \forall t \in T, k \in K \tag{5.15}$$

$$\sum_{j \in V} Y_{ijkt} + \sum_{e \in V} Y_{eikt} = 2Z_{ikt} \qquad \forall t \in T, i \in M, k \in K \tag{5.16}$$

$$Y_{ijkt} = 0 \qquad \forall t \in T, k \in K, (i-j) \in M | i = j \tag{5.17}$$

$$\sum_{j \in V} Y_{ijkt} \leq 1 \qquad \forall t \in T, i \in M, k \in K \tag{5.18}$$

$$\sum_{i \in V} Y_{ijkt} \leq 1 \qquad \forall t \in T, j \in M, k \in K \tag{5.19}$$

$$\sum_{i \in L} \sum_{j \in L | i > j} Y_{ijkt} \leq \sum_{i \in L} Zikt - Z_{hkt} \qquad \forall L \subseteq M, \forall t \in T, h \in L, k \in K \tag{5.20}$$

$$\sum_{(i-j) \in A} \sum_{t \in T} \sum_{k \in K} C_{ij} Y_{ijkt} \leq P \tag{5.21}$$

$$B_t, X_{nkt}, S_{nt}, I_{nt} \geq 0 \qquad Z_{nky}, Y_{ijkt} \in 0, 1 \tag{5.22}$$

Constraints 5.3 calculates the inventory level at depot. Equations 5.4 establishes the initial inventory level for the depot while 5.5 ensures that the depot is not allowed to send more than its existences. Inventory definition and initial inventory for distribution points are calculated in 5.6 and 5.7. In 5.8, 5.9 and 5.10 the observation of distribution points' capacity is made. Constraints 5.11 considers vehicles capacity while 5.12 guarantees each vehicle visiting a distribution point must deliver humanitarian aid. Equations 5.13 , 5.14 and 5.15 assures each vehicle must start its route from the depot. Flow conservation constraints are presented in 5.16 where each vehicle visiting a depot must leave. In 5.17 vehicles are forbidden to visit a distribution point and then go to the same distribution point again. In 5.18 and 5.19 it is contemplated that each vehicle can visit only one time per period the same distribution point. Constraints 5.20 are the sub-tours elimination constraints. Equations 5.21 are the budget constraints for travel costs and finally 5.22 are the non-negativity and binary constraints for the decision variables. Pérez-Rodríguez & Holguín-Veras in its 2015 paper regarding social costs in [46] made some practical contributions that can be applied to this work enhancing the previous model. When humanitarian aid in form of kits or units are delivered to distribution points it has to meet the distribution points' demand for at least t periods of time. In other words, no partial deliveries could be allowed and the quantities taken to distribution points have to be large enough to meet victims' requirements. For example, assume a distribution point $i \in N$ which has a demand $D_{nt} = 30$. This distribution point receives a delivery of 10 kits. To distribute the kits over the 30 victims, they have to be opened and redistributed among them and the humanitarian needs are not fulfilled completely. That is why partial deliveries should not be allowed and if there are shortages it cannot be partial. Furthermore, in [47] the authors studied deprivation times regarding deprivation cost functions. They demonstrated the impact of consecutive days having water shortages. Additionally, based on the Colombian humanitarian operations report of the previous subsection we consider that shortages more than 48 hours should not be allowed in distribution points. The previous practical considerations can be integrated in the mathematical model in the following way. It is worth considering that 24 hours corresponds to one period in the model. We introduce the decision variable β_{nt}, which takes value of 1 if there is shortage in distribution point n in period t, 0 otherwise. The equations 5.23-5.25 are also introduced.

$$S_{nt} = D_{nt}\,\beta_{nt} \qquad \forall t \in T, n \in M \tag{5.23}$$

$$\beta_{nt} + \beta_{nt+1} + \beta_{nt+2} \leq 2 \qquad \forall t \in T, n \in M | t < G-1 \tag{5.24}$$

$$\beta_{nt} \in \{0,1\} \tag{5.25}$$

Constraints 5.23 avoids partial shortages in distribution points and 5.24 forbids three consecutive days with shortages at any distribution point. In 5.25 the nature of the new decision variable is defined.

5.3 ε-constraint Solution Methodology

There are several methods of multi-objective optimization that have been successfully tested in the literature and in real life problems. These methods find quality solutions where there is no single optimal solution that optimizes all the objective functions at once. Methodologies such as goal programming (GP), ε-constraint method and the Reference Point Method (RPM) are among the most used multi-objective methodologies [48]. In this work, the ε-constraint method is used to solve our multi-objective optimization problem. To do so, first we optimize one objective function using the other as constraints and incorporating them in the constraint part of the mathematical model. Finally, the parametrical variations in the right-hand side (RHS) of the constrained objective functions e_i give efficient solutions which are in the pareto frontier. In this problem, the objective function of shortage is minimized as seen in equation 5.26, while the inventory at risk objective is considered as constraint and defining the highest acceptable limit for that objective e_2 as shown in 5.27. This process is done multiple times obtaining the non-dominated solutions and the pareto efficiency front for the problem.

$$Min\ OF1 \sum_{n \in M} \sum_{t \in T} S_{nt} \tag{5.26}$$

$$OF2 \sum_{n \in M} \sum_{t \in T'} I_{nt} R_n \leq e_2 \tag{5.27}$$

5.4 Implementation and results

To test the proposed mathematical model in a static context, we adapted the abs1n5 to abs5n5 instances from [45] as follows. In a planning horizon of $t = 6$ days, $n = 5$ distribution point have to be served from a single depot using $k = 2$ vehicles and an available budget of \$2500. Each distribution point has a capacity of 500 units and a initial inventory level of 50 units. The location (coordinates) of depot and the distribution points are obtained from the instance, as well as distribution points' demand. Distances between locations are euclidean and the travel cost correspond to 1\$ per distance unit. Table 5.1 contains vehicle capacity (same for all vehicles, initial inventory level in depot (obtained from the instances) and donations which were estimated to generate shortages. Lastly, we set the risk level for distribution points in the following way. Distribution point 1 has a minimum risk level ($R_n = 1$), Distribution point 4 and 5 have a medium risk level ($R_n = 3$) and distribution points 2 and 3 have a high risk level ($R_n = 5$).

Table 5.1 Description of adapted instances

Instance	Vehicle capacity	Depot initial inv. level	Donations (period)
abs1n5	507	875	600 (1), 200 (4)
abs2n5	405	781	200 (3)
abs3n5	438	668	100 (3)
abs4n5	471	676	400 (3)
abs5n5	369	649	300 (3)

To perform the ε-constraint solution methodology for the instances, we set an inventory at risk level of $e_2 = 2000$ units and this value is decreased 50 units for each run until no more solutions are found. This value is chosen due to the high computational times faced in the experimentation even though we used a tolerable gap of 5%. It is worth noting that with an inventory at risk level greater than 2000 non dominated solutions were not found. Next, Table 5.2 presents the general results of the experimentation with its performance metrics.

Table 5.2 ε-constraint instances results

Instance	Number of solutions	ND	D	Error rate (ER)	Generation Distance (GD)	Spread Metric
abs1n5	17	11	6	35.29%	11.174	0.53634
abs2n5	22	15	7	31.82%	42.056	0.62137
abs3n5	13	11	2	15.38%	5.53	0.10379
abs4n5	20	15	5	25.00%	16.490	0.38967
abs5n5	15	11	4	26.67%	23.388	0.32740

D: dominated solution, ND non-dominated solution

Figure 5.1 shows the obtained pareto approximate front from instance abs1n5. Figure 5.2 and Figure 5.3 present a detailed IRP sequence for one solution from abs2n5 y abs4n5 respectively. In the next subsection these solutions are discussed.

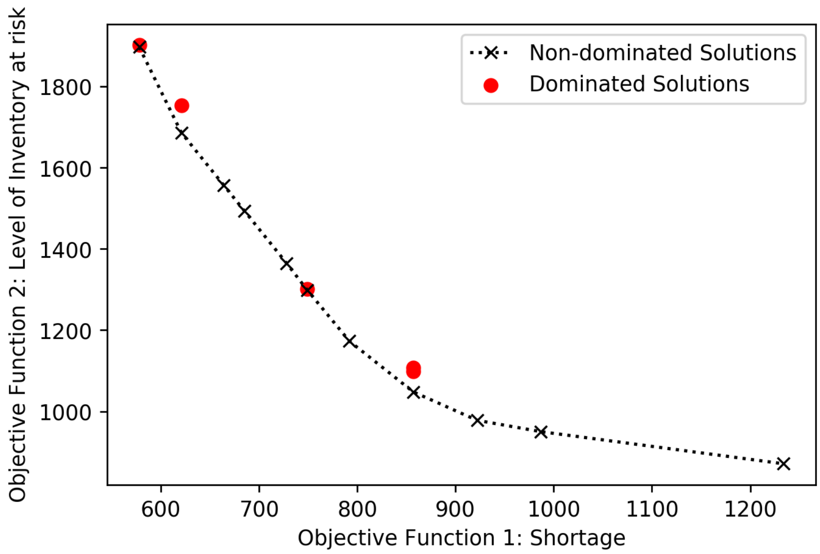

Fig. 5.1 Pareto approximate Front instance abs1n5

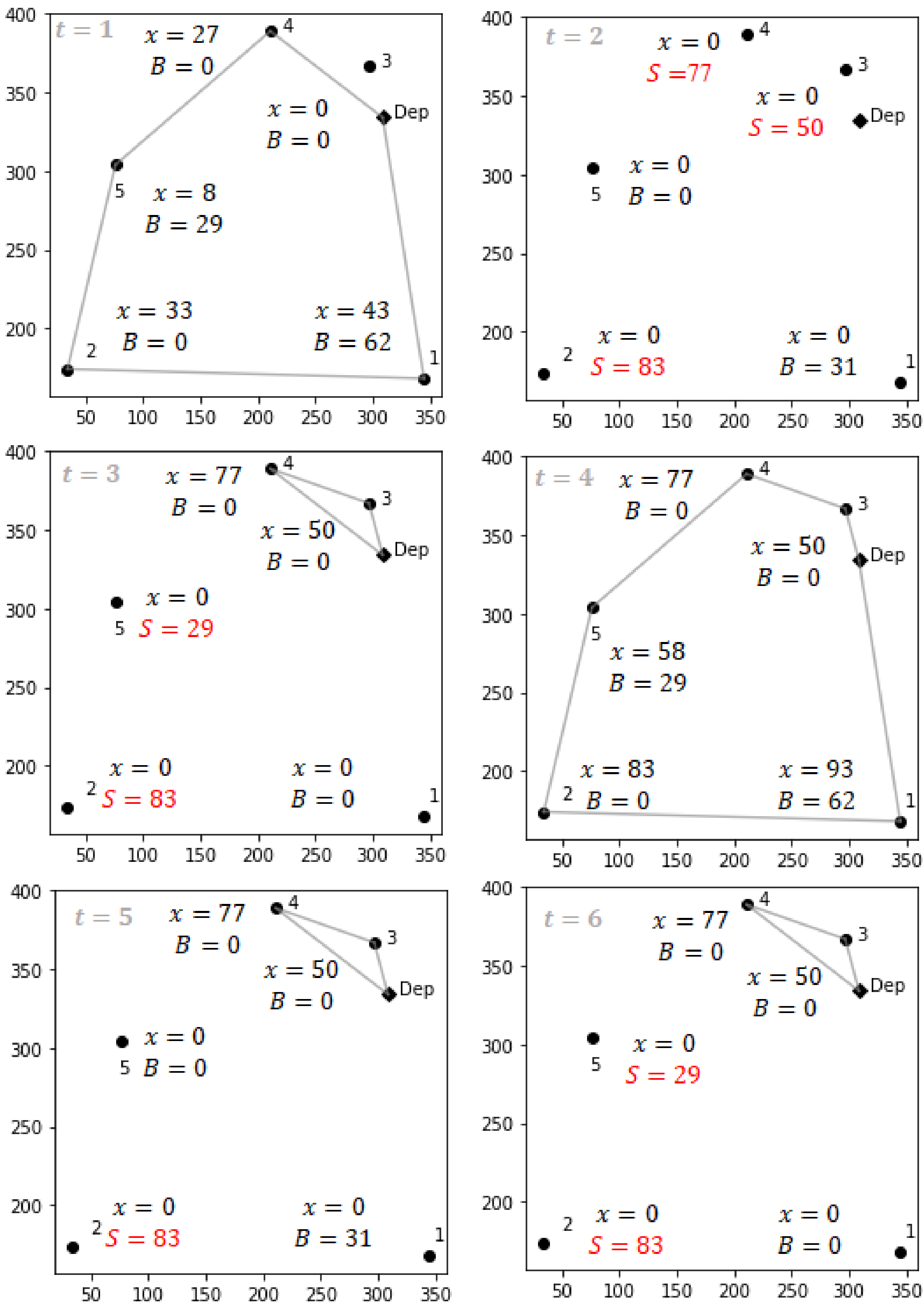

Fig. 5.2 Optimal routes solution $OF1 = 517$, $OF2 = 1210$ of instance abs2n5, shortages for distribution points are in red

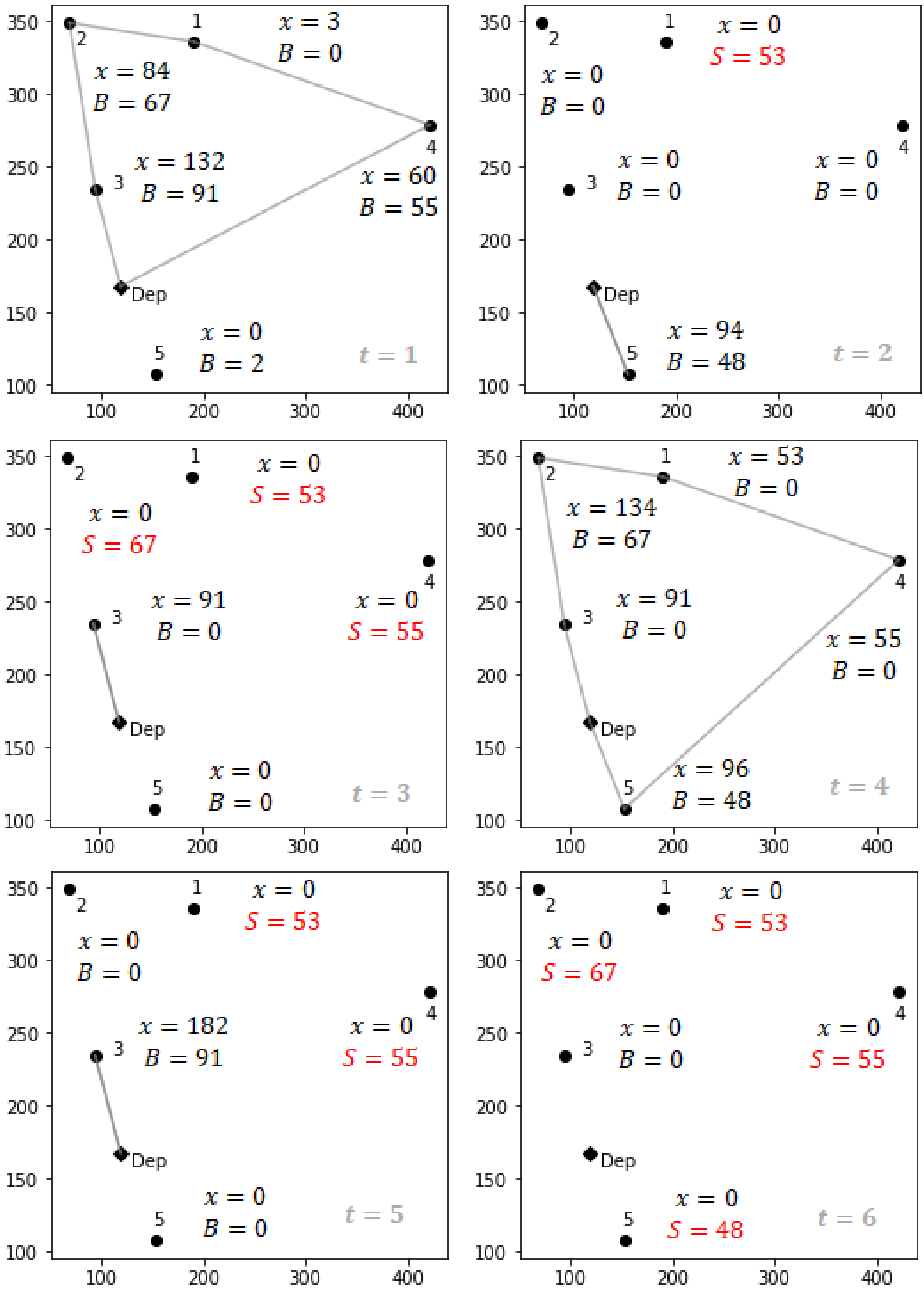

Fig. 5.3 Optimal routes solution $OF1 = 559, OF2 = 1500$ of instance abs4n5, shortages for distribution points are in red

5.5 Discussion

Now, we analyse in detail the Figure 5.2 which presents the inventory routing scheme for a solution with shortage ($OF1 = 571$) and inventory at risk level ($OF2 = 1210$) from instance abs2n5. Table 5.3 complements the information for the IRP solution and summarizes shortage and inventory levels in the planning horizon.

Table 5.3 Distribution points' shortage and inventory levels for abs2n5 solution

Distribution point	Risk level	Accumulated shortage	Periods in shortage	Accumulated inventory
1	1	0	0	186
2	5	332	4	0
3	5	50	1	0
4	3	77	1	0
5	3	58	2	58

From Table 5.3 and Figure 5.2 we can make the following conclusions. In distribution point 1 the model allows high inventory levels in several periods due to its low level risk. Furthermore, even though distribution point 5 has a medium risk level, the model prefers risking inventory rather than causing shortages. Moreover, it is interesting to notice that although distribution point 3 has the highest risk level, it has lower shortages than distribution points 4 and 5. It is due to the closeness and the low transport cost between the depot and distribution point 3. Lastly, distribution point 2 has the highest shortage level and more periods in shortage due to its high risk level and the long distance to the depot. In this way, it can be seen that the model aims to find a balance between shortages, risk level, and transportation costs. Next we analyse in detail a solution from instance abs4n5. Table 5.4 complements the information this solution.

Table 5.4 Distribution points' shortage and inventory levels for abs4n5 solution

Distribution point	Risk level	Accumulated shortage	Periods in shortage	Accumulated inventory
1	5	212	4	0
2	3	134	2	134
3	1	0	0	182
4	3	165	3	55
5	1	48	1	98

From Table 5.3 and Figure 5.3 we can conclude the following. Distribution point 1, with the highest risk level and located far from the depot, did not store inventory and had the highest shortage levels and periods. Next, distribution point 2 has a medium risk level. However, it storages inventory due it is the farthest distribution point to the depot, and visiting it is costly. Lastly, distribution points 3 and 5 have the highest accumulated inventory due to their low-risk level. In this way, the model finds a balance between shortages, risk level, and transportation costs.

The results of this chapter were published in [49]:

Espejo-Díaz, J. A., & Guerrero, W. J. (2019). A Bi-objective Model for the Humanitarian Aid Distribution Problem: Analyzing the Trade-off Between Shortage and Inventory at Risk. In Applied Computer Sciences in Engineering (pp. 752–763). Springer International Publishing.

https://doi.org/10.1007/978-3-030-31019-6_63

Chapter 6

AGENT BASED SIMULATION MODEL

Humanitarian operations in the aftermath of a disaster can be seen as a system where multiple stakeholders participate intending to relieve the suffering of the affected people. Among the multiple actors who participate in the system are the victims, decision-makers, or distribution points of humanitarian aid. From the individual decisions of each stakeholder, the communication and interaction between them, the overall system's behavior emerges. The above suggests that the humanitarian response operation can be represented using the agent-based modeling paradigm. Additionally, in the system, there is a clear differentiation of each entity and the main interactions between them can be extracted and translated computationally.

To represent the humanitarian response operation as an agent-based model, we follow the methodology presented in Figure 2.1. Subsection 6.1 presents the first four phases of the methodology, which are the definition of agents, their environment, methods, and interactions. Next, in section 6.2, we make some remarks on the utilization of the optimization model in the simulation framework. There we define the way some optimization parameters will be handled in the simulation model. Last, in section 6.3, we present the last phase of the methodology, which corresponds to the computational implementation in a software. There we detail the variables, parameters, collections, algorithms, and in general, the computational structure of the agent-based simulation model. Additionally, in this section, we also present hybridization with the optimization model of Ch.5.

Finally, it is worth noting that the scope of the simulation model is limited to the operational component in the humanitarian response operation. To be more specific, the scope corresponds to the distribution of humanitarian aid in pre-determined distribution points over an affected area. We do not consider previous steps in the humanitarian supply chain, such as procurement of humanitarian aid or other strategical/tactical decisions. With that in mind, next, we present the design and implementation of the agent-based simulation model.

6.1 Design phase

In this section, we present the design of the agent-based simulation model. To do so, first, we define individually each entity and the environment they live in. Then we present each agent methods and interactions for performing their activities to pursue their objectives.

6.1.1 Definition of agents and their environment

Victim

It represents the persons who suffered a disaster but managed to survive it. Most victims will have several hardships waiting for them shortly. One of the most critical hardships is the lack of adequate supplies such as water, food, or hygiene items. Therefore, they have to commute to a distribution point to get these supplies. Victims can either stay in the distribution point if it is designed to shelter people or can get their supplies and return after they run out of supplies. Disaster victims can decide whether to keep going (or staying) in the distribution point or leaving it. This decision is mainly motivated by the availability of supplies in it and how much time they are willing to endure without supplies.

Additionally, disaster victims communicate with each other (word of mouth) and can inform other victims when in their distribution points the humanitarian aid is available or not. In this way, each disaster victim integrates the experiences and information of other victims. With that in mind, they can decide where to move if shortages appear in its current distribution point. The disaster victims' environment at the beginning is their home or place of residence. When the disaster strikes and after the distribution points were set-up, victims move to them and stay there to get their supplies. From that point on, the victims' environment is the distribution point. Last, we assumed that no organizations or institutions assign victims to distribution points. Therefore, the victims decide which distribution point they decide to go.

Distribution point

This entity represents the physical locations where victims receive humanitarian aid in the response phase of a disaster. As mentioned earlier in this document, the distribution points can be located in existing facilities such as schools, universities, coliseums, stadiums, or other big spaces. Ideally, these locations have the required area and infrastructure to storage humanitarian aid. Additionally, these distribution points can serve as shelters if their infrastructure is adapted to offer physical protection to the victims. For instance, these facilities can have tents, plastic sheeting, or other similar forms of temporary housing. On the contrary, they can serve only as distribution points without offering habitation facilities to victims. In this work, we consider both cases as distribution points regardless of the victim stays there or not. The distribution points' environment is the affected region because they are geographically distributed there.

Depot

It represents the physical location where the humanitarian aid is consolidated and distributed to the different distribution points. Ideally, these locations are large enough to store large quantities of humanitarian aid in the form of humanitarian kits, food, water, medical supplies, hygiene items, and others. In this work, we consider the distribution of humanitarian aid in the form of kits. These kits contain the quantity and types of humanitarian aid required for a family for a specific time unit. The depot environment corresponds to secure areas with a low risk of being struck by another disaster and without security concerns.

Vehicle

This entity is in charge of transporting humanitarian aid in the form of kits to the distribution points. It starts and finishes its routes at the corresponding depot location. It has associated a maximum capacity and generates a cost proportional to the traveled distance. Its environment corresponds to the affected region's roads or paths from the depot to shelters. It is worth noting that in this work, we do not consider road disruptions, such as blockages or unstable roads.

Crisis room

This entity is in charge of making the humanitarian aid inventory routing decisions. To do so, it collects the system information from the distribution points, depot, and vehicles. Then, using an optimization algorithm to decide the routes vehicles follow and the quantities to deliver to each distribution point. The crisis room environment is a facility not necessarily in the damaged area with computational software to use the optimization model. Additionally, this facility has the option of communicating with the depot and the different distribution points in real-time to asses the needs in the system.

Next, Figure 6.1 presents the activity diagram summarizing the activities described previously for each entity.

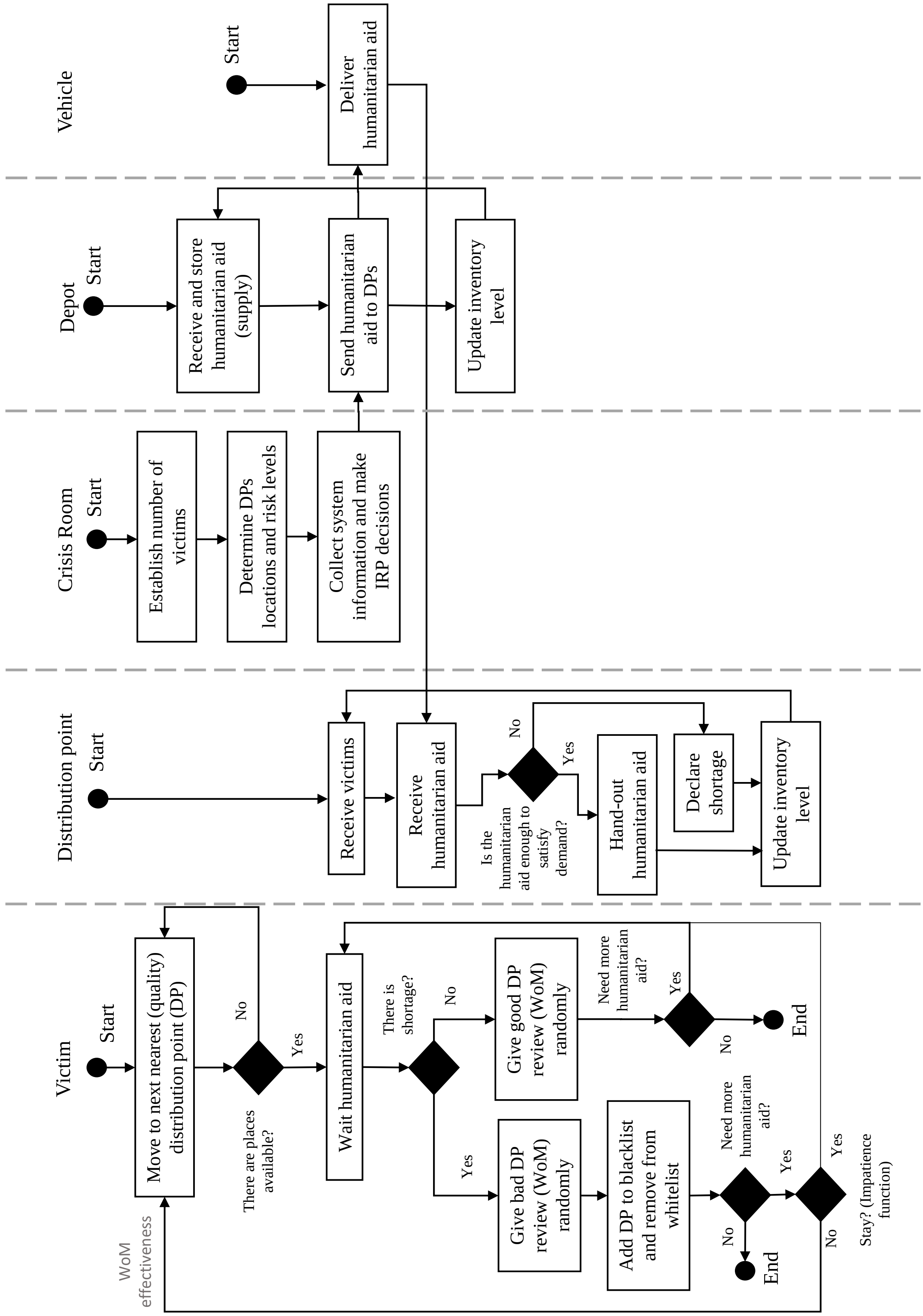

Fig. 6.1 Agent-based model activity diagram

6.1.2 Agents' methods and interactions

In this section, we describe the methods and the interactions between the entities introduced in the previous subsection.

First, it is important to consider that victims in their vulnerability condition will make the decisions that benefit them the most. Therefore, after the disaster occurs and the distribution points are available, they move quickly to the nearest one. Additionally, If the victim experiences shortages, it can decide to seek another distribution point to get their supplies or stay there waiting to be served the next period. This decision is given by the victim's impatience function as follows. If there is no shortage, the probability of leaving the distribution point is 0%. This probability increases until 100% when there are three periods in constant shortage. The victim does not care if it may alter the operational planning in the humanitarian response and is highly reactive to shortages due to their vulnerability state.

Simultaneously, each victim agent has a whitelist and a blacklist that represent the go and no-go distribution points, respectively. These lists collect their experiences; for instance, if the victim experiences a shortage, it will remove the distribution point from the whitelist and add it to the blacklist. Additionally, via word of mouth (WoM), victims communicate and share their experiences with other agents in their social circle. If a victim is in shortage, it will send a message (e.g., social media or call) to a randomly selected victim, indicating that this distribution point is in shortage. The receptor victim will update their lists by removing the distribution point in shortage from the whitelist and adding it to its blacklist. If the receptor agent decides to move from its current distribution point, it will decide between the ones in its whitelist. Additionally, in our work we consider positive WoM. It works including distribution points which are handing-out humanitarian aid in the victim's whitelist. It is worth noting that not all victims who receive word of mouth (positive and negative) believe and process it. Therefore, a WoM effectiveness parameter is set.

Furthermore, distribution points interact with victims by providing humanitarian aid (when possible). Another interaction is given when a victim commutes to a distribution point, which is full. Therefore, the distribution point denies the victims' entry, and it must seek another distribution point. Finally, the crisis room interacts with the depot, distribution points, and vehicles via messages and events as follows. At the beginning of the planning horizon and each t periods, the distribution points and the depot send their inventory level, and the latter informs how many victims are being served. Then the crisis room runs the optimization model and informs the depot of the quantities and routes to deliver the humanitarian aid to the distribution points. Figure 6.2 presents the sequence diagram summarizing the communication and interactions described previously for each entity. The dotted line represents part of the processes which are dynamic in the model.

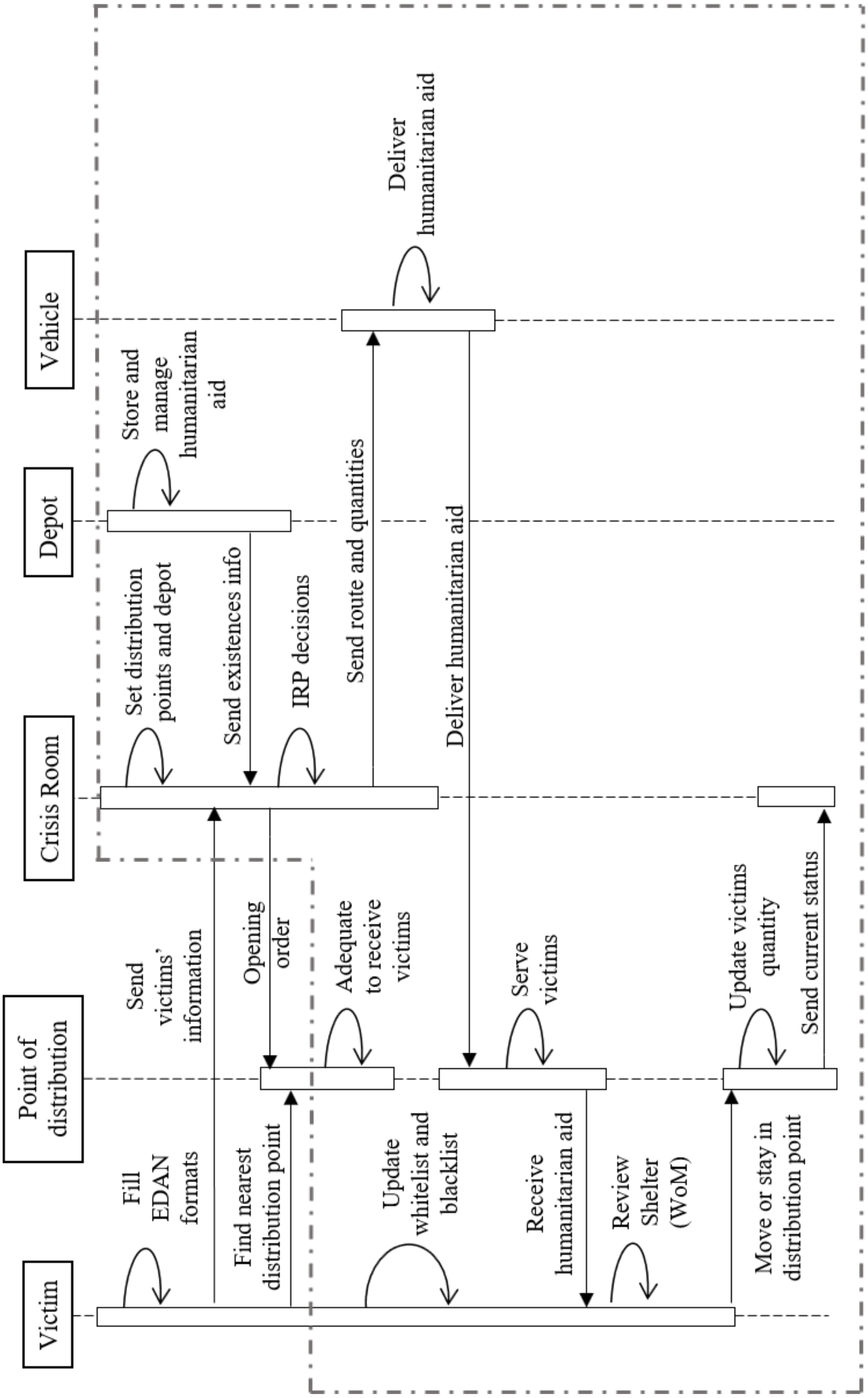

Fig. 6.2 Agent-based model sequence diagram

6.2 Configuration of optimization parameters

As previously stated, the agent-based simulation model uses an optimization model to make inventory routing decisions. This optimization model (Ch. 5) has two objective functions and is solved using a ε-constraint solution methodology. The model aims to find a balance between shortage, inventory at risk, and transportation costs and is set as seen in figure Figure 6.3.

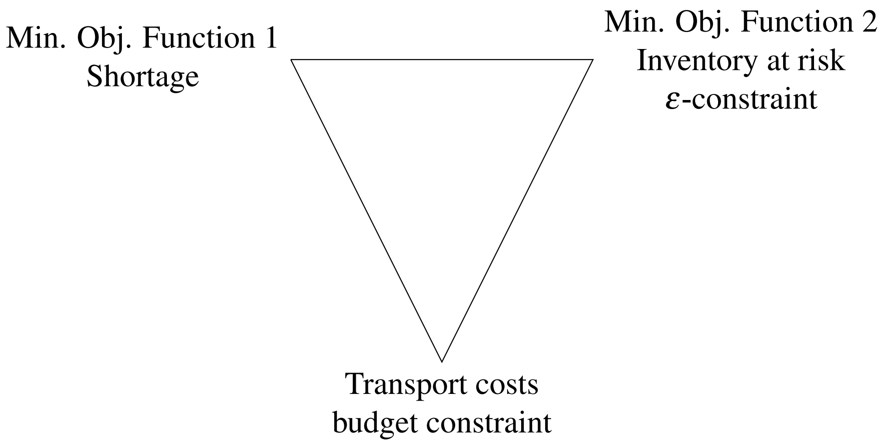

Fig. 6.3 Optimization model configuration

This model is highly sensitive to the transportation budget P presented in constraint 5.21. Now we analyze the extreme cases in the budged assignment. On the one hand, if the model has a tight budget, the vehicles can visit distribution points only on one or on a few occasions leading to high inventory at risk levels. On the other hand, if this budget is high, vehicles would visit distribution points in all periods, there would not be inventory at risk, and a useful budget would be wasted. The latter scenario is not frequent due to the budget limitation of humanitarian operations.

It is worth noting that in the real-life, this parameter is established by endogenous variables that are out of the scope of this work. For instance, it can be determined by government decisions, budget availability, or financial donations. Additionally, the decision-maker can modify this parameter to evaluate more scenarios. However, to create academic instances that allow the simulation to evaluate the impact of the "word of mouth" factor and shortages in the IRP decisions, we have to estimate this parameter balancing the shortage and inventory at risk. Thus, we propose estimating the budget using the traveling salesman problem (TSP) as follows.

To begin with, the TPS aims to find the shortest possible route that visits all nodes once [50]. Additionally, the length of the planning horizon should be considered in estimating the transportation budget. The greater the planning horizon, the higher budget has to be assigned to the inventory transportation. Equation 6.1 presents the budget calculation for the simulation model, where P is the recommended budget, t is the length of the planning horizon, and $TSP(Cost)$ is the optimal cost found in the TSP optimization model. It is worth noting that we use the Miller Tucker Zemlin (MTZ) subtour elimination constraints and the TSP formulation presented in [50].

$$P = TSP(Cost)\,\frac{t}{2} \tag{6.1}$$

Next, for the sake of simplicity and without loss of generality, the simulation model will not implement the ε-constraint solution methodology proposed in chapter 5. It means that the simulation model will not test multiple values of inventory at risk and produce an approximate Pareto front. We establish the following inventory at risk policy of equation 6.2. $\overline{D}_n$ corresponds to the average demand for distribution point $n \in N$ and R_n corresponds to the risk level of distribution point $n \in N$. It means that we allow a maximum inventory at risk of the average of the distribution points' demand in the planning horizon.

$$Max.IAR = \sum_{n \in M} \overline{D}_n\, R_n \tag{6.2}$$

Therefore, in the simulation model, constraints 5.21 and 5.27 are replaced by constraints 6.3 and 6.4 respectively. In this way, the simulation model will have an objective function that corresponds to the minimization of shortage in distribution points.

$$\sum_{(i-j) \in A} \sum_{t \in T} \sum_{k \in K} C_{ij} Y_{ijkt} \,\leq\, TSP(Cost)\,\frac{t}{2} \tag{6.3}$$

$$\sum_{n \in M} \sum_{t \in T'} I_{nt} R_n \leq \sum_{n \in M} \overline{D}_n\, R_n \tag{6.4}$$

6.3 Implementation phase

The last phase in developing an agent-based simulation model is the implementation in a specialized software. Anylogic was selected as the software most suitable for the studied problem. It is a powerful simulation software that supports the following modeling methods: agent-based, discrete event, and system dynamics, as shown in Figure 6.4 [51]. Its multi-method functionality and flexibility was the main reason for choosing it over other software.

To model the dynamic disaster relief distribution, we combine the agent-based and the discrete-event paradigms. The remaining of this section is organized as follows. Next, we introduce the Anylogic features used for modeling the problem. Subsection 6.3.1 presents in detail the computational agent types created for representing the problem. Last, subsection 6.3.2 presents the auxiliary Java classes created to include the optimization models in the simulation.

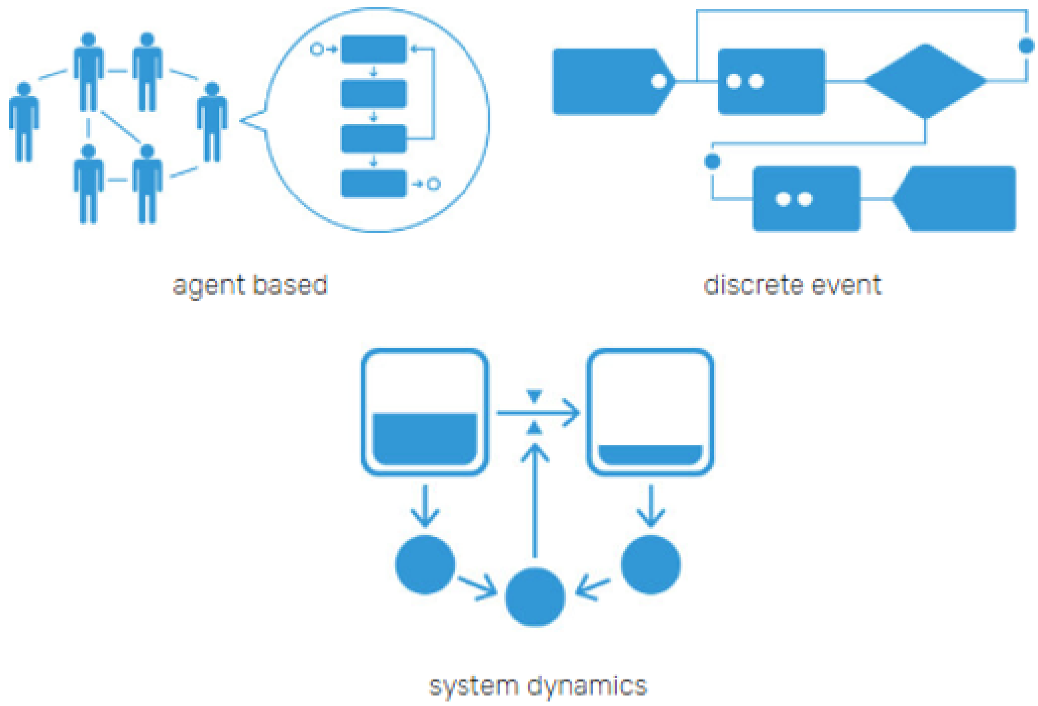

Fig. 6.4 Anylogic multimethod modeling environment, source [51]

Statecharts

State transition diagrams o statecharts are a powerful way to represent complex agent behaviors. Its main components are states and transitions. The first denotes a particular location of control where events or conditions are true. The latter denotes the switch from one state to another. There are multiple transition types such as timeouts, rates, conditions, messages, or agent arrivals. An example of states and transitions is a victim waiting for humanitarian aid. The victim receives a message from the distribution point, indicating that there is not humanitarian aid available for this period. The message triggers a transition from the waiting for humanitarian aid state to in shortage state. In the latter state, the victim performs other actions, such as seeking another distribution point. Finally, it is worth noting that for each statechart, the agent is in one state at a time.

Process modeling library

In the Anylogic environment, the process modeling library is a powerful tool to model logistic operations in manufacturing, delivering, healthcare, etc., with a dynamic nature. This library contains elements such as queues, delays, gates, sources, sinks, and others, which allow building models with high detail. Another useful feature is that agents can enter and go through process flows combining discrete events with agent-based modeling. Additionally, within the process, agents can trigger transitions in statecharts. For instance, an agent in a queue can send messages to different agents in the simulation. An example of its utilization is a victim going through the process flow of entering a distribution point and receiving humanitarian aid. It has to check first if there is space available for it and then wait for the delivery.

Option Lists

An option list is an excellent option to build structured simulation models in Anylogic. It defines the agent attributes with limited choices or alternatives. It restricts the possible outcomes of certain variables or objects. In this work, we used an option list to structure the outcomes of the different messages used in the simulation. The option list is labeled "Messages" and has the contents of Table 7.1. In the model, when an agent needs to send a message, it calls the option list, for instance, with Messages.DistributionPointFull.

Table 6.1 Choices of option list Messages

Relieved
DistributionPointFull
DistributionPointShortage
DistributionPointRelieved
Shortage
LeaveDistributionPoint

Databases

Last, Anylogic allows the modellers to integrate databases in their simulations. The modeller can read input data and write simulation outputs. In this model, we use a database to create parametrized agent populations. We create the agent type distribution point and read all its parameters from an excel spreadsheet. These parameters are explained in detail in the next subsection.

6.3.1 Agent types

In this subsection, we detail and explain the computational agents created in Anylogic.

Victim Agent

The agent type "victim" has a statechart and the elements shown in Figure 6.5. The victim's behavior is the following. First, in the statechart entry point "VictimBehavior", the agent fills the Whitelist collection with all the distribution points. At that moment, the agent does not have any bad experience and has not received any other victims' experience. Then it goes to the state "SeekingDP". There, the timeout transition "MoveToDP" is triggered, and the agent reviews the candidate distribution points in the "Whitelist" and goes to the nearest one. This transition also enters the victim in the distribution point by taking it to "Walkin" enter point of Figure 6.6. In the case of the agent finds out that the distribution point is full, the agent returns to the state "SeekingDP". If the agent enters, it stays in the state "AtDistributionPoint". There, the agent will wait for humanitarian aid. If the humanitarian aid is delivered, the victim will pass to the state "Relieved". There, the agent updates the variable "DaysWithHumAid" and send to a random victim a positive word of mouth. After, the agent returns to the "AtDistributionPoint" state.

On the contrary, if the agent experiences shortage, it will pass to the state "InShortage". There, the agent updates the "DaysInShortage" variable. Based on the victim's decision to stay or leave in the process flow of Figure 6.6, it triggers the "SearchNewDP" transition or the "Stay" transition. Finally, while "InShortage" state, the agent sends a message to other victim (chosen randomly), indicating that there is a shortage at that distribution point (negative word of mouth). Simultaneously, victims are updating its whitelist and blacklist by adding or removing distribution points from their whitelist and blacklist.

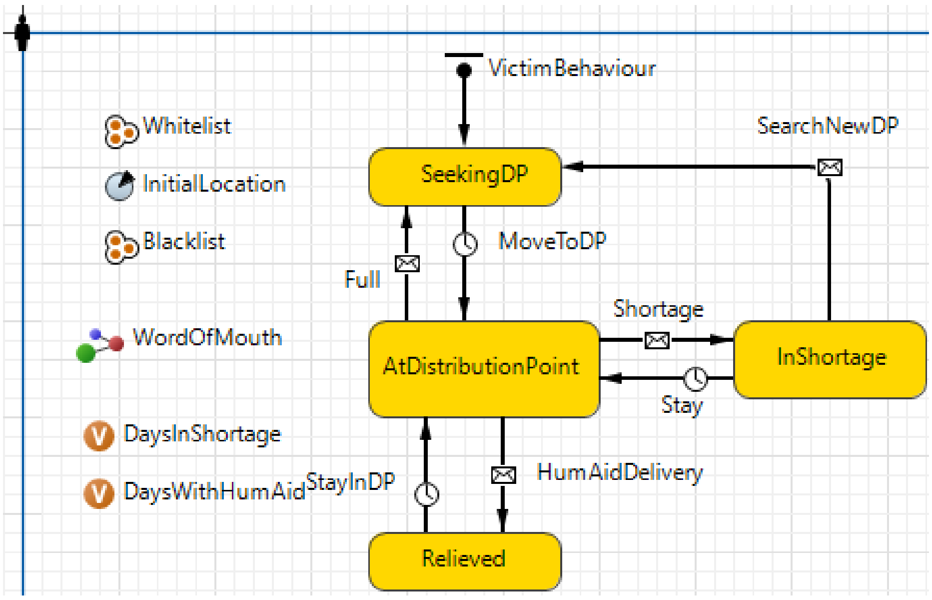

Fig. 6.5 Victim agent type statechart

Distribution Point Agent

The "distribution point" type agent is comprised of the process flow of Figure 6.6 and the statechart of Figure 6.7. First, the process flow represents the steps and choices of the "victim" agent in the distribution point as follows. The victim enters the distribution point agent in the "Walkin". There, the distribution point checks if there is space for that victim by comparing the "NumVictimsInShelter" variable with the "limit" parameter. If there is not space, the victim leaves, else, it passes to "WaitingAid". After this delay, the victim goes to the gate "Shortage". The gate checks if the victim is in state "InShortage" or not in Figure 6.5 . If in "InShortage" state, the victim updates the "Shelterqualification" variable and goes to the gate "LeavesDP". In that gate, the victim checks how many consecutive periods the distribution point has been in shortage ("AccShortage" variable). The probability of leaving increases if that variable is higher. In the case of "AccShortage" equals or higher to three periods, the probability of leaving 100%. When moving, the victim waits in "WaitingNexPeriod" and exits the distribution point. If it decides to stay, it returns to "WaitingAid". In the case of no shortage, the victim waits in "WaitNextPeriod" and returns to "WaitingAid". This process is repeated for each victim entering the distribution point.

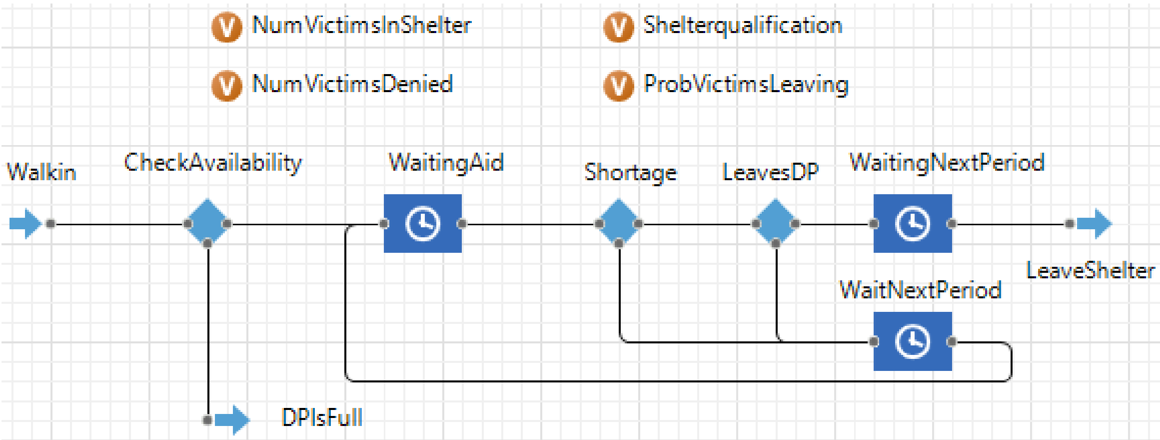

Fig. 6.6 Victim process in distribution point

Next, we review the statechart of Figure 6.7. It starts in the state "ReceivingVictims". After some hours, the distribution point requests humanitarian aid to the "depot and crisis room" agent. Then, the distribution point receives (or not) humanitarian aid and updates its inventory level. Next, it evaluates whether the inventory is enough to meet the demand (victims in the "WaitingAid" of Figure 6.6). If the inventory level is not enough, the distribution point passes to the state "InShortage" and will send a message to all victims connected to it, indicating shortage and updates the variable "AccShortage". If the amount of humanitarian aid in its inventory is enough, it passes to the state "DeliveringHA", updates the variable "AccShortage" to 0, and updates the variable "InventoryLevel". Last, the distribution point returns to the state "ReceivingVictims".

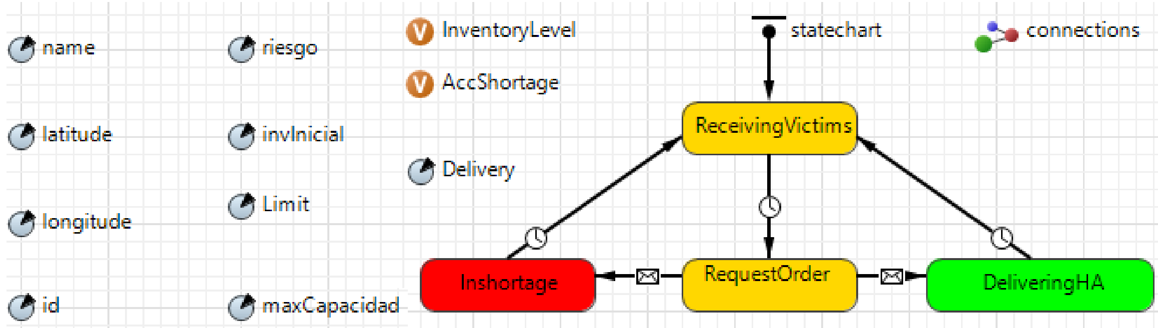

Fig. 6.7 Distribution point agent statechart

Depot & Crisis Room Agent

In this agent type, we combine the depot and the crisis room. It contains a statechart and the elements shown in Figure 6.8. Their functioning is the following. First, it waits for victims' movements. After that, the agent passes to the "SolvingIRP" state. There it collects the optimization model parameters and solves it using the "IRPHLOG" Java class deciding the quantities and routes to deliver humanitarian aid. With that information, it fills the Collection of ArrayList "Routest" and "Quantities". Then the agent goes to the "Delivering" state. There it selects from the routes and quantities that correspond to the current period and fills the collections of integers "subroutest" and "subquantities". After, this agent updates the distribution points' parameter "Delivery" indicating the quantities delivered. After that, it checks if a new run of the IRP model is needed or not until the simulation finishes.

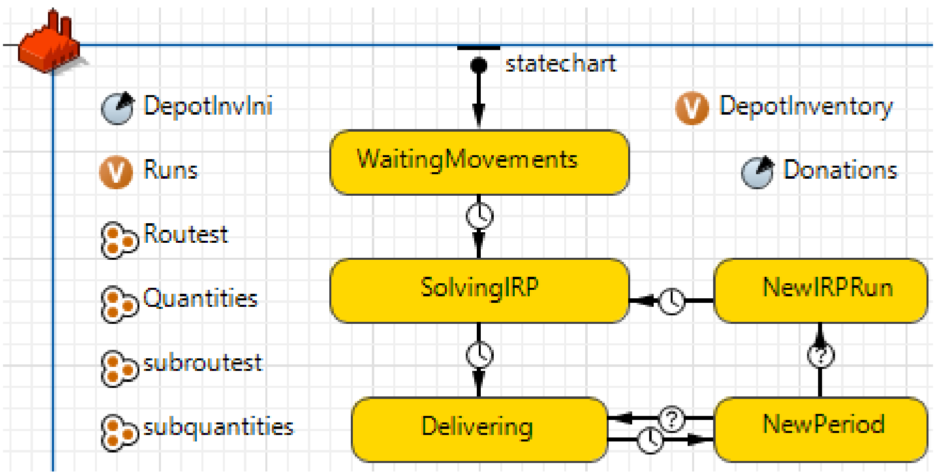

Fig. 6.8 Depot and Crisis Room statechart

Vehicle Agent

Last, the agent type vehicle is comprised for the process flow of Figure 6.9. There, the model uses the resource vehicles to deliver the humanitarian aid. When an order is received from the deport, it enters the vehicle agent and is delivered to the distribution point. Then, the vehicle is released and it moves again to the depot.

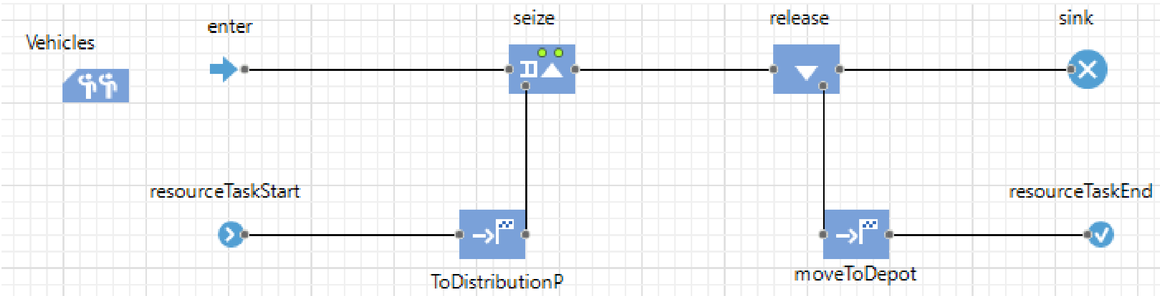

Fig. 6.9 Vehicle process flow

Main Agent

The "Main" is the top-level agent which creates the environment where the rest of the agents are generated and interact. Also, in this agent, the global variables and parameters are set and we generate time plot graphics to collect statistics on the performance of the simulation model. Figure 6.10 presents the "Main" agent with the following elements. On the left side, we included an Anylogic Geographic Information System (GIS) map and define a GIS region that represents the area affected by the disaster. In that region, a GIS point was set to establish the depot location and vehicles' initial location. Next, the distribution points' location is obtained using a database that contains their georeferentiation (latitude and longitude). Last, the victim agents are initially located randomly in the GIS region and when the simulation starts they move to their distribution points. In this way, we locate the agents geographically within the simulation.

Next to the GIS map in Figure 6.10, the variables and parameters are the following. The "TShortage" and "TRelieved" variables collect the victims in shortage and relieved in all distribution points for each period. The "DPShortage" and "DPRelieved" variables measure service levels at distribution points. The "TMoving" variable counts the number of victims moving from its current distribution point to another due to shortages. The "ParcialHumAid" variable collects information about humanitarian aid not handed-out due to not allowing partial deliveries. The InitialAffected parameter sets the number of victim agents in the simulation. Moreover, in "Main" we define the system parameters: number of vehicles, vehicles' capacity, the length of the simulation, the length of each planning horizon and the word of mouth effectiveness. Next to the variables, we create the following agents.

Victim, distribution point, and vehicle agents are created as population agents (contains more than one element). Depot & Crisis room agent was created as a single agent. Moreover, we generate two time plot graphs to illustrate the variables previously described. The first one depicts the number of victims in shortage, relieved and moving for each period in the simulation. The last graph shows the number of distribution points that are handing-out humanitarian aid and the ones in shortage.

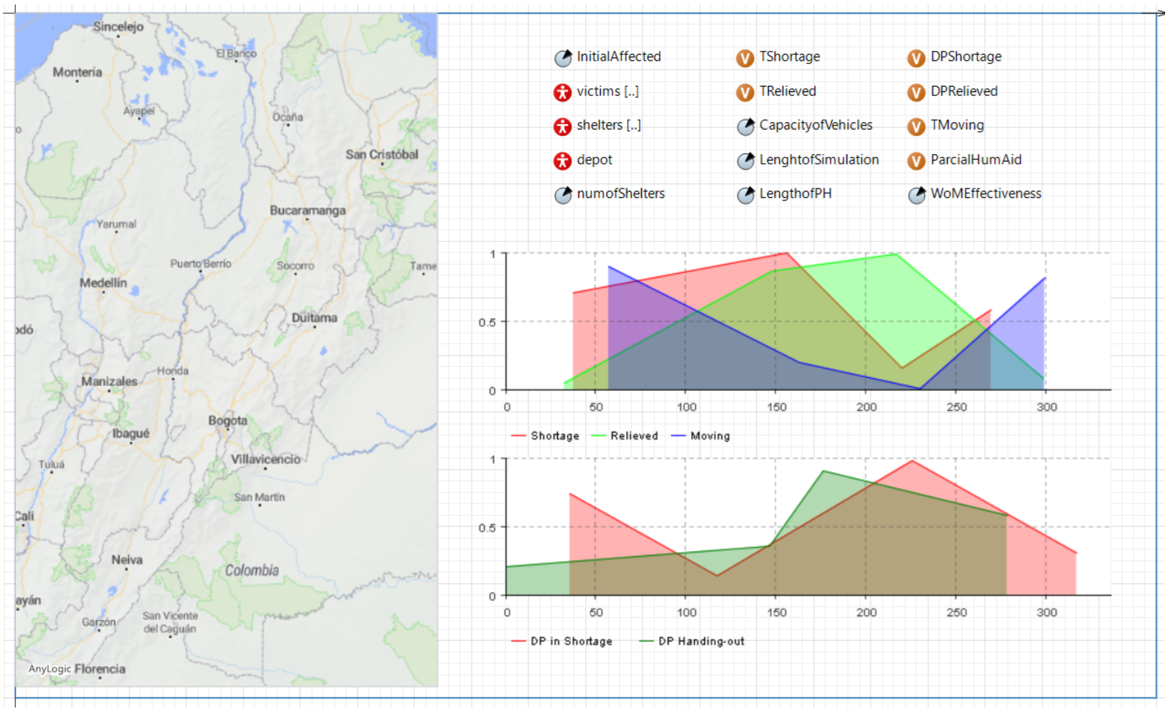

Fig. 6.10 Main agent elements

6.3.2 Java classes

In this subsection, we describe the auxiliary Java classes implemented to run the optimization models within the agent-based simulation. In this way, we hybridize the operations research methods of simulation and optimization in a single application.

IRP Class

In this Java class, the inventory routing model for humanitarian aid distribution presented in Chapter 5 is implemented. To do so, we used the Java Application Programming Interface (API) CPLEX. It allows Anylogic to compile and execute optimization models using the CPLEX solver without using other software. In this class, we imported the packages "ilog.concert" and "ilog.cplex" to create and solve the IRP mathematical model. This class returns two variables of type "ArrayList<ArrayList<Integer»" with the routes and quantities to deliver to distribution points. The depot & crisis room agent calls this Java Class in the state "SolvingIRP" depicted in Figure 6.8

TSP Class

This Java class implements an optimization model using the CPLEX Java API . In this case, the Java class creates and solves the Traveling Salesman Problem (TSP). The optimal cost of the TSP model is used to estimate the optimization budget as presented in subsection 6.2, equation 6.3. Therefore, this class returns a double variable, which indicates the maximum budget to be allocated in the travel cost of the optimization model of Chapter 5. The depot & crisis room agent calls this class while collecting the parameters to solve the IRP model.

Next, Figure 6.11 presents the interaction of the java classes with the previously described agents.

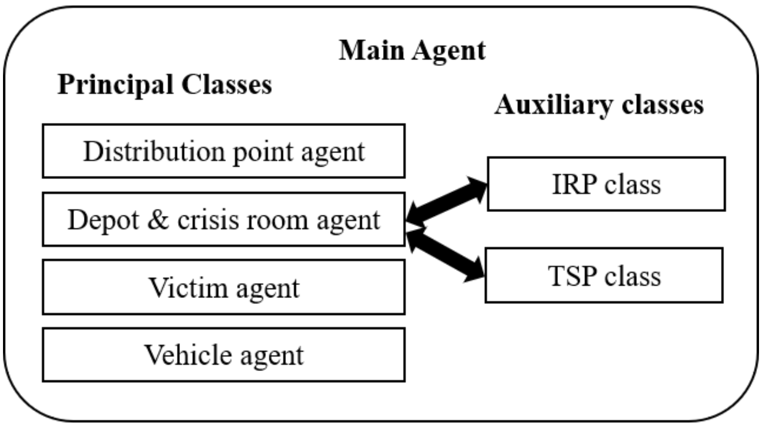

Fig. 6.11 Interaction of Java classes with agents

The methodology presented in this chapter was accepted to be published in:

Espejo-Díaz, J. A., López-Santana, E. R., & Guerrero, W. J. (2020). Evaluación de rutas de Personal Asistencial en el Cuidado a la Salud Domiciliaria mediante Programación Matemática y Simulación Multi-agente. Aplicaciones de Investigación de Operaciones en Sistemas de Salud en Colombia. Editorial Pontificia Universidad Javeriana, in press Accepted.

Chapter 7

EXPERIMENTATION

In this chapter, we present the case-study experimentation inspired by the 2017 Mocoa-Colombia landslide. First, we describe the case study and introduce the system's parameters. Then we make some remarks on the validation and verification of the simulation model. Next, we present the full factorial experimental model and last we show the main results of the experimentation.

7.1 Real world setting description

On the night of March 31^{st}, 2017 and the first hours of April 1^{st}, torrential rain in Mocoa-Colombia caused the Mulata, Mocoa, and Sangoyaco rivers to overflow originating in the early hours of April 1^{st} a landslide and mudslide which affected the urban area of Mocoa. This catastrophe killed 332 people, injured 330 and more than one hundred disappeared [52]. The mud, flood and debris rushed urban infrastructures affecting approximately 45000 people and causing damages in 17 neighborhoods [53]. After the disaster and the stabilization of the affected area, the first distribution points for humanitarian aid started to set-up. By April 5^{th}, according to the Colombian Red Cross 7^{th} situation report, there were seven distribution points in Mocoa[1] delivering humanitarian aid to the victims [54]. According to the 11^{th} situation report, on April 18^{th} these distribution points were still operating handing-out humanitarian aid. In these 14 days, the distribution points in average handed-out humanitarian aid to 2687 persons per day. Figure 7.1 shows the Mocoa map with the zones affected by the landslide and the location of the seven distribution points and the depot.

[1] Apart from handing-out humanitarian aid to the victims, the distribution points in Mocoa offered housing facilities to provide victims a place to stay (shelters). However, in this research, we consider them as distribution points

The 2018 Colombian population census established that a household is comprised of 3.1 persons on average [55]. Therefore, in the experimentation, we consider a population of 886 victims corresponding to families. Next, Table 7.1 presents the parameters for distribution points and depot.

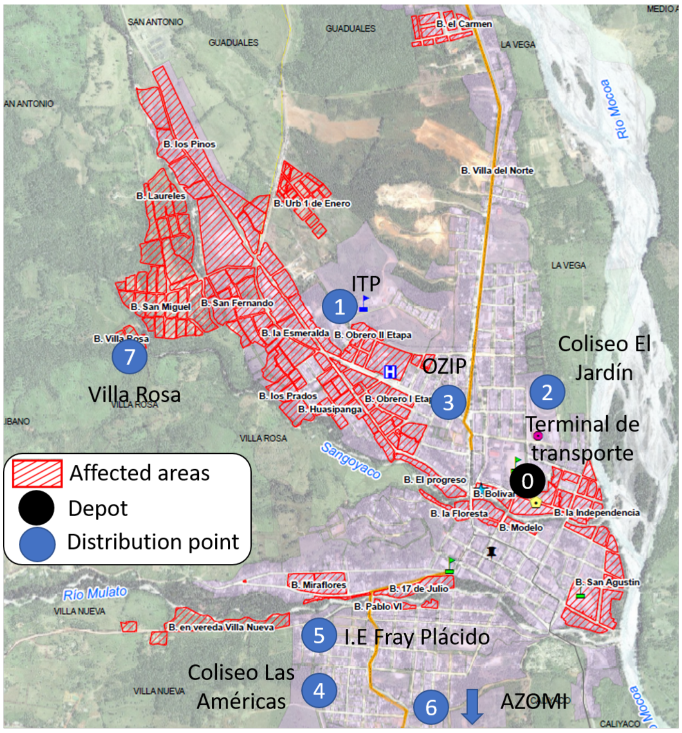

Fig. 7.1 Disaster influence zone in Mocoa 2017 Landslide, source [56]

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Table 7.1 Depot and distribution points' parameters

Distribution points					
ID	Name	Max. storage capacity (kits)	Risk Level	Initial inv. (kits)	Max. victims capacity (families)
1	Instituto Tecnológico del Putumayo	900	3	50	300
2	Coliseo El Jardín	900	1	50	300
3	OZIP	600	1	50	200
4	Coliseo Las Americas	900	2	50	300
5	I.E. Fray Placido	600	2	50	200
6	AZOMI	360	1	20	120
7	Villa Rosa	600	3	50	200

ID	Name	Initial inv. kits	Vehicles	Vehicle capacity (kits)
0	Depot (Bus terminal)	1500	1	1000

Source: own elaboration

Next, Table 7.3 presents the parameters for the agent-based simulation model.

Table 7.2 Agent-based simulation parameters

Parameter	Value(s)
Number of victim agents	886
Word of Mout effectiveness	10%, 20%, 30%
Length of simulation	14 days
Optimization frequency	1, 4, 7 and 14 days
Distribution points' requests	8:00 a. m.
Deliveries to distribution points	10:00 a. m.
Deliveries to victims	11:00 a. m.
Humanitarian aid donations (supply)	Discrete uniform [200, 800]
Impatience function	1 day: 50% ; 2 days 75%; 3 days 100%

Source: own elaboration

7.2 Verification and validation

To verify the correct functioning of the proposal, we perform preliminary tests on the simulation model's main features. First, we test the IRP motor decision. In the experiment, we set an optimization frequency to 4 days. In other words, the simulation engine would run the optimization model every four days. Results show that the simulation runs the IRP at the beginning of the first, fifth, ninth, and thirteenth day as requested. Additionally, the system successfully delivers the humanitarian aid in the quantities and to the distribution points established by the IRP. Moreover, the inventory levels at both depot and distribution points are updated each period as intended. Besides, we test the word of mouth effectiveness parameter. We set this parameter in 10%. In the test, in the seventh period, there were 448 and 438 victim agents in shortage and relieved, respectively. Each agent selects randomly one victim in the system to give a positive or negative word of mouth. A total of 86 victim agents (10%) modified its whitelists or blacklist according to other victims' experiences.

Next, we test the victims' impatience function when experiencing shortages in their distribution points. We ran a test and collect statistics on the distribution point OZIP. This distribution point receives 76 victim agents on the first day, as seen in Figure 7.2 part a. There are no shortages in the system until the fifth day; thus, all victim agents stay in their distribution points. On the fifth day, OZIP is in shortage, and consequently, the probability of victims leaving is 50%. Figure 7.2 part b depicts that 36 victims (47%) of victims left the distribution point. On the sixth day, OZIP is still in shortage in their second consecutive day. The probability of victims leaving rises to 75% and 31 out of 40 agent victims left the distribution point. It shows that the impatience function is working correctly.

Besides, we checked if all agents were relieved or in shortage when collecting final statistics on the simulation model. It is important because we want to avoid agents moving or in another state (different than relieved or in shortage) when measuring the system's behavior.

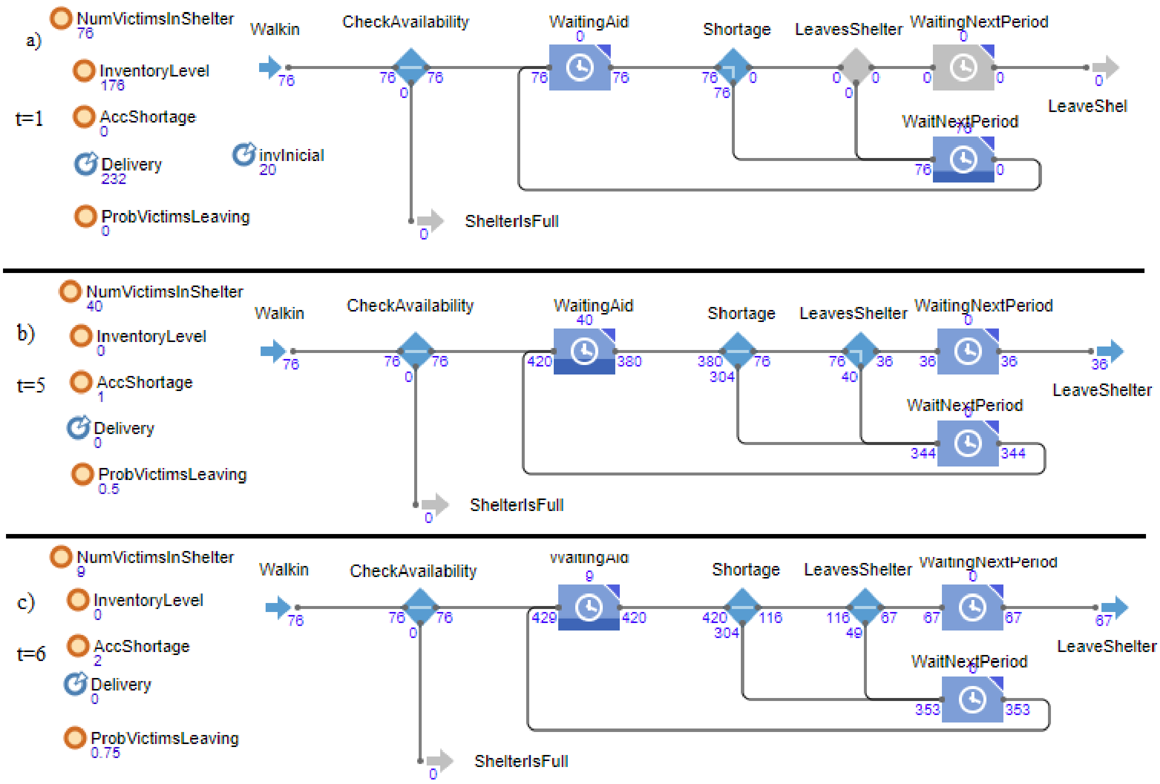

Fig. 7.2 Preliminary test in OZIP distribution point a) in the first day, b) in the fifth day and c) in the sixth day

At the end of the planning horizon, the sum of the number of victims in shortage and relieved is equal to 866 (the total number of victims). Last, we performed an extreme condition test leaving the system in full shortage (without supply) or with large amounts of humanitarian aid. The model was able to overcome these extreme conditions tests successfully. Next, we discuss the validation phase.

According to "The Palgrave Handbook of humanitarian logistics and supply chain management", agent-based simulation models are a promising tool for representing the complexity in humanitarian operations [57]. It has the advantage of being able to capture human behavior and their interactions between stakeholders. However, one significant limitation is the difficulty in the validation of such models, mainly when predicting human behavior. However, next, we make some remarks in the validation of the Mocoa landslide case-study

Although the Colombian Red cross collected information about the distribution points of humanitarian aid, it was general and did not specify shortages in the system. However, primary information sources such as newspapers collected victims' testimonies such as: "Even though the humanitarian aids don't stop coming, these have been scarce for the tragedy" [58]. The latter suggests that victims suffered shortages on distribution points and made decisions (leaving or staying in a distribution point), which altered the distribution operations. Therefore, this approach is suitable for the case study, because it studies the victims behaviour when facing shortages.

7.3 Experimental design

The target of this research is to evaluate policies that have a significant impact on the distribution of humanitarian aid operations. Thus, the factors associated with the optimization frequency in different scenarios of word of mouth effectiveness can influence these response operations. To test the hypothesis that these concepts or policies impact shortages and service levels in distribution points, we performed a full factorial design $4^1 3^1$. In the next subsections, we introduce the variables, the estimation of the number of replications, the treatments and the results for the experimentation phase.

7.3.1 Variables

We consider the following response variables (dependant), which are the matter of interest in this research project.

- **V. shortage**: The number of times in which the victims do not receive humanitarian aid in the planning horizon. This response variable is an indicator of the service level for the beneficiaries of humanitarian aid.
- **DP. shortage**: The number of times distribution points' do not hand-out humanitarian aid in the planning horizon or when they declare shortage to victims in them. This response variable is an indicator of the service level for the distribution points.
- **Routing distance**: Distance traveled by the vehicles to deliver humanitarian aid to the distribution points in the planning horizon. It can be proportional to routing costs.

Next, we introduce the factors or independent variables for the experiment. As stated before, they represent the main concepts that motivate this work.

- **Optimization frequency**: Frequency in which the depot & crisis room agent make the inventory and routing decisions in the system. For instance, if this variable is set to 1, it means that the IRP model is run each period (daily) and can be seen as an approach to an online-IRP.
- **Word of mouth effectivenes**: Percentage of the word of mouth interactions that victim agents believe and process to update their "whitelist" and "blacklist". For instance, if a victim agent receives 100 positive or negative word of mouth messages and this variable is set to 15%, this victim agent would only process 15 messages. Evaluating this factor will allow us to see the impact of communication between beneficiaries, for example through social networks.

7.3.2 Treatments

In this subsection, we detail the treatments for this full factorial $4^1 3^1$ experiment design. The four levels for the first factor (optimization frequency) are the following. The first level corresponds to optimizing each period or an online-IRP. The second level corresponds to optimizing every four periods. The third level every seven periods and the last level corresponds to optimizing every 14 periods (the static case). The three levels for the second factor (word of mouth defectiveness) are the following. The low level corresponds to a 5%, the medium level 15% and the high level corresponds to a 30% acceptance rate of word of mouth. Table 7.3 summarizes the previous information.

Table 7.3 Factor levels

Factor/Level	First	Second	Third	Fourth
A: Optimization frequency	1	4	7	14
B: WoM effectiveness	5%	15%	25%	-

The combination of the previous factors gives the total number of treatments. Therefore, this full factorial $4^1 3^1$ experiment design has 12 treatments.

7.3.3 Number of replications

Now, we calculate the number of replications needed to achieve the confidence level desired. To do so, we did a pilot test and observed the main response variable, which is the "V. shortage". In the pilot test, we make six replications for each treatment for a total of 72 replications. The maximum standard deviation (169.72) was obtained using an optimization frequency of 7 and a word of mouth of 15%.

Next, we use the equation 7.1 from [59] for estimating the total number of replications where t is the t-distribution with $\alpha/2$ significance level and $n-1$ degree levels, s the estimated standard deviation from the pilot test and h_0 the target or desired half width.

$$n = \frac{(t_{\alpha/2,n-1})^2 \, s^2}{(h_0)^2} \tag{7.1}$$

We used a significance level $\alpha = 0.5$, a target shortage level of $h_0 = 30$, and the previously reported standard deviation of 170. Considering that both sides of the equation depend on n we solved the equation numerically. The result suggests performing 126 replications for each treatment for a total of 1512 replications or runs. Last, it is worth noting that the replications are usually ordered randomly before to avoid bias in the results. However, this is not normally required in discrete event and agent-based simulation studies. Each simulation replica is initiated with a different random seed. Therefore, each victim agent appear in a different point in the map, its impatience probability is different and the victim receives different word of mouth interactions. These replications were set-up using the "Parameter Variation module" in Anylogic. This module sets the seed randomly for each simulation run. All test replications were run on an Intel Core i7-6700, 32GB RAM, 3.4GHz of processor and MS-Windows 10.

7.4 Results

In this subsection, we present and analyze the main results of the experimentation described previously. First, Table 7.4 presents the minimum, average and maximum results of the response variables for each treatment considering all replications.

Table 7.4 Descriptive statistics of the experimentation results

Treatments (factors)		V. shortage			DP. shortage			Routing distance		
Freq.	WoM	Min	Average	Max	Min	Average	Max	Min	Average	Max
1	0.05	3411	3452.881	3536	23	27.429	33	119.906	149.71	173.129
1	0.15	3418	3452.889	3542	23	28.095	32	117.171	148.56	170.351
1	0.25	3307	3450.000	3514	24	28.119	33	121.132	149.49	176.048
4	0.05	3563	4033.929	4733	23	27.579	33	105.214	131.22	167.305
4	0.15	3551	4079.540	4552	22	27.937	33	103.746	131.46	161.63
4	0.25	3528	4073.913	4555	23	28.063	33	92.28	129.34	164.479
7	0.05	3775	4221.405	4675	25	28.254	34	74.098	119.74	156.512
7	0.15	3820	4235.127	4850	25	28.230	34	67.789	115.75	160.35
7	0.25	3680	4202.535	4715	24	27.946	33	77.393	115.32	161.119
14	0.05	3974	4417.016	5007	24	27.960	32	84.826	124.59	168.037
14	0.15	3883	4400.008	5256	25	28.119	33	67.52	124.62	171.587
14	0.25	3889	4335.421	5080	23	27.762	32	67.536	123.92	160.875

Different conclusions can be drawn from the information contained in Table 7.4. First, from the response variable "V. shortage," the lowest values are obtained optimizing each period (on-line IRP). Victims' shortages tend to increase with larger optimization frequencies in concordance with the box-plot of Figure 7.3. Regarding the response variable "DP. shortage," the box-plot of Figure 7.4 suggests that there is no significant difference between treatments. Besides, results indicate that with the strategy of optimizing each period, the routing distance is the highest and decreases with larger optimization periods, as seen in the box-plot of Figure 7.5. Concerning the word of mouth effectiveness factor, results show that it does not have significant influence over the response variables.

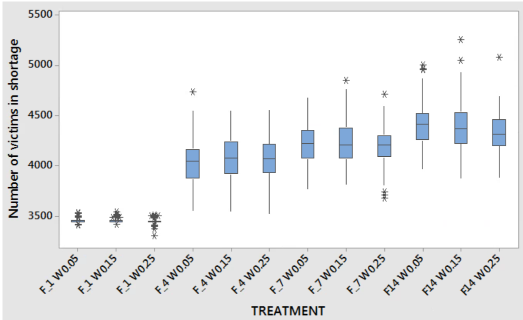

Fig. 7.3 Box plot of response variable V. shortage

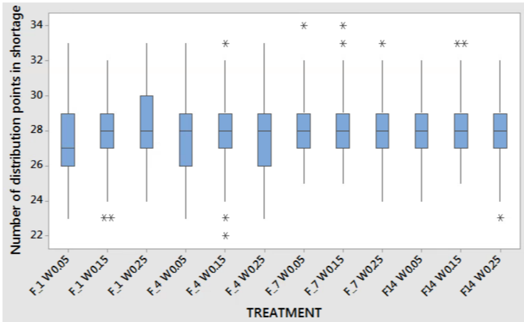

Fig. 7.4 Box plot of response variable DP. shortage

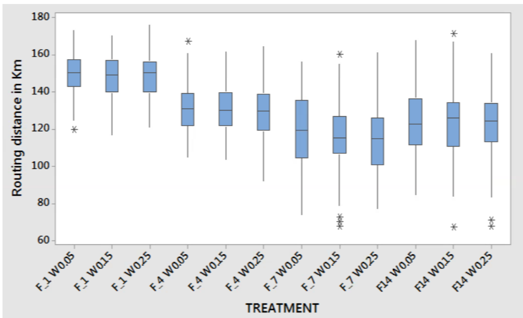

Fig. 7.5 Box plot of response variable Routing distance

Next, we present a statistical analysis of the previous results. We used the Minitab software in its 18.1 version [60]. We performed an ANOVA test with a significance level of 5%. Figure 7.6 shows the histogram for the response variables where a normal distribution is suggested for the "DP. shortage" and "Routing distance variables." However, neither the Anderson-Darling nor the Kolmogorov-Smirnov normality tests indicate that any of the response variables meet the normality assumption with a $p-value < 0.05$. Additionally, the residuals of the ANOVA do not follow a normal distribution with a $p-value < 0.05$.

It can be the result of the simulation model features such as the impatience function or the use of blacklists to avoid distribution points with accumulated shortages. Therefore, we applied the Kruskal-Wallis test, which does not assume that the residuals are normal. Results of Kruskal-Wallis tests on the response variables confirm that the simple effects have statistical significance for the simple effects. However, conclusions for the interactions are not reachable with this test because it does not evaluate interactions effects. Next, we analyze the simple effects with statistical significance for the response variables from which conclusions can be drawn.

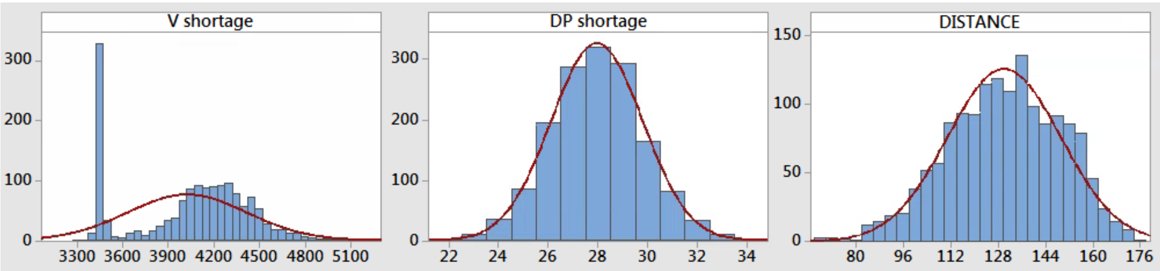

Fig. 7.6 Histogram of the response variables

Figure 7.7 and Figure 7.8 present the Pareto chart of the standardized effects, where A is the optimization frequency factor and B is the word of mouth factor. The Pareto charts of standardized effects confirm that the optimization frequency has the biggest effect on the victims' shortages and routing distance. Regarding the effects in response variable "DP. shortage," only the interaction of the factors has statistical significance. However, no conclusions can be obtained because the Kruskal-Wallis test does not confirm the effect of interactions.

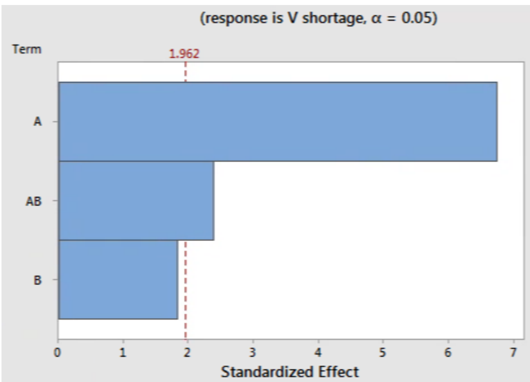

Fig. 7.7 Pareto chart of the standardized effects V. shortage variable

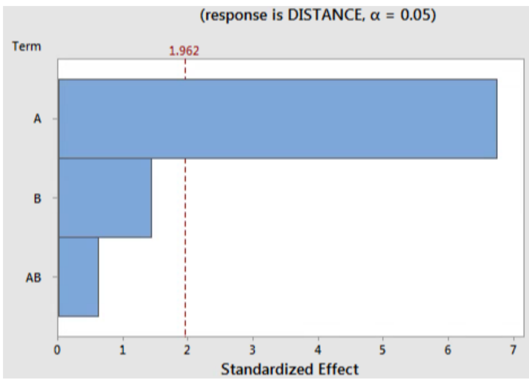

Fig. 7.8 Pareto chart of the standardized effects Routing distance variable

Last, we analyse the effects of the optimization model of Ch. 5 in the simulation approach. Lets consider that this MILP aims to find a balance between shortage, inventory at risk and transportation costs as seen in Figure 6.3. With that in mind, we analyse the relation of risk levels and periods in shortages at the distribution points in for different optimization frequencies. For distribution points with high risk levels we conclude the following. On the one hand, with a strategy of optimizing frequently (e.g. daily), the average number of periods in shortage are higher. On the other hand, optimizing less frequently, leads to lower number of periods in shortage. As an example of the previous conclusion we present the box plot of Villa Rosa of Figure 7.9. For distribution points with medium or low risk levels the average periods in shortage are constant, as seen in the example of El Jardín box plot of Figure 7.10.

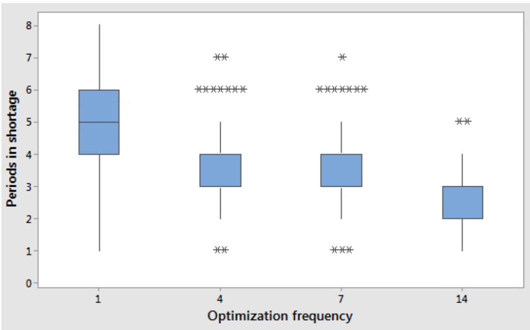

Fig. 7.9 Box-plot of Villa Rosa distribution point

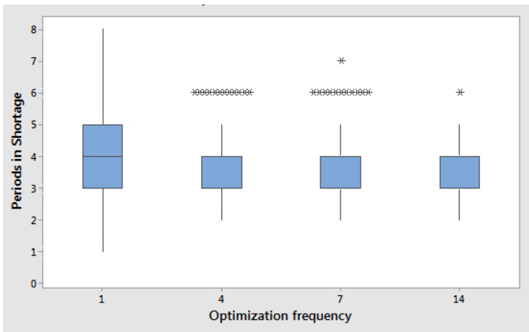

Fig. 7.10 Box-plot of El Jardín distribution point

The results of this chapter and chapter 6 were submitted as:
Espejo-Díaz, J. A. & Guerrero, W. J. (2020). A multi-agent approach for solving the dynamic post-disaster relief distribution problem Computers & Industrial Engineering. IN SUBMISSION

Chapter 8

CONCLUSIONS AND FUTURE WORK

This thesis studies the dynamic humanitarian aid distribution problem. To do so, we proposed a simulation-based optimization approach that combines a mixed-integer linear programming (MILP) model with an agent-based simulation model. On the one hand, the MILP solves the inventory routing problem determining the optimal quantities of humanitarian aid in the form of kits to deliver to distribution points. These decisions are made seeking to minimize shortage levels and inventory at risk levels while restraining the routing budget. On the other hand, the simulation model represents the humanitarian supply chain in the response phase of a disaster. In the simulation, we incorporate important aspects of human behavior in a disaster context such as the word of mouth interactions and victims' impatience. In this manner, we recreate realistic conditions that have an impact on humanitarian response operations. The main results of the thesis show that optimizing more frequently leads to fewer victims in shortage in the planning horizon. However, the routing costs are higher with shorter optimization periods. The decision-makers have to balance the shortage levels allowed in the system and the routing costs for transporting humanitarian aid. Besides, the results show the importance of considering aspects such as the victims' impatience and word-of-mouth interaction. These aspects determine the victims' decision to leave their current distribution point (impatience function) and move to another based on other victims' experiences (word of mouth) and their own experiences (blacklists and whitelists). Thus, including such aspects in the computational proposal with shorter optimization frequencies contribute to making better humanitarian aid distribution plans. On the contrary, ignoring the impatience function and word of mouth can make decision-makers to underestimate the demand and make less effective distribution schemes.

Next, we conclude on the mathematical model presented in chapter 5. The proposed mathematical model can provide operational view of the delivery operations in the aftermath of a catastrophe. The decision-maker has the routes and quantities to deliver in any optimal solution he/she chooses while minimizing shortage and inventory at risk levels at distribution points. These objectives are in conflict, since less shortage may put more inventory at risk or less inventory at risk would cause more shortage levels. Therefore, if the humanitarian logistics decision-maker wants to avoid as much as possible shortage putting at risk inventory, the proposal will give him/her the distribution plan. On the other hand, if the decision-maker is more conservative and allow some shortage risking less inventory, the proposal will also provide him/her the delivery scheme with the routes and quantities. In the experiments using literature based instances, a clear Pareto front was found, showing the extreme values of the objective functions and the others non-dominated solutions, showing that the epsilon-constraint methodology tackled efficiently the bi-objective model and found a balance between shortage and inventory at risk.

At last, some conclusions are drawn from the document analysis of chapter 4. In this part, we studied the Colombian regulations which establish the entities and their responsibilities when responding to disasters. We reviewed various emergency operation plans or "Estrategia de respuesta a emergencias" ERE (for its Spanish acronym) for different territorial entities. The main conclusion of this documental analysis is the following. The lack of standardization in the roles of the entities which carry out the response activities can delay or difficult the humanitarian relief operations. For instance, the Colombian Red cross is responsible for specific response activities (e.g., search and rescue) in a territory (e.g., a department). In another area, it is responsible for different activities (EDAN census). Moreover, there is no clear guide on which response activities have to be in the EREs. Some territorial entities have a detailed and extensive list of them, while others only have few of them. The previous issues in the worst case can cause lack of coordination when responding to disasters that may need the support of entities with jurisdiction in other territories. Future work in this area can be directed to analyze the response activities and the entities responsible for them. Then, propose a series of standardized and general response activities for all territories with their corresponding support and responsible entities. It can be useful for future updates of the emergency operation plans or EREs and be input for future public policies in the field.

Multiple research directions for future work are derived from this thesis. Regarding the mathematical model, future work should be directed at developing methodologies to parametrize the inventory at risk level, considering more factors such as security issues or including experts' choices. Additionally, although the computational times are not an obstacle in the case-study, bigger problems with more locations or vehicles would require developing procedures such as heuristics or metaheuristics which will speed up finding the model solutions. Moreover, future works in the mathematical model should include uncertainty in parameters such as demand, travel times, and supply.

Concerning the simulation approach, research efforts should be focused on incorporating more aspects of victims' behavior and factors of real life. For instance, the decision to leave a distribution point can also be motivated by the distance to other distribution points. Moreover, in the future, researchers can study in more detail the victims' behavior (e.g., word of mouth) and identify other important decisions that may alter the demand for humanitarian aid in distribution points. It is worth noting that an important limitation when conducting the experiments is computational efficiency. In this research, we used a relatively small case study with approximately 900 victim agents. However, preliminary tests with more than two thousand victim agents required too many computational resources and become intractable. In larger disaster settings, there could be thousands of victims agents interacting simultaneously and making decisions that impact the humanitarian supply chain. Therefore, methodologies for working with limited and representative areas can be studied or limiting the number of replications for obtaining statistically significant results. Other related research works can incorporate and test different demand forecasting strategies.

The following participation in scientific conferences were derived from the research project.

- Organization and oral presentation in the I Symposium on humanitarian logistics & disruptive supply chains 2018.

- Organization and poster presentation in the II Symposium on humanitarian logistics & disruptive supply chains 2019.

- Oral presentation in the III Congreso Colombiano de Investigación de Operaciones - ASOCIO 2019.

Last, Table 8.1 summarizes the validation of the research objectives and activities proposed in Table 2.1

Table 8.1 Validation of research objectives and activities

Specific Objectives	Activities		Results
Define the theoretical and technical characteristics of the disaster relief distribution problem.	1	Review and classification of academic articles related to the IRP problem in HL.	Literature review of chapter 3 in which we positioned the project within the existing research gaps.
	2	Analyse the protocols and responsibilities in risk management for natural disasters in Colombia	Document analysis of chapter 4 in which we identify the technical characteristics of the disaster response in a local context.
Develop a mathematical model to solve the IRP problem in HL.	3	Define the problem's characteristics.	Multi-objective mixed-integer lineal model of chapter 5 Publication: Espejo-Díaz, J. A., & Guerrero, W. J. (2019). A Bi-objective Model for the Humanitarian Aid Distribution Problem: Analyzing the Trade-off Between Shortage and Inventory at Risk.
	4	Implement the model in a specialized software.	
	5	Test the model with literature instances to validate its performance.	
Design an agent-based simulation model for the HL supply chain in the aftermath of a disaster and implement it in a specialized software.	6	Define agent types, their methods and interactions in the simulation model.	Agent-based simulation model of chapter 6. Accepted publication: Espejo-Díaz, J. A., López-Santana, E. R., & Guerrero, W. J. (2020). Evaluación de rutas de Personal Asistencial en el Cuidado a la Salud Domiciliaria mediante Programación Matemática y Simulación Multi-agente[1].
	7	Integrate the mathematical model in the simulation	
	8	Implement the simulation model in a specialized software and test it.	
Evaluate the performance of the agent-based simulation model in a real case study based on the Mocoa Landslide	9	Collect and parametrize the case study information	Case-study experimentation of chapter 7. Article: Multi-agent approach for solving the dynamic humanitarian aid distribution Computers & Industrial Engineering. In submission.
	10	Run the simulation model and evaluate scenarios	
	11	Analyse the results and conclude	

[1] The simulation-optimization approach methodology presented in chapter 6 inspired us to apply it to a home health care (HHC) routing context. In the accepted publication, we studied the case of an HHC provider in Bogotá.

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