DEVELOPMENT OF INVENTORY MANAGEMENT FRAMEWORKS FOR HUMANITARIAN OPERATIONS USING MARKOV DECISION PROCESSES AND STOCHASTIC PROGRAMMING

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Tese de Doutorado apresentada ao Programa de Pós-graduação em Engenharia de Produção, COPPE, da Universidade Federal do Rio de Janeiro, como parte dos requisitos necessários à obtenção do título de Doutor em Engenharia de Produção.

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"I put my heart and soul into my work and I have lost my mind in the process" (Van Gogh)

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Operações humanitárias envolvem muitos atores, cada um com seus próprios procedimentos, mas com o objetivo de ajudar o maior número possível de pessoas. No entanto, como seus objetivos muitas vezes se sobrepõem, as organizações podem acabar disputando os mesmos recursos e colocando em risco a eficiência da operação. Além disso, gestão de estoque de itens perecíveis é um grande desafio, pois itens deteriorados podem representar uma ameaça à população, e custos significativos devido às dificuldades relativas a políticas de descarte. Este estudo tem como objetivo desenvolver modelos de gestão de estoque para ambos os desafios. O primeiro modelo aplica um Processo de Decisão Markov para otimizar a gestão de estoque de itens perecíveis. Além disso, o segundo modelo apresenta a aquisição e distribuição colaborativas, em um sistema de fornecimento duplo. Ele combina um Processo de Decisão de Markov com um modelo Estocástico de Dois Estágios através de um algoritmo de avaliação de parâmetros. Para ilustrar a aplicabilidade de nossos modelos, propomos experimentos para demonstrar como diferentes cenários de demanda podem afetar as políticas de aquisição e distribuição. Os experimentos mostram que os modelos podem ser implantados para horizontes de longo e curto prazo para operações de pequena e grande escala, com pequenos requisitos de processamento.

Abstract of Thesis presented to COPPE/UFRJ as a partial fulfillment of the requirements for the degree of Doctor of Science (D.Sc.)

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December/2022

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Humanitarian operations involve many actors, from governmental entities to humanitarian organizations. Each has its own objectives and procedures within the overarching goal of aiding as many victims as possible. However, as their objectives often overlap, organizations may end up disputing the same scarce resources, jeopardising the efficiency of the operation. Besides, management of perishable goods is a great challenge for logistic managers, since deteriorated items may impose a threat to the population, and a huge cost due the difficulties underlying their disposal policies. This study aims at developing inventory management models for both challenges. The first model applies a Markov Decision Process to optimize the inventory management of perishable items. Further, the second model presents collaborative acquisition and distribution of goods, in a dual-sourcing system. It combines a Markov Decision Process with a Two-Stage Stochastic model through a parameter evaluation algorithm. To illustrate the applicability of our models, we propose experiments to demonstrate how different demand scenarios can affect the acquisition and distribution policies in humanitarian operations. The experiments show that the models can be deployed for both long and short term horizons for both small and large scale operations, with small processing requirements.

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List of acronyms

CR Category of Risk

DB Database

DC Distribution center

EOQ Economic Order Quantity

EM-DAT International Disasters Database

HL Humanitarian Logistics

HO Humanitarian organizations

MAP Markovian customer arrival process

MDP Markov Decision Process

RA Risk Area

RFID Radio Frequency Identification

SP Support Point

TSSP Two-Stage Stochastic Problem

VC Vulnerable communities

WFP World Food Programme

Chapter 1

Introduction

From 2016 to 2020, the *international disasters database*[1] registered 2,679 disasters, 496 in 2020 only. They disrupted the lives of over 590 million people and caused almost US$ 900 billions worth of damages. Over the same period, only approximately 60% of the disaster relief funding appeals were met[2]. Given the limited funding, cost efficiency is vital and humanitarian organizations (HO) should reduce operational costs whilst lessening the victims' suffering (Besiou and van Wassenhove 2020).

A humanitarian operation often comprises hundreds of supply chains that overlap, interact, and even compete for the same resources. They aspire to meet uncertain and highly dynamic demands with little to no information on what is needed, when or where it is needed (Holguín-Veras et al. 2014). Haiti's 2010 earthquake response, with over 200 organizations simultaneously deployed in relief operations,

To improve efficiency, organizations should work together to achieve a common objective (Dubey and Altay 2018). Humanitarian supply chains must avoid duplication of resources and services by filling gaps or preventing overlaps. Therefore, our study promotes coordination between multiple organizations which is vital to the success of a disaster operation; it involves risk and resource sharing through a coherent action plan (Li et al. 2019).

As disasters can damage the local infrastructure, disaster relief supply chains must consider uncertain road network availability, as well as possible disruptions of basic services such as water, power, communications, and fuel supplies. These may impair the relief effort, interfere with or disable machinery and vehicles used in the

[1]EM-DAT, https://www.emdat.be

[2]https://fts.unocha.org/appeals/overview/2020

relief operations (Kaatrud et al. 2003, Kovács and Spens 2007). Disasters can also affect ports, airports, public buildings, schools and other facilities typically used as shelters or relief centers, capping or preventing their use in the response (Rahmani et al. 2018). Finally, disasters may affect the supply chains of local suppliers and logistics operators, hindering their ability to contribute with the relief effort (Kovács and Spens 2007, Murray 2005).

Since purchasing from local suppliers supports the long-term recovery of the affected region, humanitarian organizations must not necessarily always seek minimum costs. Instead, they can focus on providing equal opportunities for distinct suppliers in an effort to drive the region's economic recovery (Balcik et al. 2016). This involves seeking the right compromise between promoting local services and ensuring a reliable and sustainable supply chain.

Furthermore, long-term projects are an important part of the operations of a humanitarian aid organization. Commonly called continuous aid work operations, they arise when people are exposed to disasters such as military or civil war (Afghanistan, Yemen, Congo, Syria, etc.), political insurrection (Syria), droughts (Ethiopia, Pakistan, etc.) and extreme poverty (Liberia, Sudan, etc.). In such cases, people affected by disasters are at considerable risk and the need for humanitarian assistance is clear. That includes a wide range of services from medical assistance and shelter to basic daily supplies like water, food, sanitation and hygiene products.

The uncertainty of supplying these needs is high, since the supply is strongly dependent on donations of goods such as water, food and medical supplies. Furthermore, 90% of the crises affected people live in developing countries that often cannot provide sufficient assistance themselves (Rottkemper et al. 2012). Moreover, an important feature of demand patterns in relief items is irregularity (in terms of what is needed and for whom, where it is needed, when it is needed and how much).

An important and often overlooked characteristic of supply management for humanitarian operations is perishability. Since donations come from different parts of the world, in different times, it is important to keep track of the expiration dates of the received supplies. Deteriorated goods not only can harm the people in need if distributed, but also generate disposal costs, which can be very high depending on the type of the supply, thus increasing the total inventory cost. Despite its growing influence in the inventory management of commercial supply chains, perishability of donations and procured goods is not often accounted for in the humanitarian operations literature.

As the number and complexity of humanitarian crises continue to increase, inventory management processes must adapt to face the new challenges. To help in that end, this research develops two new inventory management frameworks for humanitarian operations. The first one focused on long-term operations, and the second applicable to both long-term and short-term operations.

The first framework considers uncertainties in both donations and demand for supplies. Moreover, it accounts for perishability (limited shelf life) of items in stock, whose shelf life may expire and hinder the operation's management, also incurring additional expenses such as disposal and waste management costs. Using Markov Decision Process, the framework allows decision makers to ensure that the goods in the inventory are proper for consumption without necessarily keeping track of individual expiration dates for each item in the inventory.

The framework also accounts for possible increases in the supply obtained from the action of the decision maker. These increases may be due to inventory transfers from nearby facilities, aggressive advertisement campaigns, etc. Nonetheless, regardless of the underlying reason, these increases come at a cost. Bearing that in mind, we propose a technique to find an optimal long-term storage policy, considering inventory and perishability costs, as well the costs of the provoked increases in donations.

To illustrate the approach, we propose experiments to demonstrate how different shelf lives can affect the optimal ordering policies of critical perishable goods, such as blood packs or medicine, in humanitarian operations.

The second part of this research proposes a novel framework that includes dual source procurement under uncertainty whilst optimising the collaboration among multiple humanitarian organizations (HO) or demand points; it includes joint procurement from multiple suppliers and centralised warehousing and distribution of relief supplies to each individual HO. Recognised for their relatively low implementation costs and technological requirements, these mechanisms are conducive to the relief effort (Balcik et al. 2010).

As the local supply chain may have been disrupted by the disaster, each local supplier is a viable, albeit unreliable source of relief supplies. Hence, there is a probability that a local supplier will not deliver the procured items in a timely manner. A dual sourcing model ensures that another supplier outside the affected region can always provide the procured items at the required time, but at a higher price. To pursue a trade-off between costs and reliability, the model penalises unmet demands and missed deliveries, which cannot be timely refunded.

Our framework is also suitable to support inventory and distribution decisions from governmental agencies responding to disasters. They typically set aside a Distribution Center (DC) that is close to the shelters/demand points but still accessible from the outside world (in the case of a large-scale disaster) or is strategically located (in the case of frequent small-to-medium disasters). The DC can be an existing permanent warehouse or a set of mobile storage units (when a permanent warehouse is not an option), and it serves multiple shelters and/or demand points. The government itself can be treated as a reliable supplier that typically procures items for pre-positioning/preparedness, and can quickly deploy supplies to the DC from other regions (or even internationally), whereas local suppliers can be collectively seen as unreliable suppliers as they may be affected by the disaster.

The proposed framework integrates a two-state stochastic programming (TSSP) into a Markov decision process (MDP), to create a Parameter Evaluation Algorithm. While the MDP prescribes an optimal purchasing policy (*how much to buy?*), the TSSP splits the optimal purchasing policy into individual orders for each supplier (*where to buy?*) and identifies an optimal distribution policy in accordance with the number of acquired goods to supply the operations (*where to allocate or send?*). The innovative idea here is that we use TSSP to translate the long-term perspective of an MDP solution into several short-term solutions.

By combining the two methodologies, the framework also avoids the combinatorial explosion of scenarios imposed by multi-stage stochastic programming models for large time horizons and circumvents the limitations on the number of possible actions within an MDP that includes distribution and acquisition decisions. Exploiting the strengths of both approaches, we derive an inventory management model for multi-sourcing and integrated distribution of relief supplies that is suited for two settings: (1) disaster response or recovery operation with finite random duration, (2) long-term disaster response or recovery operation.

This study is highly motivated by the disaster response operations for the landslides and floods that constantly affect the city of Petrópolis, Brazil, more recently in February 2022. Located in the mountainous region of the state of Rio de Janeiro, the city encompasses hundreds of communities susceptible to landslides, which are mapped and categorised accordingly to landslide risks and probabilities. Municipal and State government, as well as dozens of organizations acted on the disaster response across multiple regions of the city, with virtually no coordination among them. Furthermore, the response usually is heavily reliant on donations, which is an unreliable source of supplies. Given the characteristics of these recurring disasters, it is clear that a coordinated stochastic framework for disaster response could help improve the efficiency of humanitarian operations. It is such a framework that is designed and proposed. An experiment using the 2022 Petrópolis' landslide disaster as background is presented to illustrate the frameworks applicability, as well as a numerical experiment involving hygiene kits in Indonesia, a region with recurring disasters.

All in all, this research tackles two vital and recognisable problems in inventory management for humanitarian operations: perishability (or obsolescence) of goods and unreliable supply chains. The first model developed aims to optimise the inventory management of an organization acting on slow on-set disasters, such as political crises and droughts, by presenting an easy to implement framework that implicitly accounts for perishability. The second framework presented expands the first by assuming a centralised inventory management model within a distribution center, which serves multiple demand points, humanitarian organizations acting on the disaster, and sources of supply, while considering that some supliers may be unreliable. The second framework can be applied to long-term operations, slow-onset disasters or operations where the time horizon, although finite, is not perfectly defined, suitable for humanitarian operations.

The remainder of this research is organised as follows. Chapter 2 presents a brief literature review including general aspects of inventory management and relief distribution efforts in humanitarian logistics, applications of operations research and management science to this field, as well as the experiments used to demonstrate its applicability. Chapter 3 details the inventory management for perishable items framework, introduces the mathematical formulation and presents an experiment to demonstrate its applicability in a blood bank operation, Chapter 3 was also published as a paper in the International Journal of Disaster Risk Reduction in 2018[3]. Chapter 4 presents the multi-sourcing distribution framework with unreliable supplier, including numerical experiments to illustrate the model's applicability and analyse the results and insights. Finally, Section 5 concludes the research and discusses future research directions.

1.1 General Objective

The general objective of this research is to demonstrate that the use stochastic techniques and mathematical programming can improve inventory management efficiency in humanitarian operations, for both acquisition and distribution of supplies, assuming long and short term operations.

1.2 Specific objectives

- Conceptualize humanitarian logistics and inventory management
- Present two of the greater challenges of inventory management for humanitarians operations: perishability of items and unreliability of suppliers
- To develop two stochastic mathematical models for selection of optimal ordering and distribution policies in inventory management for humanitarian operations
- Demonstrate how utilization of Markov decision processes can improve the efficiency of inventory management in humanitarian operations

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Chapter 2

Literature review

Accounting for approximately 80% of disaster relief efforts, logistics is vital for a successful humanitarian operation (Campos et al. 2012, Çelik et al. 2014). Such a prominent role led HOs to adapt conventional logistics techniques to disaster mitigation, with limited success (Besiou and van Wassenhove 2020). Despite the similarities, there are major differences between conventional logistics and the logistics of humanitarian operations - humanitarian logistics (HL), as the latter involves uncertain and intermittent demands that vary with time, location and disaster magnitude. HL should also consider destroyed or compromised infrastructure in the disaster site and its surroundings and unconventional objectives, such as mitigating suffering. It also diverges from military logistics, which have clear command and control structures, and adopt possibly different attitudes towards the principles of neutrality, impartiality and humanity (Van Wassenhove and Pedraza Martinez 2012). Such specificity renders humanitarian supply chains unique and difficult to manage (Habib et al. 2016, Kovács and Spens 2007).

By appropriately planning and responding rapidly to disasters, HL aims to promote effective recovery for the affected population and to reduce or circumvent loss to human life and property (Mishra et al. 2020). It encompasses very different operations at different times, such as procurement, warehousing, inventory management, transportation, and distribution of products and/or resources plus radio and satellite communications, water and sanitation, construction and rehabilitation of buildings and energy provision (Balcik et al. 2016, Tabbara 2008). Despite the adverse conditions, analysts and decision makers must evaluate the needs, establish functional relationships with suppliers and consumers, and establish the required infrastructure (Tabbara 2008). In summary, as per Beamon and Kotleba's definition, Humanitarian Logistics (HL) is an operation that deals with the flow of people and materials appropriately and timely to assist victims of a disaster, with the main objective of meeting, correctly, the needs of the largest possible number of victims (Beamon and Kotleba 2006).

Although under drastically different conditions, HL and commercial logistics share the same activities. Therefore, one can measure the importance of commercial chains' key success factors to improve HL's efficiency (Lu et al. 2006, Pettit and Beresford 2009, Power et al. 2001). Abidi et al. (2013) maps 8 success factors for relief chains: strategic planning; inventory management; transportation and capacity planning; information management and technology utilisation; human resources management; collaboration; continuous improvement; and supply chain strategy.

All these operations have a common goal of aiding people in their survival needs. Such an aid requires efforts that are typically divided in two broad lines: continuous aid work, and disaster relief (Cozzolino 2012, Kovács and Spens 2007, Van Wassenhove 2006). Continuous aid work is mainly required for slow on-set disasters, such as plagues (e.g. famine and droughts) and crises (e.g. political and refugee crises). The term disaster relief is reserved for sudden on-set disasters, such as natural disasters (e.g. hurricanes and earthquakes) and man-made destructive actions, e.g. industrial accidents and terrorists attacks (Cozzolino 2012, Kovács and Spens 2007, Van Wassenhove 2006).

Habib et al. (2016) divides the humanitarian supply chain in two parts: *relief supply chain* and *relief distribution chain*. The former comprises upstream activities, such as acquisition and transport of goods from suppliers to warehouses or distribution centers. The latter is responsible for transporting and distributing goods between distribution centers and organizations assisting the affected areas. A conceptual framework of the humanitarian supply chain is depicted in Figure 2.1

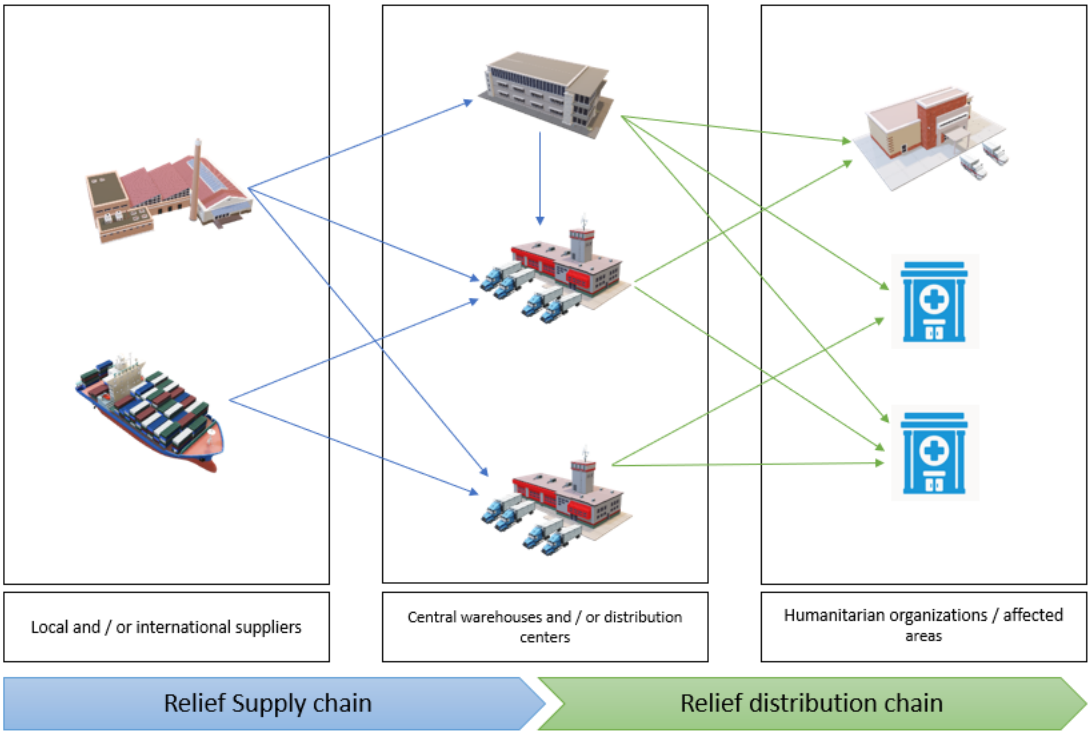

Figure 2.1: Humanitarian Supply Chain framework. Adapted from Habib et al. (2016)

However important, HL still lags behind conventional logistics in terms of infrastructure, resources and recognition (Behl and Dutta 2018). This has led to the shortage of qualified logistics professionals to act on humanitarian operations.

The first part of this research focuses on continuous aid work, more precisely on the inventory management of perishable items in long-term humanitarian operations. To this intent, we devise an inventory management model using a Markov Decision Process which allows us to account for the perishability of goods in stock without explicitly keeping track of its individual expiration dates. The experiment presented demonstrates the model's applicability in a blood bank inventory management.

Further, we extend the proposed model to include multiple suppliers and multiple recipients of aid in the supply chain, focusing on the collaboration of multiple organizations to optimise the distribution of relief supplies in a disaster response operation. We propose a centralised inventory management where a distribution center (DC) acquires and stores goods from multiple suppliers to later distribute them to different organizations serving the affected area, thereby linking the *relief supply chain* with the *relief distribution chain*, see Figure 2.1.

2.1 Continuous aid operations

January 2013 marks the beginning of the humanitarian relief operations for the civil unrest crisis in Syria, an operation that extends lasted almost 10 years. It registered over 10 million people in need of assistance in the country and over 5.6 million refugees at the surrounding countries (https://www.who.int/emergencies/situations/syria-crisis), with a death toll of approximately 60,000 people in 2013 only. The operation comprised assistance to refugees and locals that are in dire need of food, hygiene and shelter, due disruptions of basic services during the conflict (Fontainha et al. 2018).

To counter slow on-set disasters, such as the Syrian refugee crisis or famine operations in Sudan, continuous aid operations are required. Continuous aid operations (or long-term humanitarian operations) can be defined as an ongoing process for slow-onset disasters with a long-term need for supplies where organizations face relatively long planning lead times (Apte 2009). These form an important part of the operations of a humanitarian aid organization. Even though the logistics for medical supplies or aid items in a continuous aid operation can be very similar to commercial logistics, some circumstances can be very challenging, such as high and uncertain demand, uncertain donations of supplies, poor infrastructure, insecurity due geopolitical or civil unrest in the region and lack of support from the local government and/or communities (van der Laan et al. 2016).

Since the progress and impact of a slow-onset disaster generally depend on unpredictable political and/or natural events, the demand for relief items can be highly variable (Meraklı and Küçükyavuz 2019). Moreover, there are situations in which the demand may suddenly increase or a disruption may lead to a shortage of supplies, such as a new disaster in a region where aid organizations are already working, e. g. an earthquake aftershock (Rottkemper et al. 2012), or the COVID-19 outbreak. These situations add to the challenge of assessing the service needs of the affected population. Additionally, the uncertainty in long-term humanitarian operations is constantly evolving since they are highly dependent on donations of goods such as water, food and medical supplies, especially in times of economic instability (Mohan et al. 2013). Furthermore, although being recognised as a major part of relief efforts around the globe, slow on-set disasters attract less attention from media and donors than sudden on-set disasters, such as the *Brumadinho dam* disaster of 2019, or Petrópolis's landslides of 2022. Hence, they are constantly forgotten once the media loses interest, and under-financed (Apte 2009, Van Wassenhove 2006).

As stated before, in locations affected by disasters one cannot anticipate the demand's intensity, nor its location nor its time of occurrence (Balcik and Beamon 2005). However, some long-term projects, such as counter-famine operations, provide opportunity for inventory management based on formal forecasting methods to reduce stock-outs, over-stocking and shelf life expiration (van der Laan et al. 2016). A sudden disaster's response incurs immediate demand for critical supplies and warrants an urgent response and and agile supply chain focused on improved response times (Apte 2009). On the other hand, long-term operations enable increased focus on cost efficiencies, via improved resource utilisation and optimised inventory policy, while maintained the priority of serving as many affected individuals as possible (Mattos 2018).

Some studies address the uncertainties in demand and supplies for continuous aid in humanitarian operations. Rottkemper et al. (2011) proposed a distribution and inventory relocation problem for a single product, that seeks to minimise the amount of unsatisfied demand in overlapping disasters, whereby a sudden (and uncertain) change in demand can happen due a second disaster where a humanitarian operation is already in place. They employ a linear multi-period model, assuming penalty costs for unsatisfied demands to a case study of malaria vaccination in Burundi, in 2008, where a sudden change in demand could happen due to circumstances resulting from the civil war in the region. Rottkemper et al. (2012) developed a mixed integer programming model to find an optimal integrated distribution and relocation policy for supplies between depots, in regions affected by disasters, with uncertain demands. Gonçalves et al. (2013) developed a two stage linear stochastic program using a network flow model in order to minimise supply and distribution costs of the World Food Programme (WFP) operations in Ethiopia, considering uncertainty in demand and roads accessibility and “last mile” difficulties, such as flooded areas in rainy seasons. To minimise unused donation and promote an equitable service, Balcik et al. (2014) used a set partitioning model to solve a multi-vehicle sequential allocation problem and identify the optimal routes for vehicles to pick-up donations from different sources and deliver them to non-profit organizations, such as food banks. Assuming a stochastic demand that follows a Gamma distribution, they argue that route decisions highly affect the degree to which the demand can be matched. Orgut et al. (2016) presented mathematical models to ensure food bank’s effective distribution of donated food among a population at risk of hunger, where demand is proportional to the poverty of the population near the food bank area. The paper uses a network-flow approach to minimise the amount of undistributed food and uses probabilistic sensitive analysis to uncover the effect of uncertainties on donations in the optimal solution. Orgut et al. (2017) continue their study of equitable distribution of food by developing a two-stage stochastic optimisation model for equitable distribution of donated food by a regional food bank. The model seeks a balance between the amount of distributed food and wastage of goods, assuming that storage capacities at receiving warehouses are stochastic and follow a well known distribution probability.

More recently, Dillon et al. (2017) presented a two-stage decision model for blood bank inventory optimization, assuming stochastic demands and perishability. Despite also addressing blood bank inventory management, our approach distinguishes from the presented one by providing a model suited for long term optimization, whereas the presented one focus on two-stage optimization. Addressing vaccination distribution with uncertain demand, Peng et al. (2019) introduces a network-based model in a random-walk network assuming spatial constraints in order to devise an optimal vaccination intervention plan. In a similar approach, Hota and Sundaram (2019) seek to identify the optimal vaccination policies by applying game theory in a population network, where nodes decide whether or not to vaccinate themselves. To forecast demand in food bank operations, Pérez et al. (2022) analyse the donation behaviour at two food banks affected a hurricane in order recommend forecasting methods to tackle demand uncertainties. In a different approach, Lee et al. (2022) also addresses forecasting of food bank donations uncertainty, by integrating Autoregressive integrated moving average with neural network models. These approaches are very different from our own, since they aim at identifying forecasting methods and only apply to demand uncertainty.

Even though these works acknowledge stochastic demands and donations as key factors in a humanitarian operation, very few works considers uncertainties in both demand and donation/supply simultaneously. As also pointed out by the literature review presented in Lopes et al. (2022), which only identified 1 paper that address both demand and supply uncertainties at the same time: Ferreira et al. (2018), which is the paper developed and published during this research and is part of this work.

In fact, humanitarian organizations and academics have started to notice the importance of supply chain management in humanitarian operations, in order to better coordinate their efforts and minimise the waste of resources. However, sudden on-set disasters have gained more attention from the academia. According to the literature review in humanitarian logistics and humanitarian operations made by Leiras et al. (2014), only 15 out of the 227 papers reviewed considered slow on-set disasters, such as famine and droughts; none of these papers address inventory management of perishable items. Hence, this research contributes to the literature with an inventory model for slow on-set disasters that explicitly considers perishability and accounts for uncertainties in both demand and donations of supplies.

2.2 Perishable items inventory management

Inventoried items can sometimes be subject to obsolescence, and/or deterioration. Items are subjected to obsolescence when they lose value over time because of rapid changes in technology or the introduction of a new product on the market. Deterioration refers to loss due damage, spoilage and vaporisation (Goyal and Giri 2001). Items that have a maximum usable lifetime, such as meat, vegetables, bread, human blood, flowers, among others, are classified as perishable.

There are four major research areas in the literature of perishable inventory management: ordering policies, issuing policies, disposal policies and pricing policies. Ordering and issuing policies have attracted most attention in the literature, as detailed below. An ordering policy defines when to order a policy and how much of it to acquire. The issuing policy determines how to remove items from inventory. As such, it directly affects the age of inventory items. Consequently, models for issuing policies need to consider both shortages and losses due to perishability (Lee et al. 2014).

Naturally, models for deteriorating items must deal with two key factors: demand and deterioration rate. Demand often drives the entire inventory system, whereas the deterioration rate helps to characterise the inventoried goods and determine their expiration date. Price discount, shortage and the temporal value of the money are also important factors to be considered in perishable items inventory Li et al. (2010).

One can model demand either as deterministic or stochastic, with the former being more common in the literature, whereas the latter tends to be more common in practice. Chang et al. (2003) proposed a model to find the optimal replenishment policy with time dependent demand and constant deterioration rate, allowing shortages and backlogging. A deterministic demand model, proposed by Yang and Wee (2003), strives to find production and pricing policies for deteriorating items with price dependent demand, with a view at maximising the present value of profits over a finite time horizon. In a slightly different approach, Wu et al. (2006) developed a model for finding the best ordering policy for deteriorating items with stock-dependent demand, allowing shortages and with a backlogging rate depending on the waiting time for the next order.

Stochastic demand models typically model the demand as a Poisson process. For instance, Kalpakam and Shanthi (2001) studied an $(S-1, S)$ perishable inventory system under Poisson demand and exponential lifetimes, seeking to minimise the long run expected cost by means of a Markov Renewal Process. Ozbay and Ozguven (2007) developed an inventory management model to identify the safety stock of goods in order to prevent disruptions in the flow of goods (of a single commodity) to shelters, during and after a sudden on-set disaster, at minimum cost, for a finite time interval. Their model is based on the Hungarian Inventory Control Model, and proposes a solution using the p-Level Efficient Points algorithm for the time-dependent stochastic model. The model accounts for continuous delivery and consumption of goods, assuming both as stochastic processes. Even though their research does not explicitly contemplate perishability, they highlight the importance of assuring that costly supplies do not perish in stock. Ozguven and Ozbay (2013) further develop this model by assuming multi-commodity and multi-supplier stochastic inventory control. The model is then considered a part of a Radio Frequency Identification (RFID)-based emergency management framework, which aims to facilitate resource tracking during disaster response. They argue that their model could (indirectly) accommodate obsolescence by assuming higher costs due stocking requirements and higher shortage possibilities.

Sivakumar (2009) studied a continuous review inventory system with a (s, S) operating policy where demands occurring during stock-outs enter into orbit and return after a random time; they considered an exponentially distributed demand and an inventory dependent deterioration rate. Yadavalli et al. (2011) presented a multi-server facility model in which the item is delivered to the customer only after performing some service, assuming a Markovian customer arrival process (MAP), (s, S) ordering policy and exponentially distributed lead times. Alizadeh et al. (2014) implemented a modified $(S - 1, S)$ inventory policy for decaying liquids, such as Alcohol and Hydrogen Peroxide, with Poisson demand an infinite time horizon and deterministic deterioration rate, allowing shortage and backlog. Gutierrez-Alcoba et al. (2017) developed two heuristic algorithms (based on the Silver's heuristic) for the lot-sizing problem of perishable products, with non-stationary stochastic demand and deterministic deterioration rates in a finite time horizon.

Finally, Rezaei-Malek et al. (2016) developed a bi-objective mixed-integer programming model for perishable items (medical supplies). They seek the best ordering policy, as well as the optimal location-allocation plan for medical warehouses in a pre-disaster phase and the optimal distribution plan of medical supplies to the hospitals in a post-disaster phase, to seek a balance between the average response time and the operation's total cost. Their model assumes constant deterioration rate and uncertain demand based on the probabilities of possible disaster scenarios.

When it comes to deterioration rates, different approaches arise in the literature. Mahapatra and Maiti (2005) developed single-objective and multi-objective models for profit maximisation considering stochastically deteriorating items and inventory dependent demand with no shortage allowed. The deterioration function follows a two-parameter Weibull distribution in time. Dye (2006) developed a deterministic inventory model to find the optimal selling price and ordering policy for an inventory system with time dependent demand and backlog, and deterioration dependent on both price and time. The model presented by Sarkar and Sarkar (2013) considers an inventory dependent demand and a time varying deterioration rate to determine the optimal cycle length of an item in the inventory. Gunpinar and Centeno (2015) seek the the optimal ordering level for blood packs, considering a balance between shortage and wastage of blood products at a hospital. They presented deterministic (assuming a known demand) and stochastic integer programming models (assuming an uncertain demand), considering a deterministic shelf life for red blood cells and platelets. Their model, which is myopic in that it considers a finite planning horizon, needs to keep track of the age of all items in stock. Moreover, the stochastic component of the model relies on the quality of a finite number of available scenarios. Muriana (2016) presents a stochastic Economic Order Quantity (EOQ) model for inventory management of food products that seeks the optimal inventory policy under Gaussian demand, constant lead time and deterministic shelf life.

Uncertainty in inventory management is often modelled by means of stochastic programming techniques, considering a finite time horizon T. Such models, however, require linear objective functions. Moreover, the complexity has a combinatorial growth with the time horizon T, rendering the problem rather intractable for large values of T, as the scenarios become increasingly complex and unlikely. As a way to circumvent these issues, we use Markov decision processes (MDP). Due to its state space modelling that relies one-step transitions, MDP allow us to seamlessly account for uncertainties in any number of variables. In addition, the framework is flexible in that it does not impose constraints on the form of the objective function. Furthermore, MDP are especially appealing for modelling problems with infinite time horizon ($T \to \infty$) like those ensuing from long-term operations, as the solution is evaluated by a simple, easy to implement, recursive algorithm (Putterman 1994). Finally, MDP are also a solid approach for short-term operations of random duration such as the landslide relief operations considering in the second part of this work, hence they will be applied in both frameworks.

An important contribution of the first model is that deterioration is considered upon the arrival of each donated item/batch of items. The probability that the new item is incorporated to the inventory coincides with the probability that the item will be consumed before its expiration date. That prevents the need to keep track of the expiration dates of every item in stock, while still considering the possibility of expiration, thereby yielding simple inventory policies as illustrated by the examples in section 3.9. The model also considers the possibility of increased donations/acquisitions, resulting from an investment in the part of the decision maker. Such increases may be the result of inventory transfers, advertisement campaigns, direct investments, etc.

The proposed MDP model provides an adequate approach for addressing uncertainty, allowing us to derive a long-term optimisation problem that implicitly addresses every possible scenario regarding the stochastic components, as the solution is calculated in terms of steady state behaviour. That contrasts with the typical approach of using finite-horizon models that account only for the uncertainties present in the generated scenarios, and whose solutions depend upon the quality of the finite number of generated scenarios.

This research builds a foundation for further studies in the area of inventory management for long-term humanitarian operations, considering perishable items. That is because we focus on the real necessity of the humanitarian organizations on the field, since donated goods do not have infinite shelf life and, consequently, need to be properly managed. It is clear that despite the growing interest in stochastic deterioration rates in the last decade, the majority of studies developed in inventory management of perishable items focus on deterministic shelf lives. Moreover, the stochastic component is often treated by means of scenario generation for finite planning periods.

To sum up, our work strives to bridge the gap on long-term humanitarian operations reported by Leiras et al. (2014), aiming to minimise the impact of disasters over a vulnerable community in long-term operations, such as plagues, where perishable items, such as vaccines and food are vital to assist people in need. Simultaneously, we aim to develop an inventory management model which addresses perishability, enabling humanitarian operations to minimise their operational costs with a model that is easy to deploy and contemplates stochastic demand and stochastic donation.

2.3 Collaboration in humanitarian supply chains

Disaster responses often involve a large number of organizations, each with its own proceedings and organizational culture (Gustavsson 2003). Therefore, a quick, organised response requires a well-coordinated effort (Dubey and Altay 2018). The lack of coordination may hinder operations and produce mismatching information (Kovács and Spens 2007). It is noteworthy that HO frequently use the terms collaboration and coordination interchangeably (Balcik et al. 2010).

According to Gupta et al. (2017), 40% of humanitarian operations' logistics resources are wasted due to lack of coordination. Not only does it deny the necessary goods to the victims, but also imposes financial losses and environmental challenges related to disposing of the unused goods (Li et al. 2019). Furthermore, duplicated efforts can compromise the use of scarce resources (Mishra et al. 2020). Unsurprisingly, researches suggests that collaboration may lead to substantially improved humanitarian operations (Papadopoulos et al. 2017, Thomas and Kopczak 2005).

Balcik et al. (2010) define coordination as the relationships and interactions among different actors operating within the relief environment. These interactions can be categorised into two broad lines: vertical coordination and horizontal coordination. Whilst vertical coordination involves upstream and downstream activities in the supply chain, horizontal coordination is the collaboration of organizations in the same level within the supply chain.

Although collaboration mechanisms are often beneficial, there are many obstacles to their effective use: conflicting goals and organizational cultures, competitiveness among actors, technology barriers, unwillingness to share information, among others (Nurmala et al. 2017). The urgency of the relief also imposes swift time constraints for establishing and coordinating relationships (Krejci 2015). To overcome such challenges, Dubey and Altay (2018) identify 11 drivers for humanitarian operation coordination: Information and communication technologies, Information sharing, Visibility, Training, Mutual learning, Contingency leadership, Performance management systems, Swift-trust, Commitment, Cultural cohesion and Regular meetings.

Studies on coordination for humanitarian operations either focus on specific drivers or attempt to model the decision maker's behaviour (Dubey and Altay 2018). Analysing the trade-offs between different types of coordination, Jahre and Jensen (2010) conceptualise the cluster approach for a coordinated disaster response. For a discussion of the applicability of the cluster system in urban disaster relief operations, refer to (Sanderson 2019). Recently, authors used fuzzy analytic hierarchy processes to classify barriers to coordination (Kabra et al. 2015) and introduced the concepts of network orchestration and choreography for relief supply chains (Grange et al. 2020).

Studies applied simulation (Krejci 2015) and evolutionary game models (Li et al. 2019) to evaluate whether collaboration can improve the efficiency of disaster relief management, considering the expected behaviour of decision makers. Alternatively, one can design contractual strategies with purchase and surplus constraints to balance shortages and inventory losses (Nikkhoo et al. 2018). Finally, Li et al. (2018) propose a maximal covering model with coordination to seek optimal location decisions for distribution centers under uncertainty and operational constraints.

Our study covers two coordination drivers proposed by Dubey and Altay (2018): Information sharing, and Visibility. The former helps increase the accuracy of the information reaching multiple organizations, especially concerning supply and demand. The latter enables partners to coordinate better, as each can see the needs and replenished quantities of all partners. This improves transparency and leads to a more reliable decision making process.

2.4 Relief distribution

Our study advocates the need for collaboration between multiple organizations to optimise the distribution of relief supplies in a disaster response operation. Behl and Dutta (2018) report that, from 2011 to 2017, only 13% of the humanitarian logistics and supply chain papers studied coordination and collaboration. In contrast, coordination and collaboration are at the top of the practitioner's priorities (Besiou and van Wassenhove 2020). The second model developed in this research addresses this mismatch by proposing a collaboration framework wherein multiple organizations share the same suppliers and transport network. The approach centralises purchasing, warehousing and distribution decisions within a distribution center (DC). The DC acquires and stores goods from multiple suppliers to later distribute them to different organizations serving the affected area, thereby linking the *relief supply chain* with the *relief distribution chain*, see Figure 2.1. This reduces inventory management and distribution costs and promotes a better usage of the available resources to improve the assistance to the victims. Further, the collaboration mechanism prevents (or at least, reduces) the competition among organizations with similar objectives over the same scarce resources, which would have the potential to increase prices due to limited capacity and high demand. In this study, we focus on the evaluation of the benefit of this approach using a mathematical model.

After the COVID-19 pandemic highlighted the perils of maintaining a super lean supply chain, there is growing concern among practitioners regarding the inventory of vital supplies in humanitarian responses, such as drugs and medical equipment (Mishra et al. 2020) as well as relief food items (Perdana et al. 2022). This research addresses the balance between avoiding shortages and maintaining appropriate inventory levels by including shortage and penalty costs, as well as inventory holding costs. We seek an operational policy that avoids overstocking and wasting resources whilst maintaining enough inventory to minimise shortages due to peak demand.

By including a local supplier, the proposed approach also tackles another rising concern among practitioners: the need to rehabilitate and develop the local economy after a disaster (Heaslip et al. 2018). To hedge against local supply chain disruptions, the model also includes a reliable supplier outside the disaster area to ensure that HOs can properly assist the disaster victims even when local supply is unavailable. Whilst the model includes a single reliable supplier matched by a single unreliable counterpart, it is easily adaptable to multiple suppliers (both reliable and unreliable).

To tackle supplier unreliability, Iakovou et al. (2014) propose a model that includes a second supplier which is contractually remunerated to keep a reserved amount of goods in stock, to be used whenever the main supplier is unavailable. But while they assume a two-tier network design and contractual obligations with suppliers, our framework considers a three-tier supply chain network with centralised decisions at the DC. Furthermore, our framework does not imply any contractual obligation and allows the decision maker to freely choose among suppliers based on the conditions at each decision epoch. As the model is stochastic, it considers failed deliveries by the supplier.

Other studies that consider supply chain disruptions mostly focus on facility locations, often considering that possible facilities, such as distribution centers and shelters, may be disrupted by the disaster (Hamdan and Diabat 2020, Mohammadi et al. 2020, Rahmani et al. 2018). These studies consider that the disrupted locations are completely inoperative due to damaged infrastructure or compromised accessibility. Our framework is more general as it considers that disruptions do not necessarily render the unreliable supplier completely inoperative. Rather, they merely cause the supplier to miss specific delivery deadlines with a given probability. Moreover, whilst two-tier networks are relatively common in the literature, three-echelon networks, while existent, are hardly deployed, as mentioned in (Balcik et al. 2016, Behl and Dutta 2018). The present study shortens this gap by proposing a three-tier network that models the flow of supplies from their source (suppliers) to their final destination (humanitarian organizations/victims), also including the distribution center.

To model uncertainty within HL, one can use Markov decision processes. Ferreira et al. (2018) used MDPs to derive optimal inventory policies for perishable items in slow-onset disasters, whereas Meraklı and Küçükyavuz (2019) used a value at-risk MDP formulation to tackle a similar problem under parameter uncertainty. The models, however, do not include distribution decisions as these would enlarge the state and action spaces and render the approach intractable for moderately complex distribution networks (e.g., Powell 2011). To include distribution decisions, researchers often resource to two-stage stochastic programming (TSSP) (Alem et al. 2016, Noyan et al. 2019) or robust programming (Hamdan and Diabat 2020, Rahmani et al. 2018, Rezaei-Malek et al. 2016). These models, however, present a combinatorial growth with the time horizon, which renders them impractical for longer-term problems such as slow-onset disasters. Furthermore, as the time horizon grows, the scenarios become increasingly unlikely and hardly representative (e.g., Snyder 2006).

Fuzzy sets can also be utilised to tackle uncertainty. Kabra et al. (2015) use a fuzzy analytic hierarchy process to prioritise barriers for coordination in humanitarian supply chains based on their perceived severity. Representing the demand by a fuzzy parameter, Goli and Malmir (2019) introduce a new version of the Vehicle Routing Problem (VRP) that uses the covering tour approach to distribute essential goods. With a similar goal, Mohammadi et al. (2020) combine fuzzy logic and robust optimisation to route vehicles and distribute products in a multi-echelon relief distribution network.

Another approach to address uncertainty is to use simulation to test a limited number of possible solutions. For instance, Beamon and Kotleba (2006) simulate complex emergencies in South Sudan and study the interrelationships among parameters in the relief chain design, such as reorder, lot size and distribution costs. Similarly, McCoy and Brandeau (2011) simulate the interactions between a central warehouse and the downstream operations, and test distinct distribution and budget allocation decisions. Krejci (2015) studies decision maker's behaviours to find the influence of collaboration mechanisms in the operation. Using COVID-19 as a background, Malmir and Zobel (2021) propose a simulation-based approach to generate problems of different sizes with uncertain demand whilst considering deprivation and equity costs in humanitarian operations. Although simulation allows us to propagate uncertainties and compare a limited number of prescribed policies, it does not allow optimisation.

As MDPs are specially suited to long-term operations (Putterman 1994) and TSSP can effectively prescribe a shorter term distribution policy, this thesis proposes a novel framework that combines these approaches to effectively solve problems that involve both a longer-term strategic/tactical decision and short-term operational decisions. For example, government agencies responsible for disaster management typically need to set an annual budget for their inventory planning and make an operational decision to distribute the inventory to demand points whenever a disaster strikes. Another example is when a large-scale disaster strikes and the government agency knows that the response operation will take a long time, they will need to plan the inventory for the length of the operation and make short-term decisions to distribute the relief items to the victims on a regular basis (e.g. daily). To address the need for longer-term decision, we use an infinite horizon MDP formulation to derive the optimum purchasing strategy; short and medium-term operations can also be covered via the discounted cost MDP formulation that also considers the random duration of the response. We then use a TSSP optimisation model to break down the MDP's optimum purchasing strategy (*how much to buy*) into acquisition (*where to buy*) and distribution (*where to send*) policies for suppliers and organizations.

The proposed approach ensures a simple and easy to solve MDP that prescribes the number of items to purchase given the current inventory level at the DC at the start of the planning horizon (e.g. the start of the budget year, the start of a response operation). Considering the initial inventory at the DC and the number of items to be acquired, the stochastic programming (TSSP) formulation refines the purchasing decisions at each time epoch by assigning quantities to suppliers and establishes the distribution strategy under uncertainty. As it only encompasses the uncertainties of the current decision epoch, the TSSP is also simple and easy to solve. Therefore, the proposed framework takes advantages of the strengths of the MDP and TSSP formulations to derive a fast and reliable algorithm for inventory management and distribution. Our approach also addresses a real problem faced by city or state agencies who need to set a longer-term budgeting decision and short-term decisions to respond to disasters. To the best of our knowledge, this is the first approach that combines MDP and TSSP to tackle a combined long-term inventory management problem and short-term procurement/distribution problems with multiple suppliers and recipients within a three echelon supply network.

Chapter 3

Inventory management of perishable humanitarian supplies

The reality of humanitarian operations is very different from that of most of the theoretical studies in the literature. Demand is uncertain and highly unstable, as it happens suddenly in different places at different points in time (Kovács and Spens 2009). Moreover, donations are often unpredictable since they come from different kinds of donors, such as non-governmental agencies, governmental agencies (for instance the military forces), commercial partners, individuals and local retailers (Kovács and Spens 2007). They arrive at the disaster site in different amounts and in a variety of shapes and packs.

Frequently, humanitarian organizations receive unsolicited and even useless goods while responding to a disaster, such as expired medicines and food or dirty laundry, which may render the management of donations very problematic. The proper management of the received and procured goods is essential to the success of any long-term humanitarian operation (Holguín-Veras et al. 2014). That includes the proper management of perishable items that arrive on site such as food, human blood and medicines, once they can even harm individuals if not managed and stored properly. Furthermore, spoiled goods generate disposal costs, and therefore increase the total operation costs of the organizations.

This chapter aims to build a model to find the optimal ordering policy for perishable items within a continuous aid humanitarian operation, considering uncertain (stochastic) demands and donations and deterministic shelf life. The objective function is to minimise the total expected inventory cost, seeking to avoid both shortages and the deterioration of donated supplies.

The proposed problem is modelled as a Markov Decision Process (MDP), where both the demand and supply are stochastic variables. An MDP is a framework to model sequential decision problems (Putterman 1994), wherein it is possible to intervene in the system at each period (decision epoch) via control actions, and the transition between system's states is probabilistic and depends on the selected control actions. Every action has an immediate cost (or reward) associated to it, which also depends on the system's state upon the application of such an action. They are called Decision Processes, because they model the possibility of an agent to interfere regularly in the system, and Markovian because they obey the Markov property, according to which the effect of an action on a state depends both on the action and on the current state of the system.

An MDP is a tuple (S, A, T, R) comprising:

- S – Set of all possible system states;
- A – Set of feasible control actions;
- $T : S \times A \times S \to [0, 1]$ = Probability function of a system to switch to a state $s' \in S$ given the process is at state $s \in S$ and the agent action $a \in A$;
- $R : S \times A \to R$ - Cost (or reward) function for taking a decision $a \in A$ when the process is at a state $s \in S$.

3.1 Model characteristics and assumptions

1. The states of the system are the available inventory at the onset of each week. More specifically, they represent the number of items in stock which are not expected to expire before they are demanded.

   Once the model proposed is an inventory management model for perishable items, this is the most suitable choice for the states of the system. These are the base parameters upon which the manager will decide over how many items should be collected/procured in order minimise the average costs of the system (inventory, deficit and disposal costs);

2. Procurement of items is performed at the beginning of each week, based on the inventory level available. The number of items procured depends on the possible actions selected by the decision maker. The set of actions (items procured) for each possible state of the system (inventory level available), which minimises the objective function, is called optimal procurement policy;

3. The model is built upon the assumption that the warehouses used to store the procured/collected items are large enough to store the demanded goods over the decision epoch considered (see section 3.4). Hence, the inventory capacity is assumed to be infinite.

   For our experiment (discussed in section 3.9), the warehouse has enough capacity to store all donations and items procured in a month. Since we are working in a weekly basis management system (see section 3.4), the inventory capacity is not a constraint. However, for operations with limited storage capacity, we recommend assuming a shorter interval between decisions (daily procurement, for example) in order to fit the warehouse capacity, or considering a different model with inventory capacity constraint.

   In the second framework presented in this research, we generalise our model in order to assume inventory capacity constraints in different levels of the supply chain;

4. Donations are stochastic and follow a determined probabilistic distribution with known parameters;

5. Items collected or procured in a single week are considered to have the same expiration dates and are arranged in a batch of items as soon as they arrive in the warehouse. Hence, the remaining shelf life of all items in one batch is the same;

6. The demand for is stochastic and follows a Poisson distribution with mean λ. Hence, the time to consume a fixed number of items k in the inventory is given by an Erlang distribution with mean λ;

7. The probability of expiration of a batch of items is given by an Erlang distribution with parameters λ and k, where k is the number of items in stock that

are not expected to expire, at the beginning of the week. More specifically, the batch will expire if the items already in stock, which are older, are not consumed before their expiration dates.

The rationale behind the modelling choice in 7 is as follows. Once a batch of items arrives, we evaluate the probability of expiration for the whole batch. This probability coincides with the probability that all older items are consumed before their expiration date. The items then enter the stock with this probability and do not enter it otherwise. Hence, the state variable keeps count only of the number of items in stock that will not expire. This circumvents the need to monitor the age of all items in stock, while still accounting for the expiration of the items, and is one of the innovations of the model.

Under such a modelling choice, the items received in past decision epochs were accepted based on their expiration probabilities, hence they are considered appropriate for consumption in the current decision epoch. The items received/acquired currently, however, may expire. And the probability that they are accepted in the stock is the probability that they will not deteriorate before being demanded;

8. The expiration date is deterministic, i.e. the collected, procured and received items have a fixed shelf life. The model considers the shelf life of an item as the difference between the expiration date and the time of arrival of the item in the warehouse;

9. No lead-time is considered for donated or procured supplies.

3.2 Model parameters and definitions

Sets	S	System states, representing the inventory level (measured in units of products)
	A	Set of action rules $A = \{a_1, a_2, \ldots, a_n\}$
Random variables	C	Donations of items with realization $c \in C$ (measured in units)
	D	Demand of items with realization $d \in D$ (measured in units)
	V	Number of items that can be consumed before expiring (measured in units)
Parameters	ΔS	Variation in the inventory level (measured in units)
	p_a	Number of procured items given an action a
	E	Expiration date of the product
Cost function	$R(s, a)$	Cost of holding s items in inventory under action a

3.3 Objective function

The objective of this model is to minimise the long-term operational cost (which is composed of inventory holding, ordering and disposal costs) in a continuous-aid humanitarian operation that stores and distributes perishable items.

For that purpose, we adopted an average cost performance criterion for our model. Let $\Pi : S \to A$ be the set of possible stationary policies; each policy $\pi \in \Pi$ determines, for each state $s \in S$, which action should be performed each time the system visits state s. Let $R : S \times A \to (0, \infty)$ be the cost function of the system, where $R(s, a)$ is the cost of applying action a at state s. Each policy $\pi \in \Pi$ is associated to a long-term average cost

$$\eta_\pi = \lim_{T \to \infty} \frac{1}{T} E \left\{ \sum_{t=0}^{T} R(X_t, \pi(X_t)) \right\}, \tag{3.1}$$

The objective is to find an optimal policy $\pi^* \in \Pi$ such that:

$$\eta_{\pi^*} \leq \eta_\pi, \, \forall \, \pi \in \Pi. \tag{3.2}$$

3.4 Decision epoch

The decision on the collection of items takes place weekly, before the start of a new week, as long as the humanitarian aid operation lasts. Considering that continuous aid operations are often long-term operations, the model considers an infinite time horizon.

3.5 State of the system

The system states represent the available inventory level, and can be represented by units of product (blood packs, vaccine doses, etc.). Therefore, the state space is discrete and denoted by $S = \{0, 1, ..., M\}$, where $0, 1, ..., M$ are possible inventory levels at any decision epoch.

3.6 State transitions and probability

The events that cause transitions between states are:

- Demand for products, that follows a Poisson process with mean λ;
- Donations of products, which follows a discrete probabilistic distribution with mean μ;
- Expiration of products, that follows an Erlang distribution with probability density function $f(x, k, \lambda)$, where x is the elapsed time for k items to be consumed in a Poisson process with mean λ.

As explained in Section 3.1, for each batch of donated products we will consider the probability that these items will not perish before consumption, which will be calculated according to the Erlang distribution above, where k is the amount of items in stock after the arrival of the donated batch, assuming the current inventory level.

Thus, the inventory level variation, ΔS, considering demand and donation of goods, is given by the following equation:

$$\Delta S = s'_{t+1} - s_t, \tag{3.3}$$

where s'_{t+1} is the inventory level available at the beginning period $(t + 1)$, and s_t is the inventory level at the beginning of period t.

Assume that donations are independent of the demand. Then, if we do not consider deterioration, the probability of going from state s to state s' in the next period becomes

$$P^{'}(s^{'}|s = \Delta S) = \sum(P(C = c) * P(D = d), \forall c \in C, \forall d \in D | c - d = \Delta S. \tag{3.4}$$

Assume now that the probability $P(V = k|s)$ represents the probability of k newly arriving items being consumed before expiring, given the inventory level s. As stated above, this probability is evaluated making use of the Erlang distribution.

The transition probability $P(s'|s)$ considering the perishability of the items can now be expressed as follows:

$$P(s'|s = \Delta S) = \begin{cases} P'(s'|s = \Delta S) * P(V = s + \max(\Delta S)|s), & \text{if} \Delta S > 0 \\ \displaystyle\sum_{\Delta S=1}^{\max(\Delta S)} P'(s'|s = \Delta S) * [1 - P(V = s + \max(\Delta S)|s)] + P'(s'|s = 0), & \\ & \text{if} \Delta S = 0. \end{cases} \tag{3.5}$$

It is easy to see that if $\Delta S < 0$, then $P(s'|s) = P'(s'|s)$.

Let us now assume that the decision maker is able to increase the donations by taking a given action a, which results in extra p_a donated items. Typically, p_a is a random variable, and we assume in our model that this is a discrete variable with known distribution. Then, the variation in the inventory level, ΔS_a, considering a realization of p_a extra donations is given by the following equation:

$$\Delta S_a = s'_{t+1} - (s_t + p_a) \tag{3.6}$$

Hence, the transition probability $P(s'|s, a)$ accounting for the action of collecting or procuring p_a extra items in a day, becomes:

$$P(s'|s, a = \Delta S_a) = \begin{cases} P'(s'|s = \Delta S_a) * P(V = s + \max(\Delta S_a)|s), & \text{if } \Delta S_a > 0 \\ \displaystyle\sum_{\Delta S_a=1}^{\max(\Delta S_a)} P'(s'|s = \Delta S_a) * [1 - P(V = s + \max(\Delta S_a)|s)] & \\ \qquad + P'(s'|s = 0), & \text{if } \Delta S_a = 0. \end{cases} \tag{3.7}$$

Note that for $\Delta S_a < 0$, $P(s'|s, a) = P'(s'|s)$.

3.7 Cost function

The goal of any inventory system, in continuous aid work, is to minimise the costs of procurement, inventory holding and transportation of goods for those in need. When it comes to perishable items, perishability costs also need to be accounted, such as the disposal cost of deteriorated items.

However, each organization has its own cost evaluation based on its particular operations, especially considering perishable items, where medical supplies and nutrition supplies, for example, have very different disposal policies. Hence we will not establish a unique cost function for this model, being up to each organization to choose the cost function that best suits its needs.

Furthermore, although our analysis is done regarding financial costs, the model is general enough and has no constraints regarding the cost function structure. Hence, the “cost” function may represent costs in distinct dimensions, other than the financial one. The cost function may be modelled regarding carbon footprints or even social costs, for example.

3.8 Solution procedure

Our model seeks to find an optimal policy for procurement of items that minimises the total inventory costs of humanitarian aid organizations in long-term operations. In order to solve the problem with infinite horizon we used the Value Iteration Algorithm (Putterman 1994). For details on the Value Iteration Algorithm, please refer to (Putterman 1994).

3.9 Experimentation

The Value Iteration algorithm proposed in this model was programmed and solved using the C# programming language, running in a Microsoft Windows 10 (64 bits) environment, with 8 GB RAM and an Intel Core i7 2860QM CPU (8 CPUs) with approximately 2,5 GHz.

The C# language was chosen merely by convenience and availability, due the experience of the authors with the language. Although C# is a proprietary language, the model can be implemented with any programming language, such as Python or C++. Furthermore, the Value Iteration Algorithm is a well know algorithm that can be easily implemented by any employee with programming skills inside an organization, using free programming languages.

At this point, it is important to remember that our model assumes an infinite time horizon. Hence it only requires one execution during the lifetime of the humanitarian operation, in the initial stage of the operation, as soon as the parameters of the distributions of donations and demand of goods are known. The output is an optimal stationary policy that prescribes an optimal action for each state, regardless of the decision epoch (Putterman 1994). Should the parameters, such as shelf life, demand or donation distributions, suffer any change during the operation, another run is required to reflect such changes, thus resulting in a new, updated stationary policy.

Moreover, given that the model will be run only sporadically - at the onset of operations and whenever the input parameters suffer significant variations - the performance of the programming language selected to develop the model has only a marginal importance, since it will not be necessary to run the model too often.

3.9.1 Experiment Design

In order to demonstrate the applicability of our model, we designed a small experiment considering the inventory management of a blood center, responsible for collecting and distributing blood packs for city hospitals and humanitarian operations.

The data regarding demand and donations of blood packs were generated randomly, assuming demand for blood packs larger than donations. In addition to demand and donation, deterioration of the blood packs are the events that can cause an alteration in the inventory level, leading to a transition between the states of the system. The states considered in this experiment are the number blood packs available in the inventory, ranging from 0 to 2000 packs.

The demand for blood packs fits a Poisson distribution with mean 90 packs a week. The donation of blood is also stochastic and follows a Poisson distribution with mean 60 packs a week. If necessary the blood center can send vehicles to distant districts in order to motivate donations, and increase the number of blood packs donated/collected, to match the demand. There are four vehicles available in the blood center for blood packs pick-ups. We assume that each vehicle can collect up to 20 blood packs a week, when triggered. Hence, we consider a set of five possible control actions: to send zero, one, two, three or four vehicles for pick-ups, collecting at rate of 0, 20, 40, 60 and 80 blood packs, respectively. Therefore, the set $A = \{0, 20, 40, 60, 80\}$ is the set of control actions available for this experiment.

3.9.2 Immediate Cost function

The cost parameters for this experiment are well known: The inventory holding cost (h), the transportation costs for each vehicle used for blood packs pick-ups (ta), disposal costs for deteriorated items (dc), the total expected disposal cost (E(dc)), shortage costs for each blood pack (sc), and the total expected shortage cost (E(sc)).

The inventory holding cost increases linearly with the number of packs in the inventory, while the transportation/pick-up costs vary according to the number of vehicles used. Furthermore, there is a small financial incentive for each vehicle used for pick-ups. Each vehicle used grants a small reward of $60,00 from governmental organizations, in order to stimulate blood donations. The cost of sending no vehicle is the opportunity cost of not receiving the government incentive.

The total expected disposal cost is calculated considering the expected number of blood packs that will deteriorate before consumption, based on the available inventory level at each decision epoch, as equation (3.8) shows:

$$E(dc|s, a) = [1 - P(V = s + max(\Delta S_a)|s, a)] * max(\Delta S_a) * dc \tag{3.8}$$

where $1 - P(V = i|s, a)$ is the probability that i blood packs deteriorate before consumed, given the current inventory level s and dc is the disposal cost per pack.

Moreover, the expected shortage cost is calculated considering the expected lack of blood packs, based on the available inventory levels. Since we are working with inventory management for a blood center, it is highly recommended that the inventory level never reach zero, in order to avoid shortage. Thus, for each demand not met, a high penalty (sc) is applied over the blood center costs, as shown in table 3.1

The total expected shortage cost is calculated as shown below.

$$E(SC|s,a) = \sum_{i=1}^{-1*min(\Delta S_a)} P(L = i|s,a) * i * sc, \tag{3.9}$$

where$P(L = i, s)$ is the probability of a shortage of i blood packs, given the current inventory level s, and sc is the shortage cost per pack. Therefore, the cost function R(s,a) for this experiment is given by

$$R(s,a) = h * s + t_a + E(dc|s,a) + E(SC|s,a). \tag{3.10}$$

Table 3.1 summarises the cost structure of this experiment, and presents the values used for each parameter. It is important to highlight that the costs used in this experiment were generated using arbitrary values.

Table 3.1: Experiment costs

Variable transportation / pick-up costs (ta)	Cost
One vehicle	$ 120,00 / vehicle
Two vehicles	$ 85,00 / vehicle
Three vehicles	$ 75,00 / vehicle
Four vehicles	$ 70,00 / vehicle
Inventory holding cost (h)	$ 1,00 / pack
Disposal cost (p)	$ 1000,00 / pack
Shortage cost (sc)	$ 1000,00 / pack

3.9.3 Deterioration rates

Blood packs become deteriorated 42 days after being collected, thus their shelf life is deterministic. Usually the blood packs are ready to use right after they become available. However, since we are dealing with continuous aid work, and these operations often happen in underdeveloped countries whose structure does not always allow local collection, the blood packs may come from different places around the world, directly affecting their shelf life. In order to address this issue, we simulated four different scenarios considering different lead times and how these lead times affect the shelf life of blood packs. For each scenario, the demand, donation and cost parameters are maintained constant.

In the first scenario, we considered a local collection where the shelf life of a blood pack is 42 days. For the subsequent scenarios we considered lead times of 21 days, 28 days and 35 days, leading to 21 days, 14 says and 7 days of shelf life for blood packs, respectively. At this point, it is important to note that blood packs have a very specific supply chain management, often called cold chain or cold supply chain, which is not addressed in this work. Also, the lead times are used only to demonstrate how the ordering policies change with different deterioration rates or different shelf lives. Thus, they are not directly considered in the transitions of inventory levels, leading to a model with no lead time.

3.9.4 Results and discussion

After the evaluation of the model we managed to find the optimal ordering policies for the four scenarios described in the previous section. Figure 3.1 and Table 3.2 summarise the results.

The outputs of our model are the actions that must be executed at each decision epoch, as a function of the inventory level at the onset of the current decision epoch. More precisely, each action represents a different number of blood packs that must be collected, at the beginning of each week, given the number of blood packs in stock in the beginning of the week.

For each possible inventory level of blood packs available in stock, our model provides the decision maker with the number of blood packs that must be collected, in order to minimise the average inventory costs of the humanitarian operation. The set of all optimal actions, one for each inventory level, is the optimal collecting (ordering) policy for the operation.

Considering the set of 5 possible actions proposed in our experimentation, the optimal ordering policy provided by our model for the first scenario (a shelf life of 42 days, proposed in section 3.9.3), is as follows: for an inventory level smaller than or equal to 340 blood packs, 4 vehicles should be sent in order to collect an average of 80 extra blood packs. For an inventory level between 341 and 364 blood packs, 3 vehicles should be sent in order to collect 60 extra blood packs. For an inventory level between 365 and 390 blood packs, 2 vehicles should be sent in order to collect 40 extra blood packs. For an inventory level between 391 and 428 blood packs, 1 vehicle should be sent in order to collect 20 extra blood packs. For an inventory level greater than 429 blood packs, no vehicles should be sent, collecting 0 extra blood packs. The minimum average cost per week obtained for this scenario is $62.38.

The ordering policy presented above should be adopted by the decision maker in order to minimize not only the average inventory costs, but also to avoid deterioration and shortage of blood packs.

To sum up, Table 3.2 shows the optimal ordering policies for the four shelf life scenarios proposed, where the decision of how many vehicles must be used, and the respective number of blood packs collected by them, is presented based on the inventory levels available. Table 3.2 also shows how the average inventory cost varies with changes in the shelf life of blood packs.

Table 3.2: Optimal ordering policies for the given scenarios

# of vehicles used	# of Blood packs pick-ups	Shelf life = 42	Shelf life = 21	Shelf life = 14	Shelf life = 7
		Inventory level available between:			
4	80	0 – 340	0 – 87	0 – 1	– //–
3	60	341 – 364	88 – 122	2 – 41	–//–
2	40	365 – 390	123 – 148	42 – 70	0 – 5
1	20	391 – 428	149 – 180	71 – 100	6 – 32
0	0	429 – 2000	181 – 2000	101 – 2000	33 – 2000
Average Costs / week		$62,38	$97,45	$109,14	$120,85

As expected, and presented in Table 3.2 and Figure 3.1, as the inventory level increases, the number of blood packs required decreases. Once the shortage probability tends to zero, their transportation and inventory holding costs greatly surpass the expected shortage costs. Furthermore, as the shelf life decreases, the average inventory costs increase, once the items tend to perish faster, increasing the disposal costs, as shown in table 3.2.

Moreover, Figure 3.1 presents how the number of blood packs collected decreases as the inventory level increases, for each of the four scenarios considered in the experiment. The figure clearly illustrates that for bigger shelf lives (V) the number of blood packs collected decreases slowly, in order to prevent shortage, since the disposal costs for perished items are very small in comparison to the shortage costs, due to a small deterioration probability.

In addition, although we consider a huge penalty for shortage of blood packs, the expected disposal costs for perished items increases significantly as the probability of deterioration grows. It is worth noting that as the shelf lives decrease, the number of blood packs disposed due to deterioration would increase fast as the inventory level rises, leading to higher disposal costs. Hence, the optimal policies tends to avoid such an increase by prescribing less external collection.

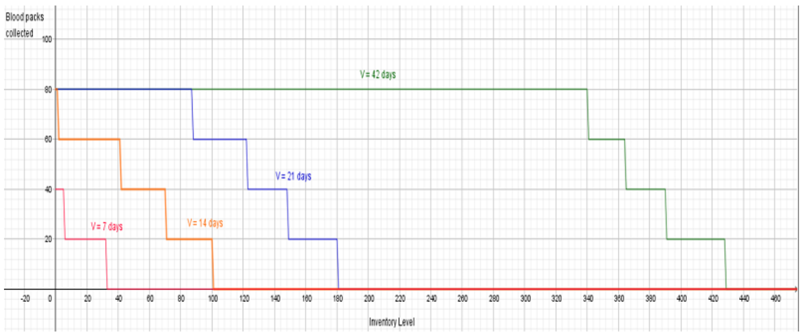

Figure 3.1: Optimal policies for blood packs pick-ups)

It is important to note that for distant communities, where the local collection of blood packs (or local procurement of perishable goods) is difficult or not possible, the low level in the inventory and the small number of blood packs pick-ups (or purchases), due the small shelf life of a product, may impose a serious risk to the health of the local community and to the humanitarian operations themselves.

Even though our model finds the optimal policies based on the minimum cost for the operation, managers need to keep in mind that the main goal of a humanitarian operation is to protect and save lives. Therefore, in order to keep the operations at optimal level and avoid putting the operation in jeopardy, researchers must be able to identify and plan the operational costs that best represent the desired goal in the model's objective function.

3.9.5 Sensitivity Analysis

To evaluate the model's robustness, and to observe the impact of changing parameters in the optimal ordering policy, a sensitivity analysis is conducted. Assuming that the set of possible actions are the same as discussed in section 3.9.1, cost parameters are the same as discussed in section 3.9.2, considering a shelf life of 42 days, and considering a regular donation of 60 blood packs per week on average, we will examine the implications of changes in the average demand on the optimal ordering policy.

In our analysis, we conduct a series of executions of the model, varying the demand distribution parameter (λ) from 60 to 100 blood packs per week, with an increment of 5 blood packs per week per execution. The results are shown in the Tables 3.3 and 3.4 and Figure 3.2.

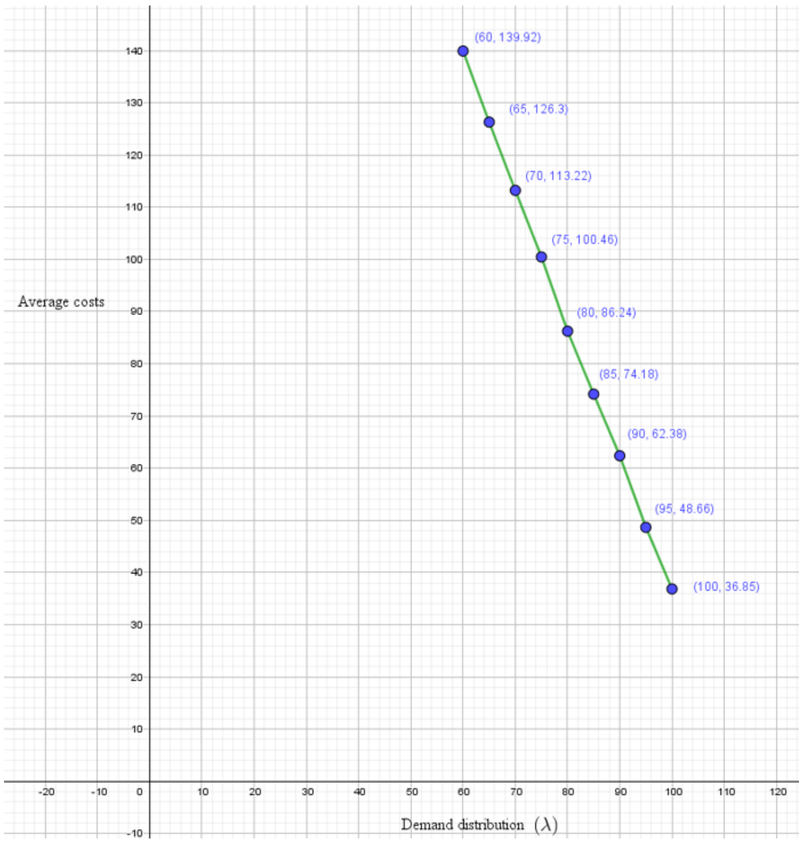

Figure 3.2: Impact of the variation of the demand parameter in the optimal average costs

Table 3.3: Optimal ordering policies and average costs for demand parameters between 60 and 80 blood packs per week

# of vehicles used	# of Blood packs pick-ups	$\lambda = 60$	$\lambda = 65$	$\lambda = 70$	$\lambda = 75$	$\lambda = 80$
		Inventory level available between:				
4	80	0 – 115	0 – 153	0 – 191	0 – 230	0 – 269
3	60	116 – 155	154 – 193	192 – 230	231 – 265	270 – 300
2	40	156 – 197	194 – 230	231 – 262	266 – 294	301 – 326
1	20	198 – 234	231 – 266	263 – 298	295 – 330	327 – 363
0	0	235 – 2000	267 – 2000	299 – 2000	331 – 2000	364 – 2000
Average Costs per week:		\$139,72	\$126,30	\$113,22	\$100,46	\$86,24

Table 3.4: Optimal ordering policies and average costs for demand parameters between 85 and 100 blood packs per week

# of vehicles used	# of Blood packs pick-ups	$\lambda = 85$	$\lambda = 90$	$\lambda = 95$	$\lambda = 100$
		Inventory level available between:			
24	80	0 – 305	0 – 340	0 – 374	0 – 407
3	60	306 – 332	341 – 364	375 – 397	408 – 429
2	40	333 – 358	365 – 390	398 – 422	430 – 454
1	20	359 – 396	391 – 428	423 – 462	455 – 495
0	0	396 – 2000	429 – 2000	463 – 2000	495 – 2000
Average Costs per week:		\$74,18	\$62,38	\$48.67	\$36,85

Tables 3.3 and 3.4 present the variation in the optimal collecting policy for blood packs with the variation of the demand. As the demand parameter (λ) grows, the number of blood packs required to prevent shortage increases. For example, Table 3.4 allows us to note that for a mean demand of 85, the number of blood pack collections required would drop from 80 to 60 once the inventory level reaches 306 blood packs, however, for a mean demand of 100, this reduction would happen only with an inventory level of 408 blood packs.

One can verify that while the costs for collecting blood packs would increase, the shortage costs would decrease. Furthermore, for higher demands the number of perished goods would decrease, leading to smaller disposal costs. Hence, as the mean demand (λ) increases, the average costs of the system (objective function) decreases, as shown by figure 3.2.

It is important to note that, in our experiment, disposal and shortage costs represent the larger part of the inventory costs, since both impose a huge penalty on the system. Consequently, decreasing both costs would lead to a significant decrease in the average costs. Moreover, the impact of changes in the shelf life of the goods is demonstrated in Table 3.2 and Figure 3.1.

Chapter 4

An inventory management model with a distribution center, multiple HOs and and unreliable suppliers

4.1 Problem Description and Mathematical Modelling

To support a disaster relief distribution effort, we study the inventory management within a distribution center (DC) that acquires items from suppliers and distributes them to distinct humanitarian organizations. Suppose that a local supplier is a viable source of relief goods, but an external supplier is also considered to ensure reliability (a local supplier here can also represent a group of local suppliers). The local supplier will henceforth be called *unreliable supplier*, as it may be affected by the disaster and fail to deliver the acquired items with a given probability. In contrast, the external supplier, henceforth called *reliable supplier*, always ensures timely delivery of the purchased goods.

The DC stores the acquired goods and distributes them to multiple HOs acting under its area of influence. The DC will thus be subject to inventory and shortage costs. Our framework permits the differentiation among shortage penalties for the different HOs. The centralised decision making in the DC also helps to coordinate the operations of multiple HOs acting in the relief effort. It should be noted that this thesis will quantify the benefit if this approach is used. We are aware that further research is needed to establish what needs to be done to implement this approach in practice.

In a disaster scenario the demand for goods is highly unpredictable, hence it is a common assumption that an HO's demand is stochastic and follows a known probability distribution. Under demand and supply uncertainty, the framework finds the optimal purchasing quantities in a dual sourcing system, as well as the optimal distribution policies to the multiple HOs responding to the disaster. A policy provides to the decision maker the actions that must be taken at every decision epoch, given the state of the system (Putterman 1994). Figure 4.1 synthesises the flow of goods in the described humanitarian supply chain.

The proposed framework combines a *two stage stochastic programming model (TSSP)*, incorporated in a Parameter Evaluation Algorithm, and a Markov Decision Process (MDP). The MDP seeks an optimal purchasing policy (total amount of products to be acquired) in order to supply the operation, using the expected costs and transition probabilities obtained by the TSSP. Meanwhile, the TSSP seeks and optimal distribution policy and the optimal split of the total order among the individual suppliers. This approach will be further explained.

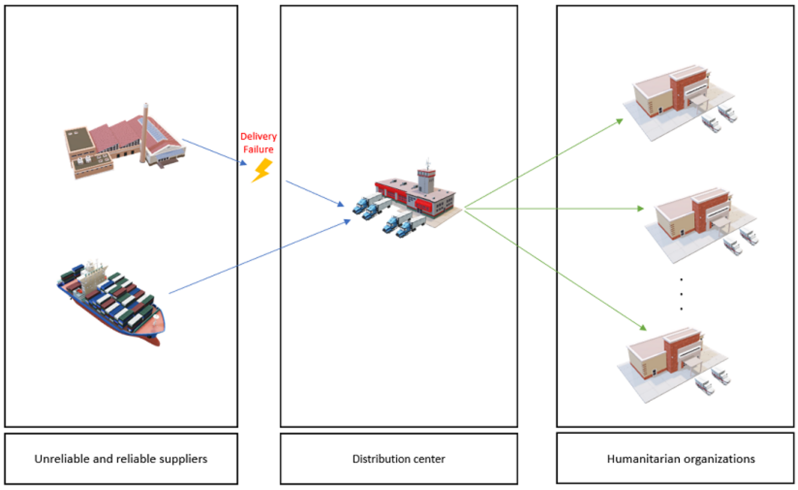

Figure 4.1: The flow of supplies in the studied problem

Figure 4.2 presents the conceptual flowchart for the proposed framework, where λ_t is the state of the system (inventory at the DC) at period t and α total number of products to be acquired (purchase policy) given that the state is λ_t. It is worth of emphasis that both the MDP state space and the action space are uni-dimensional, hence the formulation avoids by design the curse of dimensionality. To further specify the purchases, the TSSP finds an optimal policy $u(\lambda)$, that is comprised of the acquisition policy for all suppliers (where to buy) and distribution policy (where to send), and establishes the transition probabilities $p^{\alpha}_{\lambda_t \lambda'_t}$ and average costs associated with the given policy $C(\lambda_t, u(\lambda_t))$ for all possible realisations of the uncertainties. These transition probabilities and average costs will then be used as parameters in the MDP formulation.

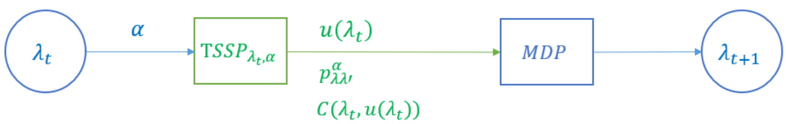

Figure 4.2: Proposed framework conceptual flowchart

4.1.1 Model characteristics and assumptions

The characteristics of our model and the assumptions used in the model are as follows.

- The demand of each organization is stochastic and follows a known probability distribution.
- Product acquisitions are performed at the beginning of each decision period. Distribution occurs after the realisation of the uncertain parameters (demand of organizations and reliability of suppliers).
- Lead times for both suppliers are sufficiently small not to encumber the system. Hence, when delivered, products acquired at a decision epoch will arrive in the same decision epoch. Such assumption is commonly applied for supply distribution in the literature (e.g., Goli and Malmir 2019, Malmir and Zobel 2021, Meraklı and Küçükyavuz 2019).
- There are two suppliers for the distribution center: one reliable, which always delivers the procured products, although at a higher cost, and one unreliable, which fails to deliver (or deliver only a portion of) the procured products, with a given probability.
- The distribution center and the organizations have a limited inventory capacity. The capacity of each supplier is also limited.
- The states of the system are the available inventory at the beginning of each decision epoch. More specifically, they represent the number of items in stock after the acquisition and distribution of the products (in the last period). These are the base parameters upon which the manager will decide over how many items should be acquired from each supplier and how many items should be distributed.
- The demand lost in a period is not backlogged for the next period. That is valid for many of the products used in short-term disaster recovery, such as water bottles, since nutrition needs of the human body do not directly accumulate between decision epochs (day, week, etc.) and the item was not available when needed. This assumption is regularly applied in the literature (e.g., Cook and Lodree 2017, Rezaei-Malek et al. 2016).
- The parameter evaluation algorithm (TSSP) aims to transform the purchasing policies (total amount of goods acquired) available into optimal acquisition policies from both suppliers. It is also responsible for identifying the optimal distribution and shortage policies for each organization, based on the inventory level of the system and the global purchase policy selected, and attributing shortage costs due missed deliveries by the unreliable supplier.
- The minimised cost of the TSSP purchase and distribution policy, given an initial inventory level (MDP state) at the DC and an the overall number of items purchased (MDP action), is used in the MDP as the cost of this respective state-action pair. Furthermore, the distribution policies for each scenario are used to calculate the possible transitions between states

(inventory levels) of the system and their probabilities, for the considered state-action pair. The calculation of state transition probabilities is described in section 4.1.6.

- The MDP is then solved to determine the optimal overall purchase for each initial inventory level at the DC; the policy only prescribes the total number, recalling that the split between suppliers is decided by the TSSP, along with the distribution policy.
- Each scenario used by the TSSP comprises the joint realisation of the demands for all HOs and the ability of the unreliable supplier to deliver the procured goods.
- Since our framework does not include routing decisions, only distribution of goods, the distances between suppliers, DC and organizations do not constrain the problem. Thy only affect the supply costs, which includes transportation costs. But the TSSP is generic enough to allow including distance constraints for Suppliers, DC or organizations, if needed.

4.1.2 Decision epoch

The decision on the acquisition and distribution of items takes place on a regular basis (e.g. daily, weekly, etc.) at the beginning of each decision epoch, for the whole planning horizon.

4.1.3 State of the system

The system states represent the available inventory level, and can be represented by units of product (blood packs, bottles of water, etc.). Therefore, the state space is discrete and denoted by $\Lambda = \{0, 1...., W_{cd}\}$, where 0, 1, $\dots$, W_{cd} are possible inventory levels at a certain decision epoch and W_{cd} is the maximum capacity of the DC.

4.1.4 Actions, cost function and long-term objective

The decisions include firstly the purchase amount (sum of purchases from all suppliers), obtained from the MDP. Then, the TSSP defines the amounts purchased from each supplier, the amount of goods distributed and the shortage allowed to each organization in order to better meet the overall demand.

The MDP aims to find an optimal stationary purchase policy $\pi^* : \Lambda \to A$ from the set of feasible purchasing policies Π. Any policy $\pi \in \Pi$ specifies a purchase $\alpha \in A_\lambda$ for each inventory level $\lambda \in \Lambda$, where A_λ denotes the set of purchase actions available at state λ and $A = \bigcup_{\lambda \in \Lambda} A_\lambda$ is the set of available actions. For each inventory level $\lambda \in \Lambda$, and purchase amount $\alpha \in A_\lambda$, a parameter evaluation algorithm distributes the purchase amount between the competing suppliers and specifies the optimal distribution policy given the state action pair (λ, α).

For each state-action pair (λ, α), the parameter evaluation algorithm solves a two-stage stochastic programming problem (TSSP). Considering the overall order α, the first stage finds the optimal orders from the reliable and unreliable suppliers, resp. a and b such that $\alpha = a + b$. Given the initial inventory λ and individual orders to the suppliers (a and b), the second stage of the TSSP algorithm defines the amount of products to be distributed to each individual humanitarian organization after the realisation of the uncertainties. The TSSP algorithms seeks to minimise the overall single-period purchase, inventory holding, distribution and shortage cost $C(\lambda, \alpha)$.

This overall cost is then fed to the MDP for multi-stage optimisation. Let t denote the time period and $(\lambda_t, a_t) \in \Lambda \times A$, $t \geq 0$ be the MDP's state-action pair at period t. The MDP's transition probabilities - $p^{\alpha}_{\lambda\lambda'} = P(\lambda_{t+1} = \lambda' | \lambda_t = \lambda, a_t = \alpha)$ - will be determined by the TSSP algorithm, as illustrated in Figure 4.2. The TSSP model used is detailed in section 4.1.5. The evolution of this process is controlled by a Markov Chain $\{Z_t, t \geq 0\}$ under a control policy $\pi \in \Pi$, where $Z_t = \lambda_t$ is the inventory level at time t. Now, let $\tau > 0$ be a random planning horizon, to account for the random duration of a disaster response. The MDP's objective is to find a policy $\pi \in \Pi$ that minimises the overall cost of the disaster response, defined as:

$$v_{\pi}(\lambda) = E_Z \left\{ \sum_{t=0}^{\tau} C(\lambda_t, \pi(\lambda_t)) | Z_0 = \lambda \right\}, \forall\, \lambda \in \Lambda \tag{4.1}$$

where τ is assumed to be a geometrically distributed random variable with parameter $0 < p = 1 - \gamma < 1$, which means that $P(\tau > t) = \gamma^t$, $t \geq 0$. Hence, it follows that:

$$v_{\pi}(\lambda) = E_Z \left\{ \sum_{t=0}^{\infty} \gamma^t C(\lambda_t, \pi(\lambda_t)) | Z_0 = \lambda \right\}, \forall\, \lambda \in \Lambda. \tag{4.2}$$

Eq. (4.2) shows how to design an equivalent infinite-horizon discounted cost MDP to optimise a finite-horizon response for a system with random response time. For finite-duration disaster responses, we seek a policy $\pi^* \in \Pi$ such that

$$v^*(\lambda) = v_{\pi^*}(\lambda) \leq v_{\pi}(\lambda), \forall \pi \in \Pi. \tag{4.3}$$

Under mild conditions, the solution to (4.3) exists and is unique (Putterman 1994).

Alternatively, for long-term responses or for systems in which an annual budget is prescribed to deal with disasters in a certain region, we can use an infinite-horizon MDP with the average cost criterion. In that case, each policy $\pi \in \Pi$ is associated to a long-term average cost given by

$$\eta_{\pi} = \lim_{T \to \infty} \frac{1}{T} E \left\{ \sum_{t=0}^{T} C(\lambda_t, \pi(\lambda_t)) \right\}, \tag{4.4}$$

recalling that $\pi(\lambda_t)$ is the action at inventory level λ_t. The objective is to find an optimal policy $\pi^* \in \Pi$ such that:

$$\eta_{\pi^*} \leq \eta_{\pi}, \forall\, \pi \in \Pi. \tag{4.5}$$

4.1.5 Two-stage stochastic model

The TSSP model seeks the optimal purchase quantity a (resp. b) from the unreliable (resp. reliable) supplier, as well as the distribution policy that minimises the single-period cost $C(\lambda, \alpha)$ for an initial inventory λ and a total purchase $\alpha = a + b$. At each time period, the unreliable supplier fails to deliver the requested products with a given probability, in which case the acquisition cost is lost. The probability of delivery fail is a parameter of the model, as is the demand distribution for each individual humanitarian organization.

We assume that both the organizations and the distribution center have a limited storage capacity and both suppliers have limited supply capacity. However, the inventory level is fixed at α for the parameter evaluation algorithm, hence we do not need to include the distribution center capacity at this TSSP. The decision variables and parameters of the TSSP algorithm are described below.

Table 4.1: Decision variables

Variable	Description
a_t	amount purchased from supplier a (reliable) on period t
b_t	amount purchased from supplier b (unreliable) on period t
x_{it}	amount sent to organization i on period t
y_{it}	amount of shortage allowed to the organization i on period t

Table 4.2: Parameters and sets

Parameter	Description
I	set of humanitarian organizations
q_a	purchase cost per unit from supplier a
q_b	purchase cost per unit from supplier b
q_h	inventory holding cost
h_t	inventory level at the beginning or period t
α	total purchased amount
q_{e_i}	delivery cost per unit to organization i
q_{f_i}	shortage cost per unit to organization i
W_i	storage capacity of organization i
W_a	capacity of the reliable supplier
W_b	capacity of the unreliable supplier
s	Scenario, comprised of the join realization of demand and unreliability

Table 4.3: Uncertain Parameters

Parameter	Description
R_t	Realization of the delivered goods by the unreliable supplier
D_t	set of the demands of all organizations on a given period t
d_{it}	demand of organization i on a given of period t
ξ_t	random vector with finite realizations $\xi_t^1, ..., \xi_t^s$ on period t, where $\xi_t^s = (D_t^s, R_t^s)$ is a random vector that represents the joint realization (s) of D_t and R_t for a given scenario s

The two-stage model described below decides the purchase quantities a_1 and b_1 at the first state and the distribution policy at the second stage:

$$\text{Minimise } q_a a_1 + q_b b_1 + q_h h_1 + E[Q_2^s(a_1, b_1, \xi_2^s)] \tag{4.6}$$

subject to:

$$a_1 + b_1 = \alpha \tag{4.7}$$

$$a_1 \leq W_a \tag{4.8}$$

$$b_1 \leq W_b \tag{4.9}$$

$$a_1, b_1 \in \mathbb{Z}^+, \tag{4.10}$$

where:

$$Q_2^s(a_1, b_1, \xi_2^s) = \min \sum_i (q_{e_i} x_{i2}(\xi_2^s) + q_{f_i} y_{i2}(\xi_2^s)) \tag{4.11}$$

subject to:

$$a_1 + b_1 R(\xi_2^s) + h_1 - \sum_i x_{i2}(\xi_2^s) \geq 0 \tag{4.12}$$

$$x_{i2}(\xi_2^s) + y_{i2}(\xi_2^s) = d_{i2}(\xi_2^s),\ \forall\, i \in I \tag{4.13}$$

$$x_{i2}(\xi_2^s) \leq W_i,\ \forall\, i \in I \tag{4.14}$$

$$x_{i2}(\xi_2^s), y_{i2}(\xi_2^s) \in \mathbb{Z}^+ \tag{4.15}$$

The objective function (4.6) aims to minimise the inventory holding and purchase costs, from both suppliers. Equation (4.7) ensures that the number of items purchased match the value obtained by the MDP algorithm. Equations (4.8) and (4.9) represent the supplier capacity constraints. Equation (4.10) expresses the integer nature of the variables of the first stage.

At the second stage, Eq. (4.11) represents the total distribution and shortage costs. Equation (4.12) represents the inventory balance and ensures that the amount of distributed goods cannot exceed the amount purchased plus the initial inventory. The balance between the amount sent to each organization and the shortage allowed for each organization is enforced by Eq. (4.13). Equation (4.14) ensures that the inventory capacity of each organization is respected. Equation (4.15) expresses the integer nature of the variables of the second stage. The cost $C(\lambda, a)$ returned to the MDP is the solution of (4.6).

4.1.6 The parameter evaluation algorithm

As previously detailed, the parameter evaluation algorithm uses a TSSP to find the optimal acquisition and distribution policy, as well as the MDP parameters for each state-action pair. The detailed acquisition and distribution policies, as well as the one-period cost $C(\lambda, \alpha)$, are directly obtained from (4.6). Now let $p^{\alpha}_{\lambda\lambda'}$ be the probability of transitioning from inventory level $\lambda \in \Lambda$ to $\lambda' \in \Lambda$ in two subsequent periods, given that the total purchase is $\alpha \in A$.

To evaluate the transition probabilities $p^{a}_{\lambda\lambda'}$, we evaluate the new DC's inventory level λ' at the outset of the next period for each demand scenario, under the optimal distribution and acquisition policy. Each instance of the algorithm finds at most N new DC inventory levels, where N is the total number of demand scenarios. For each of these new inventory levels, it is also possible to identify the MDP's available action set $A_{\lambda'}$, by considering the DC storage capacity, meaning that an action $\alpha \in A_{\lambda'}$ if $\lambda' + \alpha \leq W_{dc}$

The reasoning behind the development of the algorithm is twofold. Firstly, it avoids the combinatorial explosion of the number of possible actions when dealing with acquisition from multiple suppliers and distribution for multiple organizations, which could render the MDP intractable. Secondly, it provides scalability to the proposed framework, supporting the growth of the problem by adding more suppliers or receiving HOs with simple changes in the TSSP, without sacrificing the MDP's performance.

Execution

Assume that $TSSP^{\lambda,\alpha}$ is the two-stage stochastic problem described with parameters $h_t = \lambda$ and the total acquisition of α items. Then $C(\lambda, \alpha) = Z^{\lambda,\alpha}$, where the latter is the value of the objective function for the $TSSP^{\lambda,\alpha}$. Finally, let

$$h_{t+1}(\xi^s_t) = a_t + b_t R(\xi^s_t) + h_t - \sum_i x_{it}(\xi^s_t) \tag{4.16}$$

be the inventory at period $t+1$, given scenario ξ^s_t. Then

$$p^{\alpha}_{\lambda\lambda'} = \sum P(\xi^s_t) \mathbb{1}_{\{h_{t+1}(\xi^s_t)=\lambda' | h_t = \lambda\}} \tag{4.17}$$

where $\mathbb{1}_{\{\cdot\}}$ is the indicator function and $P(\xi^s_t)$ is the probability of such scenario. Thus, $p^{\alpha}_{\lambda\lambda'}$ is the overall probability that the next state will be λ' considering all possible scenarios, initial inventory λ and overall purchase α. Each realisation ξ^s_t is comprised of a demand realisation $D = D^s_t$ and a realisation of the delivered purchase $R = R^s_t$, and has probability $P(\xi^s_t)$.

Now, to solve the MDP and obtain the optimal purchasing total for each initial state $\lambda \in \Lambda$, we input the costs and transition probabilities for each state-action pair into the respective MDP formulation, i.e. (4.3) for finite-horizon planning and (4.5) for the long-term average cost formulation and solve the MDP via classical value or policy iteration (Putterman 1994).

Finally, assuming that $\pi^*(\lambda) = \alpha$ is the optimal total purchase at state $\lambda \in \Lambda$, then the detailed purchase plan a and b such that $a + b = \alpha$ and the detailed distribution plan for each realised scenario will be obtained from the corresponding $TSSP^{\lambda,\alpha}$ formulation (4.6).

4.2 Experimentation

The two-stage stochastic programming (TSSP) model is implemented using the Xpress Workbench 3.3.2 tool, running in Microsoft Windows 10 (64 bits), with 16 GB RAM and an Intel Core i7-8650U CPU (8 CPUs) with approximately 2.11 GHz. The Value Iteration algorithm was programmed and solved using the C# programming language, using the Xpress Workbench library to interface with the TSSP model.

To demonstrate the model's applicability, we present 2 different numerical experiments. First we explore the distribution of water supplies from a distribution center (DC) to Support Points (SP) for landslide relief operations in the city of Petrópolis (Brazil), assuming a relatively short-term operation, leading to a finite time horizon implementation. Then, we analyse the distribution of hygiene kits (tooth paste, tooth brush, etc.) to different municipalities in the West Java province (Indonesia), which needs to make procurement decisions regularly (on a monthly basis). Therefore, we assume a long term operation, with an infinite time horizon implementation. We present both experiments to show that the presented model can be applied to both long and short term operations.

4.2.1 Petrópolis experiment

Petrópolis is located in the mountainous region of the state of Rio de Janeiro, approximately 70 km west of the state capital. Comprised of steep slopes subjected to tropical weather with with no drought season and a high volume of precipitation throughout the year, the region is highly susceptible to mass movements (landslides), a problem that is aggravated by the illegal occupation in the hillsides and deforestation and poses a serious threat to the population (Ferreira et al. 2017). Between 1991 and 2013, 18 landslides were registered in the city, with a death toll of 146 people, which corresponds to 27% of the total of deaths due landslides in Brazil in that period (Ferreira et al. 2017). More recently, in February 2022, a precipitation volume of 258 ml in only 2 hours triggered landslides across different regions of the city, leading to 233 fatal victims and over 3.000 families affected and displaced from their homes (CNNBrasil 2022). Such a background highlights the importance of preparedness and quick response for landslides in the city.

Landslide response operations are very challenging, as the surroundings of the affected areas become unstable and new landslides can follow even after the rainy period is over. This jeopardises rescue operations, hinders or even prevents the return of families to their homes. Moreover, even non affected locations that are classified as 'risk areas' will also require evacuation until weather conditions improve. Hence, the relief operation may last from a few days to weeks after the event, and the needs of the region must be constantly analysed and updated.

Therefore, we implement our framework to response operations for landslides in the city. We assume that a municipal distribution center (DC) will supply different SPs in each district of the city, which in return will provide the required assistance to the affected communities. Since new landslides or evacuation orders can be triggered constantly, the decision on the number of goods to be supplied at each period needs to be constantly revised, based on the probabilities of events in each region. This makes our framework a good match for the needs of the landslide relief operations.

The city is divided in 5 different districts (Centro, Cascatinha, Itaipava, Pedro do Rio and Posse). The city center (Centro) is the most populous area, with higher number of areas prone to landslides (Vulnerable Communities – VC). The Petrópolis Municipal Plan of Mass Movement Risk Reduction (Theopratique 2017) identified 233 VCs in the city, distributed across the districts as detailed in table 4.4.

Table 4.4: Number of vulnerable communities (VC) per district

	Centro	Cascatinha	Itaipava	Petro do Rio	Posse
# of VC	101	39	35	32	26

According to Theopratique (2017), each VC in the city can be divided into Risk Areas (RA). Each RA assigned one of seven possible categories of risk (CR), which are classified according to the probability of a landslide event and the magnitude of an impact in the RA, based on the geological and physical characteristics of the site. Table 4.5 shows the probabilities of landslide and the respective impact for each category of risk, according to Theopratique (2017). These CR are applied to all RA of the city.

Table 4.5: Categories of risk

Category of risk	I	II	III	IV	V	VI	VII
Probability	0.083	0.13	0.11	0.25	0.19	0	0.22
Risk factor	0.3	0.5	0.4	0.9	0.7	0	0.8
New category of risk	VI	IV	V	I	III	VII	II

To simplify the interpretation of the experiment and the analysis of the results, we reorganise the CRs by Risk Factor, as shown in the tables 4.5 and 4.6, where CR I has the highest Risk factor, and so on. This results in the *new category of risk* which will henceforth be referred to as CRs. In our experiment, we assume each CR as an impact scenario, where with the given probability, the RAs assigned to the CR will be evacuated due an landslide and the number of people living under the RAs determine the demand for aid.

Figures 4.3, 4.4 and 4.5 the risk area (RA) composition of *Oswero Vilaça*, one of the communities with highest risk of landslides in the city, as can be observed in the level curves in figure 4.3. The coloured areas in figure 4.3 represent the respective CR, presented in table 4.5.

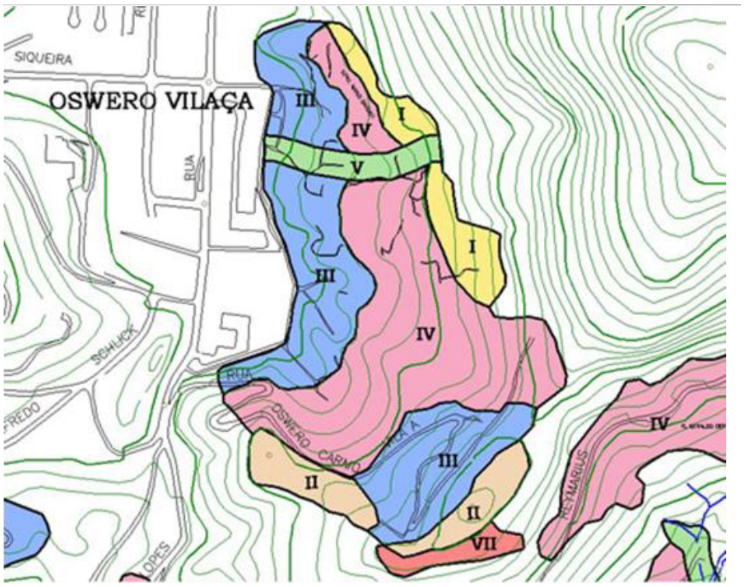

Figure 4.3: Risk Areas for Oswero Vilaça Community

Figure 4.4: Satellite view of Oswero Vilaça Community

Figure 4.5: Overview of Oswero Vilaça Community

Table 4.6: Number of houses per CR per district

Category of risk	I	II	III	IV	V	VI
Centro	3748	1913	1495	2523	4691	747
Cascatinha	234	171	1133	501	2389	1334
Itaipava	23	258	880	84	1682	387
Pedro do Rio	287	110	404	29	601	292
Posse	362	44	323	60	476	393

Furthermore, we assume that if an area with a given risk factor is impacted, all areas with a higher risk factor will also need evacuation, hence, we assume a cumulative demand, where, for instance, if the RAs with CR II are evacuated (risk factor = 0.8), the RAs with CR I (risk factor = 0.9) will also need evacuation. The reasoning behind this assumption is simple: since risk factors are calculated based on the magnitude of impact in the area, if a landslide is powerful enough to trigger an evacuation of an area, it is certainly powerful enough to evacuate all areas with a higher impact factor as well (more susceptible to landslides). Finally, we assume an average number of 4 people per residence in each RA. Hence, the total demand for each CR in each district of the city is given by the sum of houses in each RA under the CR, multiplied by 4. Table 4.6 depicts the total number of houses per district per CR. It is also important to note that CR VII has Risk factor equals 0, hence no evacuation or impact is expected in these RA, therefore we omitted it in table 4.6.

To support the evacuees from risk areas during landslides, we assume that each district installs a Support Point (SP), to provide shelter, food and to support rescue operations. Each SP is supplied by the municipal DC, which centralizes the distribution of supplies. The DC can be supplied by donations of goods (unreliable supplier) or acquire the required goods from a commercial supplier (reliable supplier). In our experiment, we assume the distribution of one commodity: water bottles. It is believed that the human body needs around 2 litters (l) of water daily to survive. Since $2l$ water bottles are common in Brazil, we assume a daily need of 1 water bottle / person / day (decision epoch).

In each decision epoch the DC will choose the amount of goods to acquire from the reliable supplier and the amount of goods it will request to the community as donations. The amount of goods received as donations each period after the DC's plea vary according a binomial distribution $X \sim \mathcal{B}(3, 0.5)$, according to the table 4.7.

Later, to analyse how unreliability affects the optimal acquisition policies, we present the optimal acquisition policies for both suppliers under the same action set (A_1), assuming a more reliable flow of donations, which follows a binomial distribution $X \sim \mathcal{B}(3, 0.6)$ and a less reliable flow of donations, which follows a binomial distribution $X \sim \mathcal{B}(3, 0.4)$, as presented in table 4.7.

Table 4.7: Probability of percentage of donations received

% of plea received	25	50	75	100
Baseline Probability	0.125	0.375	0.375	0.125
Less reliable scenario	0.216	0.432	0.288	0.064
More reliable scenario	0.064	0.288	0.432	0.216

Therefore, for every CR (impact scenario), we have 4 different problem scenarios, one for each percentage of plea met, that directly affect the distribution capacity of the DC. Hence, our experiment has a total of 24 scenarios, which accounts for the different risk areas (6 CRs) and percentage of donations received. For each support point (SP) we assume an arbitrary storage capacity, which constraints its ability to receive goods. Table 4.8 summarises stock capacity per SP in units of product.

Table 4.8: Storage capacity in units of product for each SP

	Support Points (SP)				
	Centro	Cascatinha	Itaipava	Pedro do Rio	Posse
Storage capacity	70,000	25,000	15,000	10,000	10,000

Moreover, the DC has a storage capacity of 120,000 units of product. The supply capacity for the reliable supplier is 100,000. There is no limitation on the amount of goods the DC can request as donation, hence, we assume it up to the total DC capacity of 120,00 units. The logistical costs assumed in the experiment are presented in Table 4.9, where the values are arbitrarily chosen, with shortage costs being a much higher value than delivery costs, in order to penalise shortages in the objective function.

Table 4.9: Experiment costs

Cost set	Value
Purchase + transport + handling per unit from the reliable supplier (a)	$ 04.00
handling + sorting per unit from donations - unreliable supplier (b)	$ 01.60
Inventory holding cost per unit	$ 01.00
Shortage cost per unit to a SP	$ 35.00
Delivery cost per unit to a SP	$ 05.00

We also perform another quick sensitive analysis regarding costs by increasing the shortage costs from \$ 35.00 to \$ 45.00, to evaluate how an increase on the shortage costs affects the acquisition policies.

We analyse our experiment under 3 different action sets A, recalling that each element in $\alpha \in A$ represents the total number of items to be acquire at a given period. The first action set assumes 11 possible actions, ranging from acquiring 0 units to acquiring 100,000 units, with increments of 10,000; this yields

$$A_1 = \{0; 10,000; 20,000; 30,000; 40,000; 50,000; 60,000; 70,000; 80,000; 90,000; 100,000\}.$$

The second set (A_2) also ranges from 0 to 100,000 units, but with increments of 5,000 units, yielding to 21 possible actions. Finally, the third set (A_3) ranges from 0 to 100,000 units with increments of 2,500 units, leading to 41 possible actions. This not only acts as sensitivity analysis for the proposed model, but also allows us to assess how the model behaves regarding the time and memory need for different problem sizes.

Finally, to determine the duration of response operations in the region, we gathered information from fifteen Non-Governmental organizations (NGO) that acted in the relief operations from the last landslide disaster in the city, in February 2022. Governmental information was not yet available during the execution of this experiment. We used a curve fitting method (executed in python) and verified that the empirical data received fits a geometric distribution with parameter $p = 0.0185$ and mean = 66 days, as can be observed in figure 4.6, which compares the empirical cumulative probability distribution obtained with the cumulative geometrical probability distribution with $p = 0.018$. The discount factor is then set up as $\gamma = 1 - p = 0.9815$ in the objective function - Eq. (4.2).

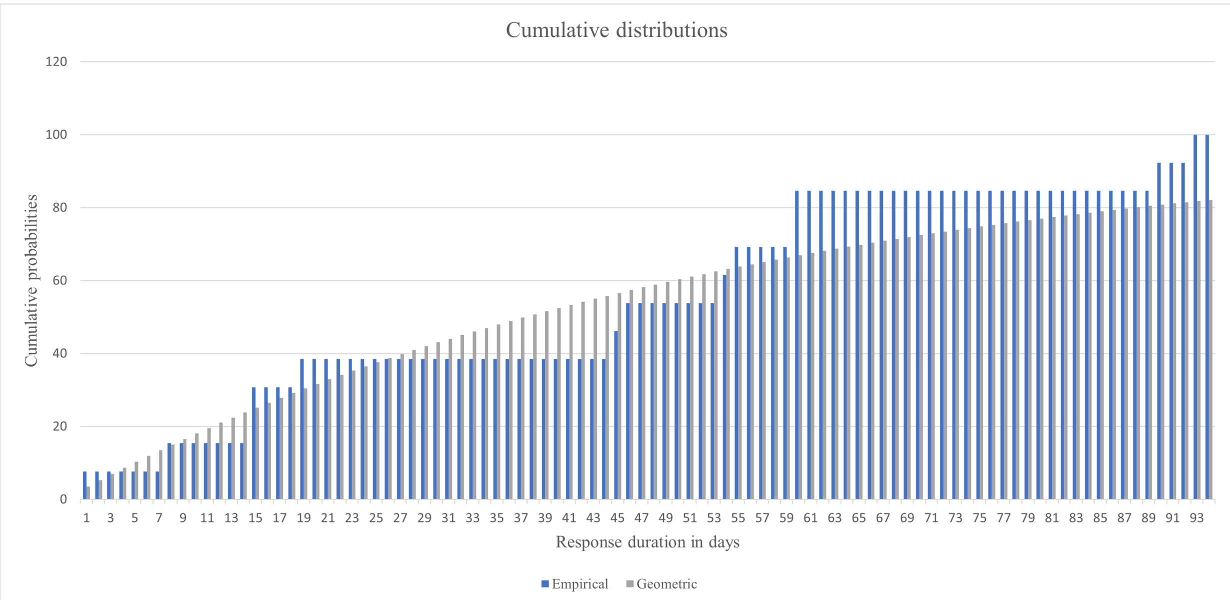

Figure 4.6: Comparison of empirical and geometrical cumulative probability distribution

The Q-Q graph presented in Figure 4.7 contrast the empirical distribution with the fitted geometric distribution and shows that their quantiles indeed have a good match overall, with a minor distortion after the 8-th decile, where empirical data seems to be a little higher than the exponential distribution. The trend line for the Q-Q dispersion also demonstrates that the empirical data does not stray too far from the x=y line and that the empirical data gathered is more dispersed than the geometrical distribution. However, it is noteworthy that not all organizations acting on the disaster provided sufficient data and official data is still not available, adding more data points to the distribution could provide a smoother fit for the distributions.

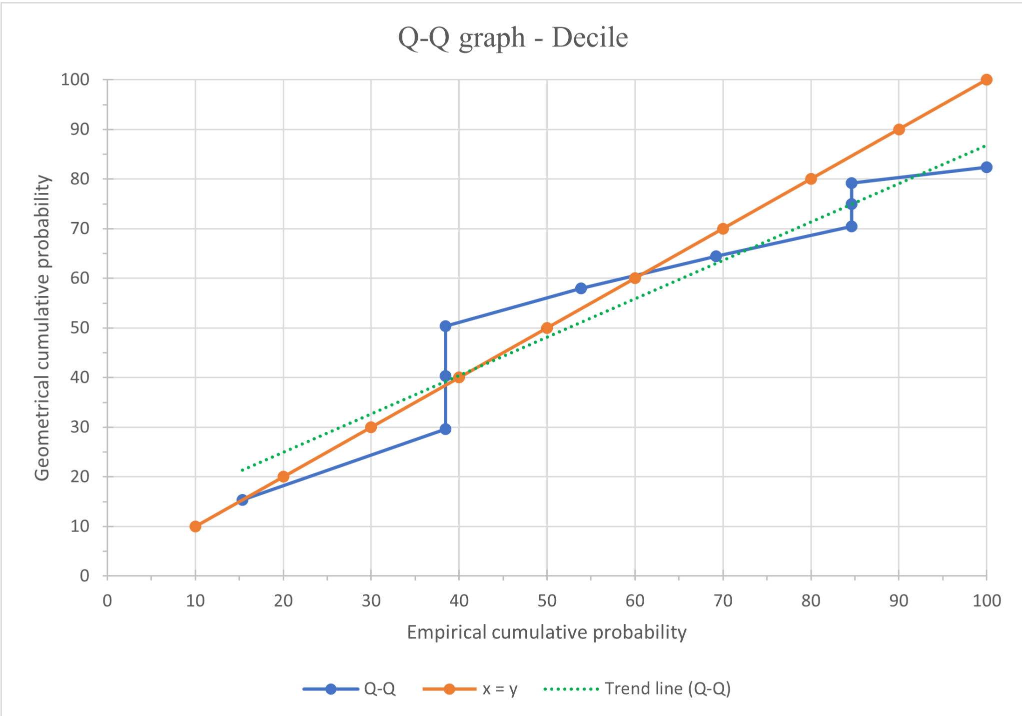

Figure 4.7: Q-Q graph for comparison of deciles between empirical and geometrical distributions

4.2.2 Results

This section discusses and summarises the experimental results. Firstly, we present the information that the framework offers to the decision maker in order to optimise the relief distribution. Then we briefly analyse the efficiency of the proposed algorithms in solving relatively large-scale models, demonstrating that the model provides optimal results quickly enough to be used in real operations.

Decision making

Table 4.10 shows the optimal purchase policy for the DC, assuming a set of 11 available actions (A_1). The table displays the optimal purchase amount for each range of inventory levels. Which means that, for instance, with an inventory level ranging from 0 to 19.999, the decision maker should acquire 100.000 units of product.

Table 4.10: Optimal policy for A_1

Inventory level (units)	Optimal purchase amount (units)
0 - 19,999	100,000
20,000 - 29,999	90,000
30,000 - 39,999	80,000
40,000 - 49,999	70,000
50,000 - 59,999	60,000
60,000 - 69,999	50,000
70,000 - 79,999	40,000
80,000 - 89,999	30,000
90,000 - 99,999	20,000
100,000 - 120,000	10,000

Along with Table 4.10, Figure 4.8 shows how the purchase policy varies with the inventory levels of the DC, for 11 available actions. These allow us to observe how the optimal purchase quantities decrease as the inventory level grows. This behaviour is expected, since the inventory in hand starts playing a bigger role in supplying the organizations as the DC's stock increases.

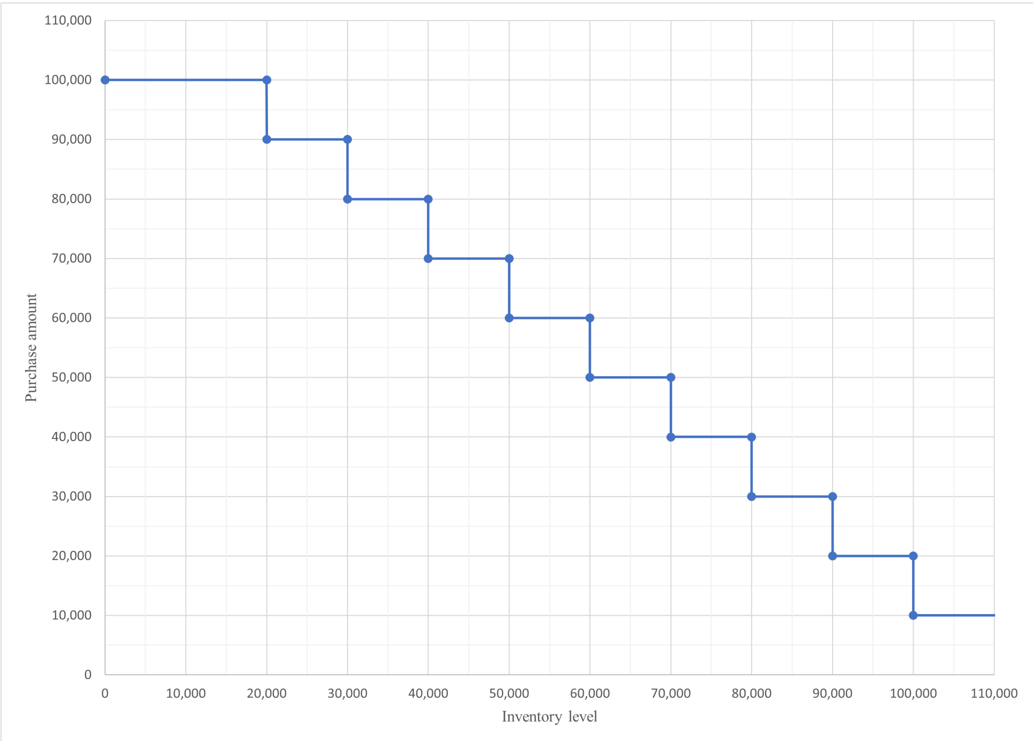

Figure 4.8: Optimal policies 11 available actions

Figures 4.9 and 4.10 show the optimal policies assuming 21 (A_2) and 41 (A_3) actions, respectively. They show the same overall behaviour, with the order sizes decreasing as the stock level grows. It is also important to note that the more actions the decision maker can take, the faster the number of purchased items diminishes. This can be easily explained by the fact that the decision maker can make more precise acquisitions accordingly to his/her needs, avoiding overstocking whilst also avoiding shortages for the Support Points.

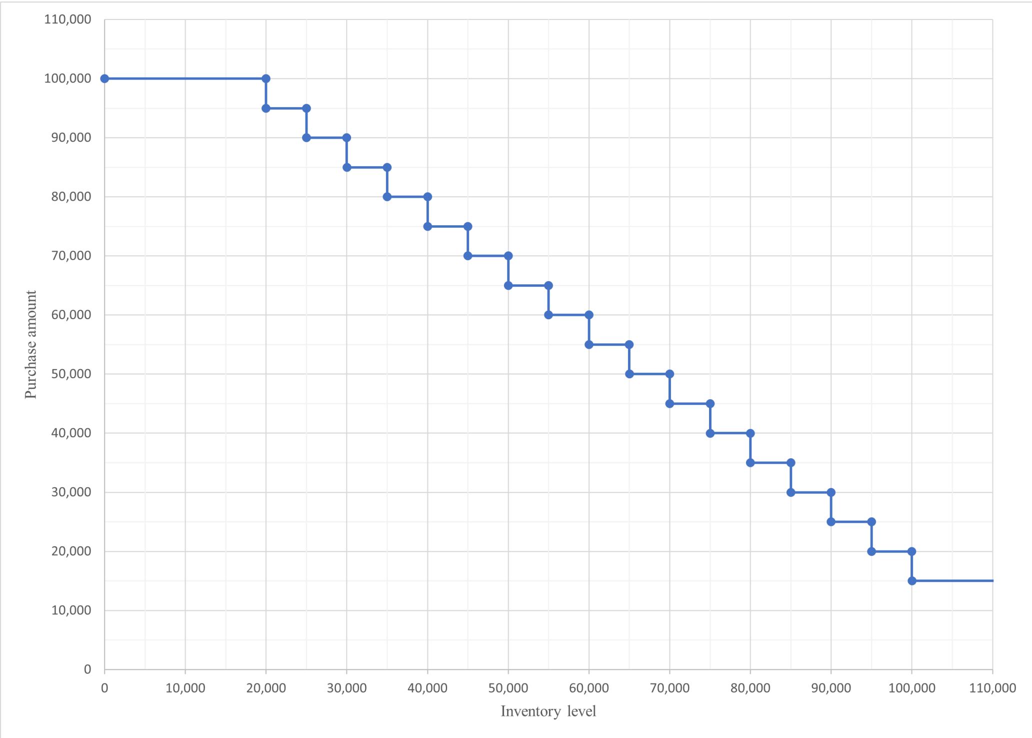

Figure 4.9: Optimal policies for 21 available actions

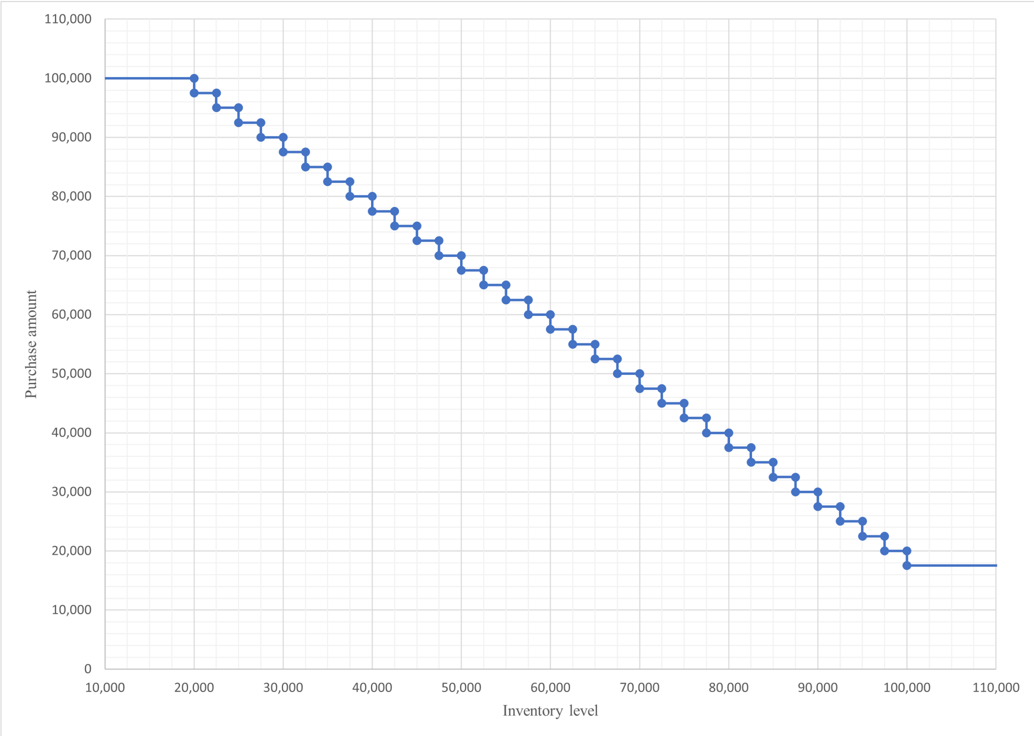

Figure 4.10: Optimal policies for 41 available actions

Table 4.11 complements Figures 4.8, 4.9 and 4.8, and unfolds the expected average costs for each action set. It demonstrates that with more available actions one can reduce the long-term cost, as additional purchasing actions can lead to smaller purchase costs.

Table 4.11: Average costs ($) for action sets studied

	11 actions	21 actions	41 actions
Average costs	507,426.61	506,818.76	505,884.84

Figure 4.11 summarises and compares the optimal policies for all studied action sets. It shows that adding granularity to the action space allows for more flexible policies which, as depicted in Table 4.11, yield better long-term costs.

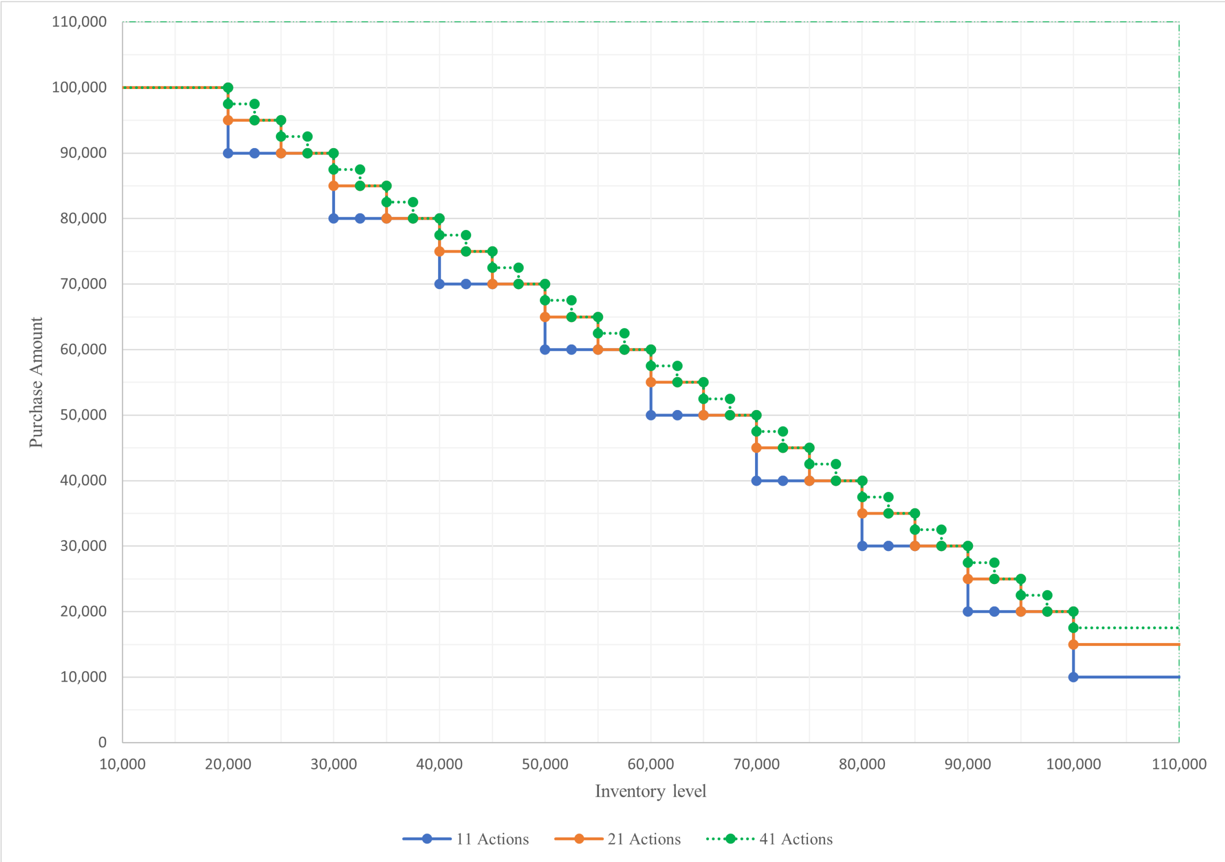

Figure 4.11: Summary of optimal policies for all available action sets

The optimal distribution policies and detailed acquisition policies for both suppliers are obtained through the execution of the TSSP, with inventory level and total purchase action taken as input parameters. This execution takes place in the parameter evaluation algorithm, as detailed in Section 4.1.6. Figure 4.12 shows the variation on the acquisition amounts from both suppliers with the inventory level of the DC, for A_1 action set.

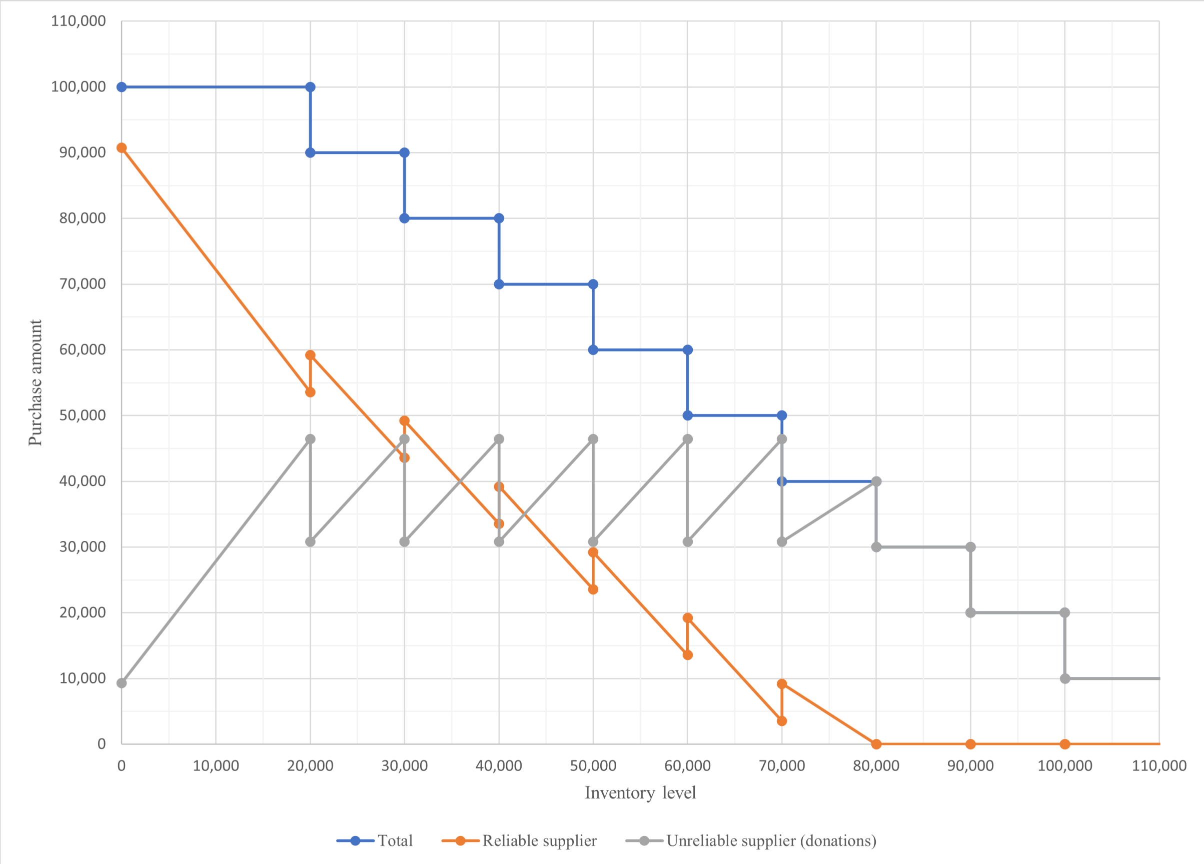

Figure 4.12: Acquisition variation per supplier for A_1 action set

It is noticeable that as the inventory level rises, the amount of purchased items from the reliable supplier diminishes and the amount acquired from the unreliable supplier increases. This can also be explained by the amount of items the decision maker has at hand, items in stock can *replace* items acquired from the reliable supplier, allowing the decision maker to choose to buy from the unreliable supplier at a smaller cost.

Figure 4.12 also allows us to observe a saw-tooth behaviour for the acquisition policies of both suppliers, with the unreliable supplier being more stable whilst the reliable supplier sees their requests decreased. The spikes in the acquisitions from the reliable supplier match the decrease of the total amount of products purchased. With a smaller quantity purchased, the decision maker has a smaller slack to deal with unreliability, which leads to small increases in the acquisitions from the reliable supplier when the total purchase amount is reduced.

Finally, it shows that from 80,000 items in stock onward, all the requests can be made from the unreliable supplier, since the DC already have enough stock at hand, allowing the decision maker to choose the cheapest option, assuming more risks due unreliability, without jeopardizing the operation. Here, it is important to note that in figure 4.12, the "Total" line is superposed by the "Unreliable supplier" line, because all the purchases are made to the unreliable supplier.

Figures 4.13 and 4.14 represents the purchase policies for reliable and unreliable supplier (donations), for both the less and more reliable donations scenarios, respectively. Along side Figure 4.12, they display how the acquisition policy for the reliable supplier diminishes faster with a more reliable flow of donations. This is an expected behaviour, since donations are much cheaper than acquisitions from a reliable supplier, leading to smaller overall costs, presented in table 4.12, if the decision maker can rely on them to run the operation.

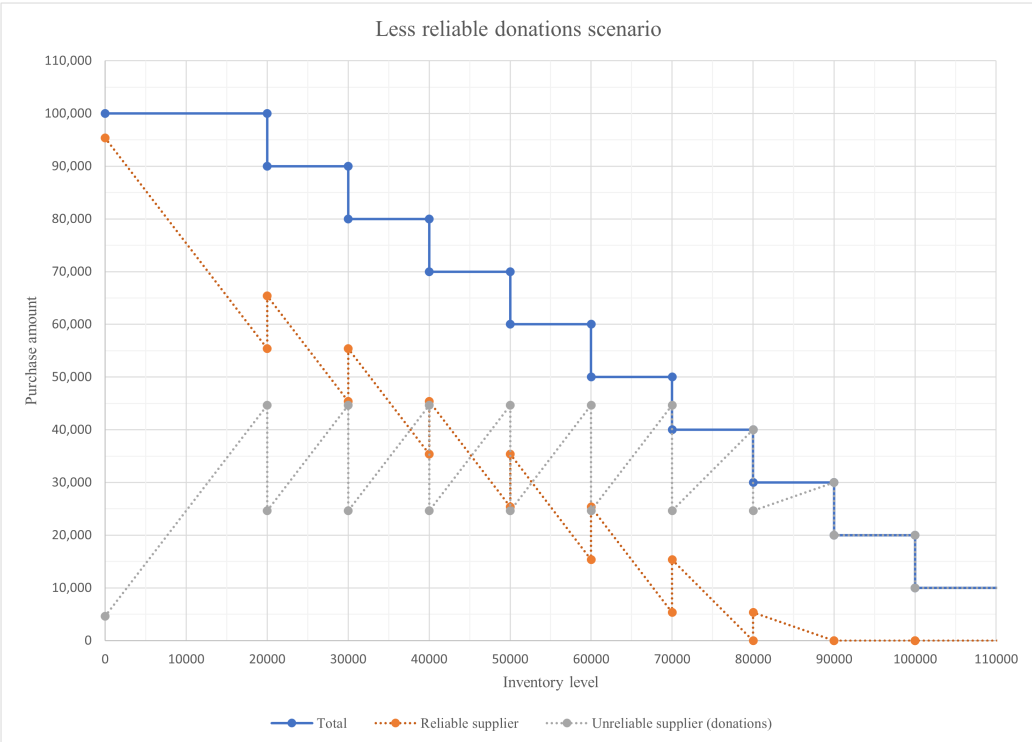

Figure 4.13: Acquisition variation per supplier for A_1 action set with less reliable donations ($\mathcal{B}(3, 0.4)$)

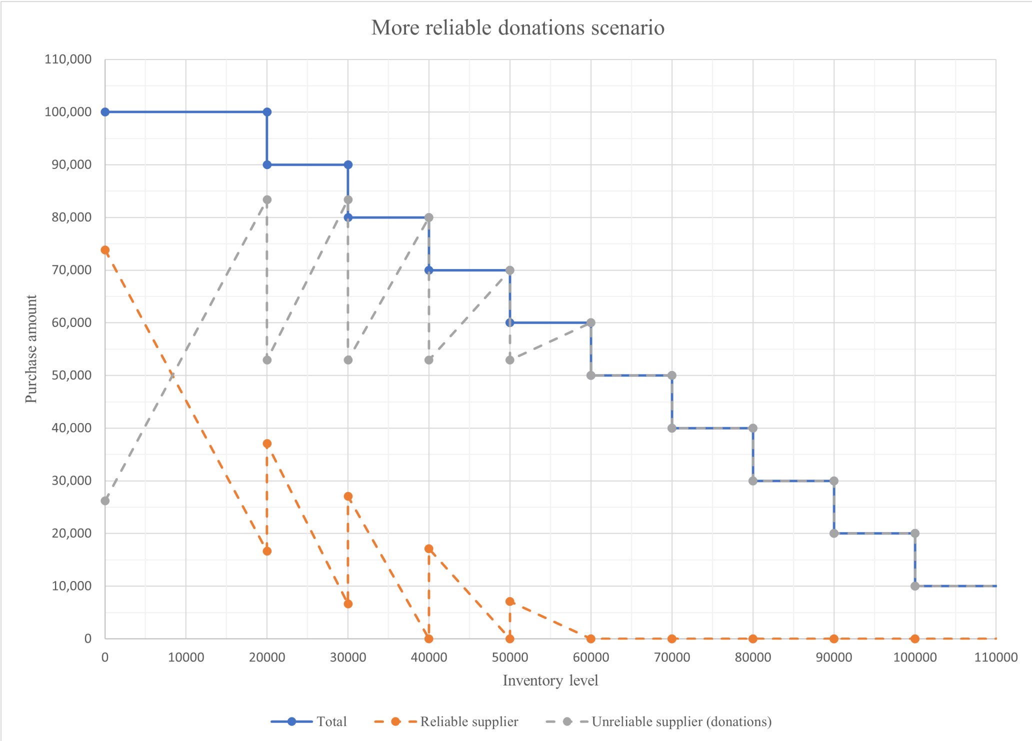

Figure 4.14: Acquisition variation per supplier for A_1 action set with more reliable donations ($\mathcal{B}(3, 0.6)$)

Table 4.12: Average costs ($) for different levels of reliability of donations, assuming A_1 action set

	Less reliable scenario	Baseline scenario	More reliable scenario
Average costs	514,641.47	507,426.61	488,141.65

The results obtained by increasing the shortage costs of the system can be observed in Figure 4.15. We observe that the total acquisition amounts do not change, however, since shortage now have a much deeper impact on the overall costs of the system, the amount acquired from the unreliable supplier is smaller is comparison to the baseline scenario with A_1. For instance, for an inventory level of 0, in the baseline scenario we acquire a total of 90,736 units from the reliable supplier and 9,264 units from the unreliable supplier, whereas in the increased shortage costs scenario the acquisition policies for reliable and unreliable supplier is 95,368 and 4,632 units, respectively.

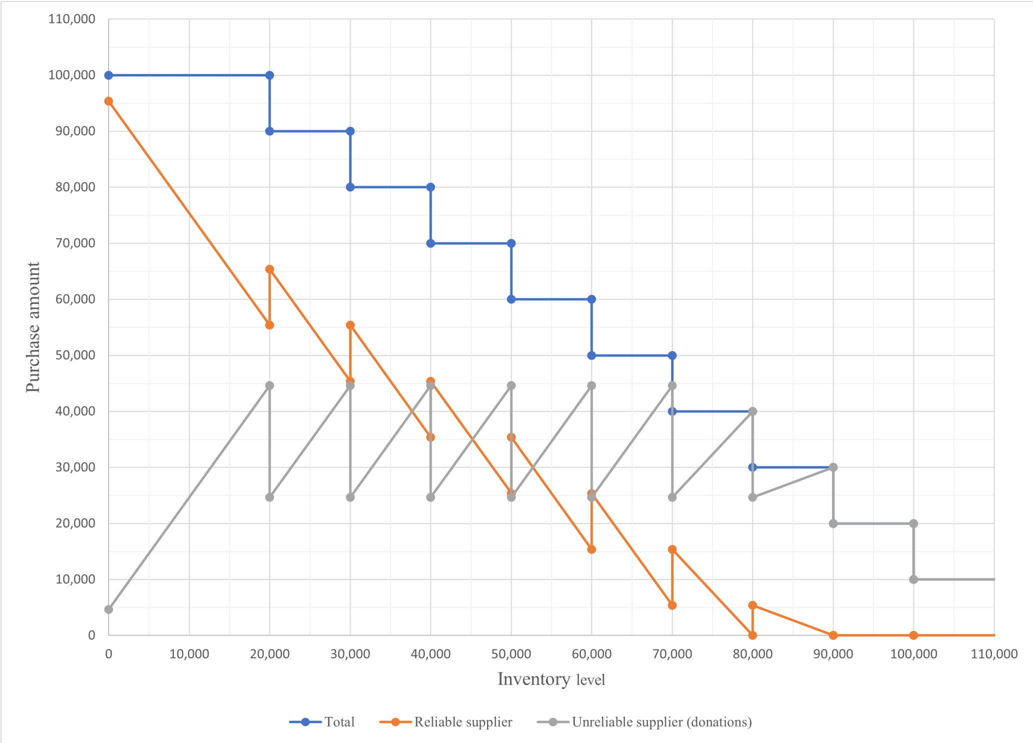

Figure 4.15: Acquisition variation per supplier for A_1 action set with increased shortage costs

Finally, an example of distribution policy is given in Figures 4.16, 4.17, 4.18 and 4.19 which convey an optimal distribution policy for A_1, assuming an inventory level equal to 0, for which Table 4.10 presents an optimal purchase policy of 100,000 items

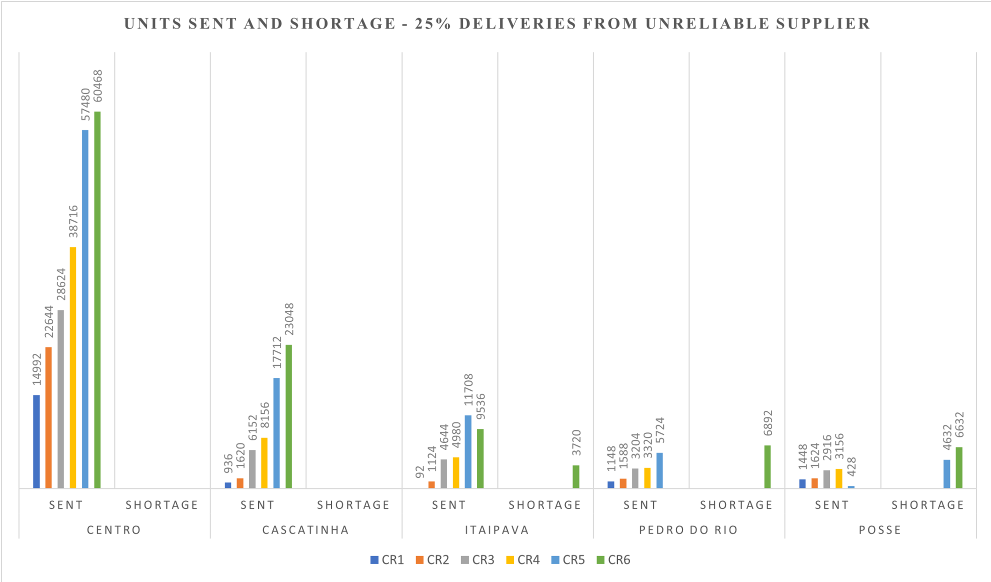

Figure 4.16: Units of product sent to each SP per scenario for 25% of requested donations received

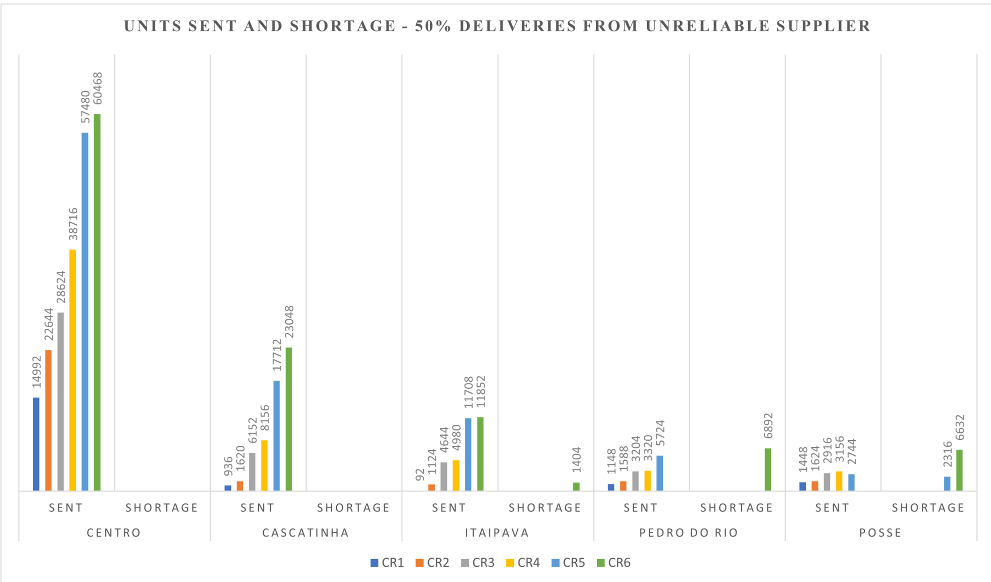

Figure 4.17: Units of product sent to each SP per scenario for 50% of requested donations received

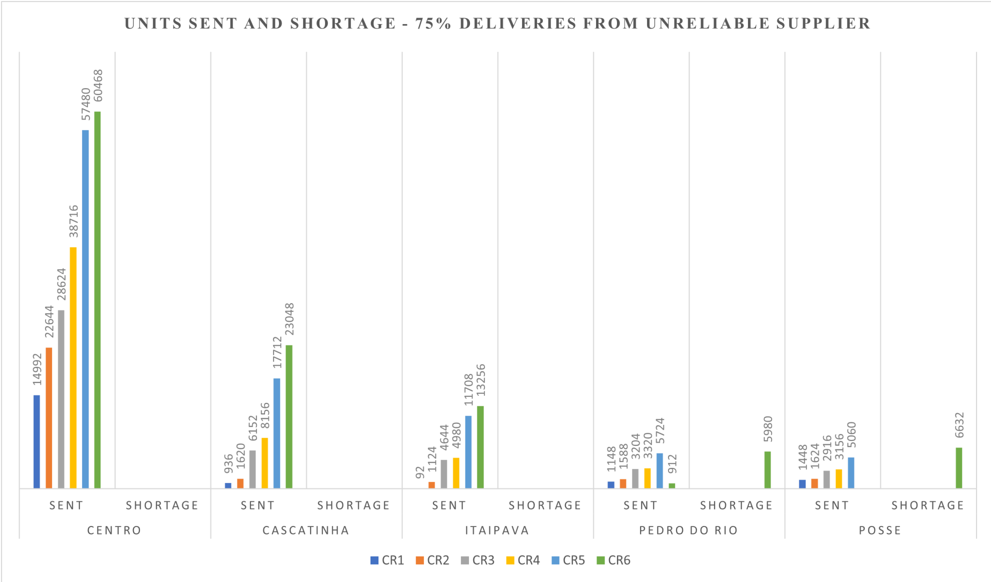

Figure 4.18: Units of product sent to each SP per scenario for 75% of requested donations received

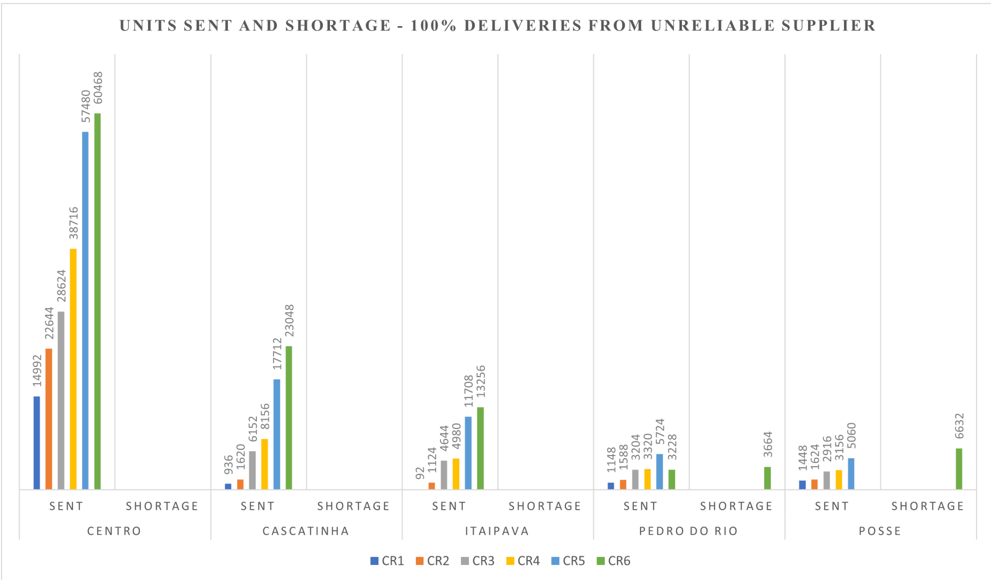

Figure 4.19: Units of product sent to each SP per scenario for 100% of requested donations received

Figure 4.16 presents the amount of goods sent to each SP for scenarios 1 to 6 (CR 1 to CR 6). In this example we assume that only 25% of the requested donations were received, hence, the DC could not meet the demand of all SP. However, we can see that the received goods were distributed according to the SP demands and that the overall shortage of the system is low.

Figures 4.17, 4.18 and 4.19 represent a percentage of delivery of donations of 50%, 75% and 100%, respectively. We can observe that the overall shortage of the system reduces as the number of satisfied requests increase, with the smaller SP receiving less goods in event of shortages. However, it also allows us to conclude that even at 100% of request satisfaction, the system still can not fulfil the demand of all SPs when the DC inventory level is 0 and demands are at its peak (CR6). Although the peak demands probability is low, 8.3%, it indicates that the decision maker may need to include higher purchase options in the system.

Implementation and computational remarks

Table 4.13 below summarise the computational results for the experiments. It shows the execution times (in seconds) and amount of physical memory (RAM, in megabytes) required to execute both algorithms that comprise the proposed framework, for each action set studied.

Table 4.13: Computational results

KPI	11 actions			21 actions			41 actions		
	TSSP	MDP	Total	TSSP	MDP	Total	TSSP	MDP	Total
Time (s)	3,251.69	60.33	3,312.02	6,234.51	108.94	6,343.45	11,855.16	207,03	12,062.19
RAM (MB)	324	69	393	601	85	686	1,153	332	1,485

One can observe that both algorithms perform efficiently, using few resources and low execution times, even for relatively large problems such as the scenarios with 41 available actions. Both processing times and physical memory usage grow linearly with the number of actions considered. The TSSP which carries the heaviest load of the processing time, because it is responsible for the execution of all integer models and calculation of future states of the systems and the transition probability matrix, takes an average of 3 hours to run for 120.000 states and 41 available actions, and the MDP takes around 4 minutes to run.

Furthermore, the parameter evaluation algorithm takes more time for a high number of available actions, once the number of executions of the TSSP directly depends on the number of actions being considered. However, since the framework needs to be executed only once during the lifetime of the operations, the total execution time of the framework is not prohibitive, as can be observed in table 4.13.

It is noticeable that the TSSP executions require more physical memory than the MDP, for every scenario studied, and the amount of physical memory required to run the framework is stacked up. However, since the MDP adds a very little load to the overall framework, this is not a limitation for current computers.

Furthermore, the proposed experiment uses the maximum granularity for inventory management, which leads us to 120,000 possible states of the system, which greatly increases the problem size. The decision maker can choose a smaller granularity for the system, and discretize the inventory levels in bigger intervals. Simply changing the inventory level interval do 2 units instead of one already reduces the problem size by half, which reduces the amount of resources used and allow the decision maker to increase the number of actions in the action set, if needed.

4.2.3 West Java experiment

The West Java province in Indonesia comprises of 27 municipalities, 23 of which are recurrently hit by disasters. At the province level, the responsibility for the management of disaster, from mitigation and preparedness to response and recovery, lies with West Java Regional Disaster Management Agency (BPBD Jabar). When responding to a disaster, they work closely with the Municipal-Level Disaster Management Agencies and humanitarian organizations. Henceforward, we will refer to Municipal-Level Disaster Management Agencies and municipalities interchangeably.

In this case, we focus on the aggregated procurement policy at province level. BPBD Jabar has a warehouse (Command center) which is responsible for acquisition and storage of relief items. In the event of a disaster, the command center then redistributes the relief items to the municipalities, according to their needs. Likewise, each municipality has a warehouse that receives and distributes relief goods to the victims within its boundaries. Figure 4.20 illustrates this configuration.

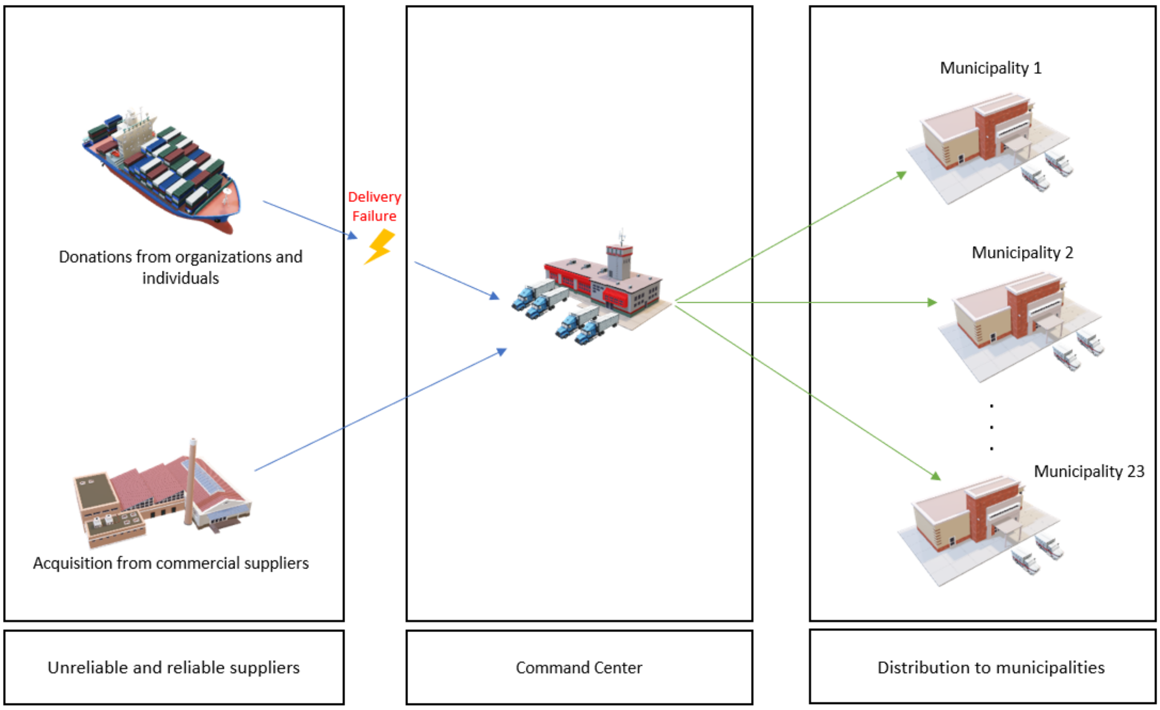

Figure 4.20: West Java distribution model

As mentioned in Onggo et al. (2021), this province experiences small-to-medium level disasters on daily basis. Hence, they need to make the procurement decision regularly (i.e., how many relief items to buy/stock). In this case, we study the acquisition and distribution of hygiene kits (tooth brush, tooth paste, shampoo, etc.), to disaster victims in the affected areas, assuming that each person requires one unit of hygiene kits per month.

We assume that the decision making is done monthly, once it is cheaper to aggregate purchases. When a disaster happens, the demand on the Command Center is fulfilled from the commercial suppliers (reliable suppliers) and donations of supplies (unreliable source of supplies). The accessibility in West Java province is good, which means that the relief items can be delivered very quickly (typically within 24 hours), therefore, we can assume that are no lead times between acquisition and delivery of goods. Furthermore, since the province is hit by disaster on a regular basis, the problem presents itself as an infinite time horizon model, according to the formulation presented in equations (4.4) and (4.5)

The command center has a storage capacity of 60,000 units, whereas the all the Municipal-Level Disaster Management Agencies have a similar configuration, presenting a storage/receiving capacity of 15,000 units. At the same time, the local commercial suppliers have availability to provide 60,000 units every month, and there is no limitation for the number of donations received, other than the Command center storage capacity.

The demands for each of the 23 municipalities in the event of a disaster varies according to 4 different disaster scenarios, calculated using historical data, according to the magnitude of the disaster. The demands for each scenario, as well as the scenario probability are presented in table 4.14

Table 4.14: Demand and probability for each scenario - Java study case

Code	Municipality	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Mun 1	Kab.Bandung Barat	38	278	51	370
Mun 2	Kab.Bandung	14502	4018	369	7506
Mun 3	Kab.Bekasi	552	120	0	250
Mun 4	Kab.Bogor	6378	610	21	87
Mun 5	Kab.Ciamis	18	0	0	254
Mun 6	Kab.Cianjur	51	0	18	33
Mun 7	Kab.Cirebon	3323	170	0	40
Mun 8	Kab.Garut	805	101	2531	190
Mun 9	Kab.Indramayu	1442	1400	0	0
Mun 10	Kab.Karawang	18871	1221	7143	89
Mun 11	Kab.Kuningan	30	2	16	19
Mun 12	Kab.Majalengka	30	65	0	0
Mun 13	Kab.Pangandaran	162	13	3	4881
Mun 14	Kab.Subang	1216	1588	0	9
Mun 15	Kab.Sukabumi	364	228	1029	4
Mun 16	Kab.Sumedang	495	407	7	27
Mun 17	Kab.Tasikmalaya	65	0	244	1614
Mun 18	Kota.Banjar	15	0	0	0
Mun 19	Kota.Bekasi	11041	15	0	0
Mun 20	Kota.Bogor	64	29	42	35
Mun 21	Kota.Cimahi	46	111	0	34
Mun 22	Kota.Depok	3	0	0	0
Mun 23	Kota.Tasikmalaya	10	0	0	17
	Probability	0.61	0.11	0.12	0.16

In a similar approach to the one applied to Petrópolis experiment, we study the Java case under three different action sets, and three different unreliability scenarios. The first action set assumes 11 possible actions, ranging from acquiring 0 units to acquiring 60,000 units, with increments of

6,000; this yields

$$A_1 = \{0; 6,000; 12,000; 18,000; 24,000; 30,000; 36,000; 42,000; 48,000; 54,000; 60,000\}.$$

The second set (A_2) uses the same range, but with increments of 3,000 units, yielding to 21 possible actions. The third and final action set (A_3) is comprised of increments of 1,500 units, leading to a set of 41 elements.

As far as unreliability is concerned, we assume the same values and analyses presented for the Petrópolis case. At each decision epoch the Command center chooses the amount of goods to acquire from the commercial suppliers and the amount of goods it will request to the community as donations. The amount of goods received as donations each period after the Command center's request vary according a binomial distribution $X \sim \mathcal{B}(3, 0.5)$. Later, we present the optimal acquisition policies for both suppliers under the same action set (A_1), assuming a more reliable flow of donations, which follows a binomial distribution $X \sim \mathcal{B}(3, 0.6)$ and a less reliable flow of donations, which follows a binomial distribution $X \sim \mathcal{B}(3, 0.4)$, according to the table 4.15.

Table 4.15: Probability of percentage of donations received - Java Study Case

% of requests received	25	50	75	100
Baseline Probability	0.125	0.375	0.375	0.125
Less reliable scenario	0.216	0.432	0.288	0.064
More reliable scenario	0.064	0.288	0.432	0.216

Finally, we assume arbitrary logistical costs for this experiment, as presented in table 4.16. And once again, we select shortage costs much higher than than delivery costs, in order to penalise shortages in the objective function.

Table 4.16: Experiment costs

Cost set	Value
Purchase + transport + handling per unit from the reliable supplier (a)	\$ 03.00
handling + sorting per unit from donations - unreliable supplier (b)	\$ 01.00
Inventory holding cost per unit	\$ 01.00
Shortage cost per unit to a SP	\$ 35.00
Delivery cost per unit to a SP	\$ 05.00

4.2.4 Results

In this session, we discuss the results for the West Java experimnent, with focus on the information the framework provides to the decision maker, to improve the efficiency of the operation. Then, we briefly discuss the computational assessment of the execution of the proposed framework.

Decision making

The optimal acquisition policies for the Command center, in the West Java case, assuming scenarios with 11 actions, 21 actions and 41 actions, can be observed through figure 4.21. It presents how the optimal acquisition policies, including both suppliers, vary with the inventory levels of the Command center.

It allow us to compare how the optimal purchase decreases with the inventory level of the Command center, and to observe a similar behaviour from the one observed in the Petrópolis experiment, where the amount of products acquired decreases as the inventory level increases.

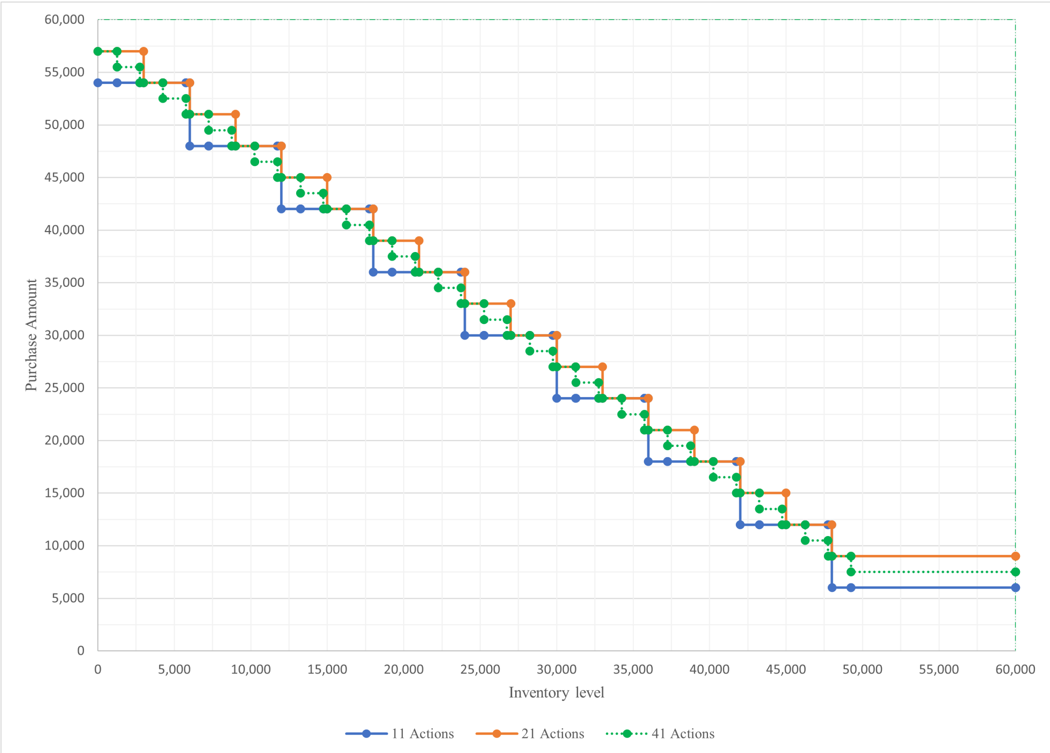

Figure 4.21: Summary of optimal policies for all available action sets - West Java case

Moreover, it allows us to compare the behaviour of the acquisition policies for the different actions sets studied, and with that highlight how the granularity of the action sets directly impacts in the acquisition policies. We can observe that the optimal policy for the action set A_3 (41 actions) runs between the optimal policies for A_1 and A_2. This can be explained by the freedom given to the decision maker, providing the ability to make more precise calls on the needs of the operation and find a better balance between overstocking and shortages allowed whilst tending to the demands of the operation. This leads to smaller operation costs, as complemented by table 4.17.

Table 4.17: Average costs ($) for action sets studied - West Java case

	11 actions	21 actions	41 actions
Average costs	533,451.09	530,762.04	529,866.34

The breakdown of the optimal acquisition policies into purchase policies for both suppliers, assuming action set A_1, is displayed in figure 4.22.

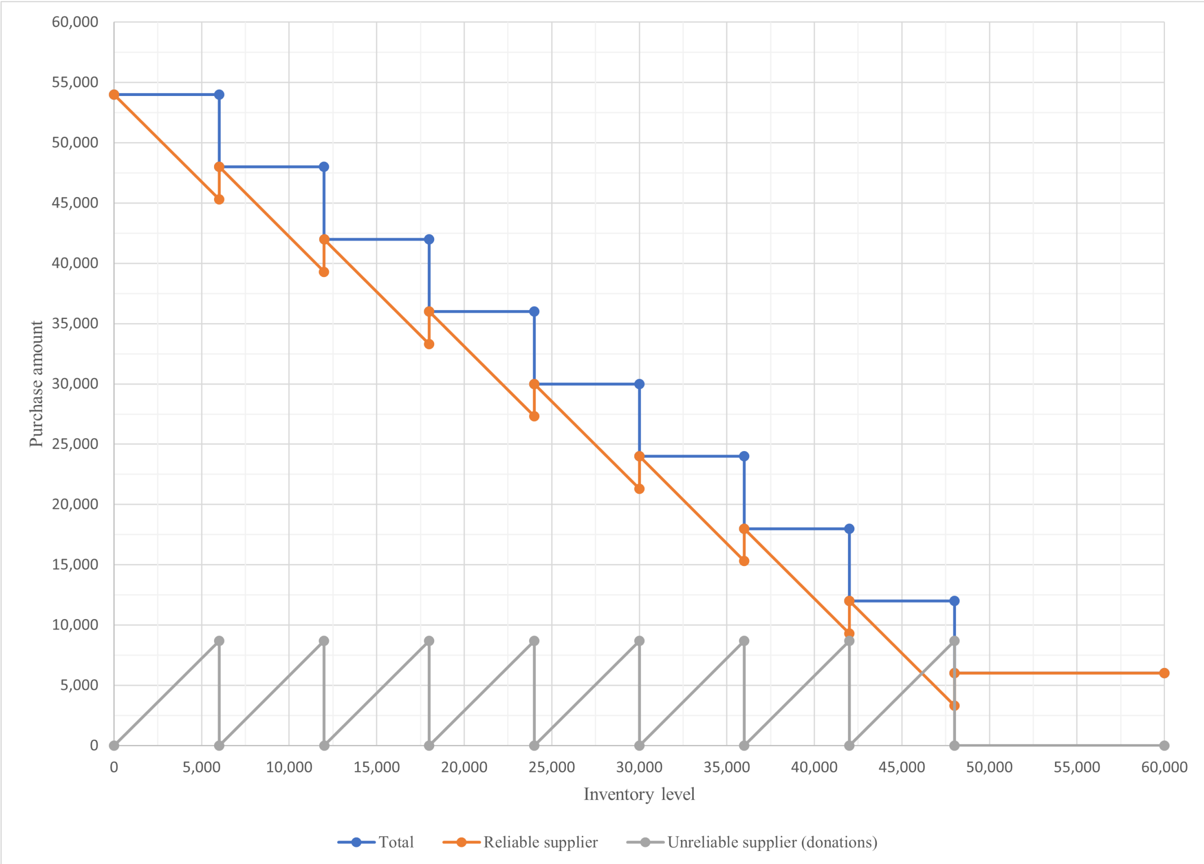

Figure 4.22: Acquisition variation per supplier for A_1 action set - West Java case

Just like Petrópolis case, the same saw-tooth behaviour for both suppliers is expected. Figure 4.22 shows that as the inventory level of the Command center grows the total acquisition diminishes, as well as the amount acquired from the reliable supplier. Additionally, the amount acquired from the unreliable supplier (received as donations) grows up to a point where the total acquisition amount drops, and with it also does the amount expected from the unreliable supplier. This behaviour is also explained by the smaller slack that the decision maker has to deal with unreliability when the inventory level is low, which yields small increases in the acquisitions from the reliable supplier and reduction on the acquisitions from the unreliable supplier, once failed deliveries would increase the shortage and consequently the operation costs.

Figures 4.23 and 4.25 present the acquisition policies for both suppliers for the less and more reliable donations scenarios, respectively. We can observe that for the less reliable scenario, the amount received from the unreliable supplier is much smaller than that for the baseline scenario or the more reliable scenario. Not only the fact that the reliability of donations is smaller, but also the gap between costs from both suppliers is short, as explained above, which makes the unreliable supplier much less appealing for the decision maker.

In fact, the amount is smaller than the actual drop in the total amount acquired between states, which leads to a drop in acquisition from both suppliers simultaneously. This drop is so small (two hundred units) in comparison to the remainder of the acquisition policies that it is barely shown in figure 4.23. Hence, we included a snapshot of a portion of the plot, in figure 4.24, to illustrate this reduction.

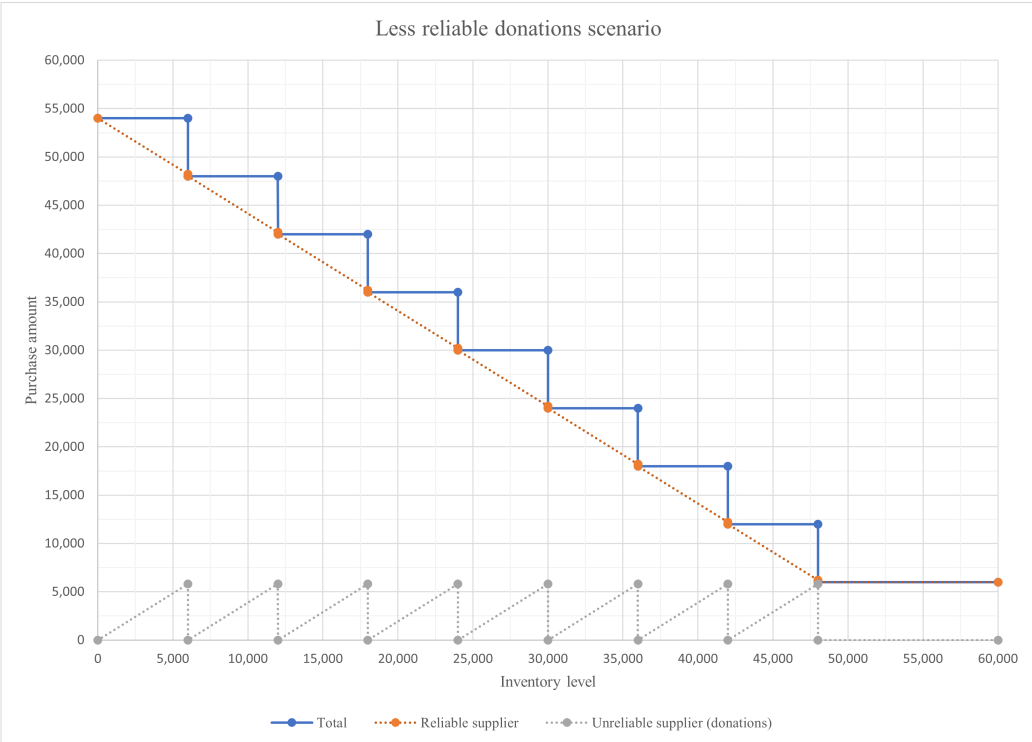

Figure 4.23: Acquisition variation per supplier for A_1 action set with less reliable donations ($\mathcal{B}(3, 0.4)$) - West Java case

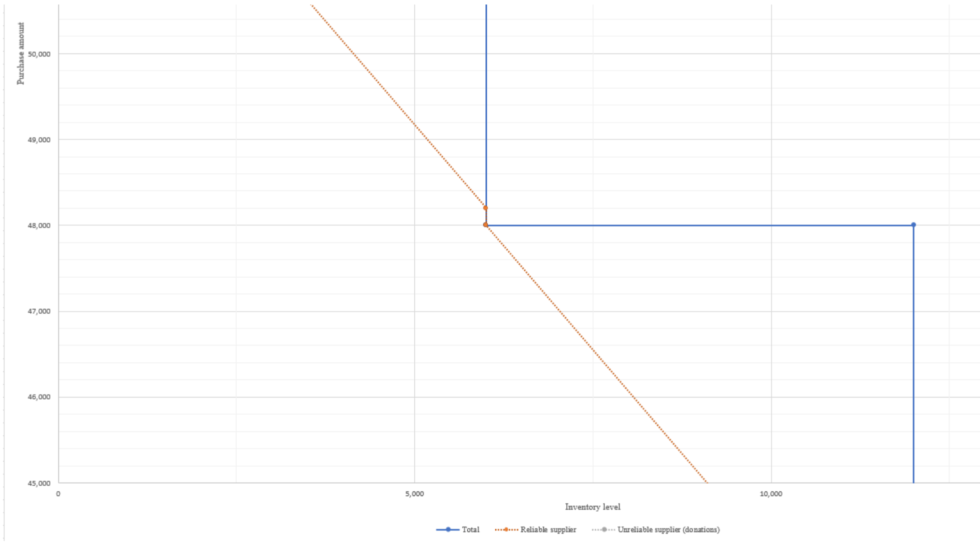

Figure 4.24: Drop in the acquisition amount for the reliable supplier for A_1 action set with less reliable donations ($\mathcal{B}(3, 0.4)$) - West Java case

On the other hand, the more reliable donations scenario presents no difference in the acquisition policies from the baseline scenario. This can be explained by the fact that the reward/risk rate for a small increase in the reliability is not large enough to justify an increase in the acquisitions from the unreliable supplier, because a shortage would incur a much larger penalty than the savings. This can be explained by the small gap between reliable and unreliable supplier costs, especially noting that the biggest demands have a much bigger probability in the West Java experiment, hence a reduction in the amount acquired from the reliable supplier lead to a higher risk of shortage overall.

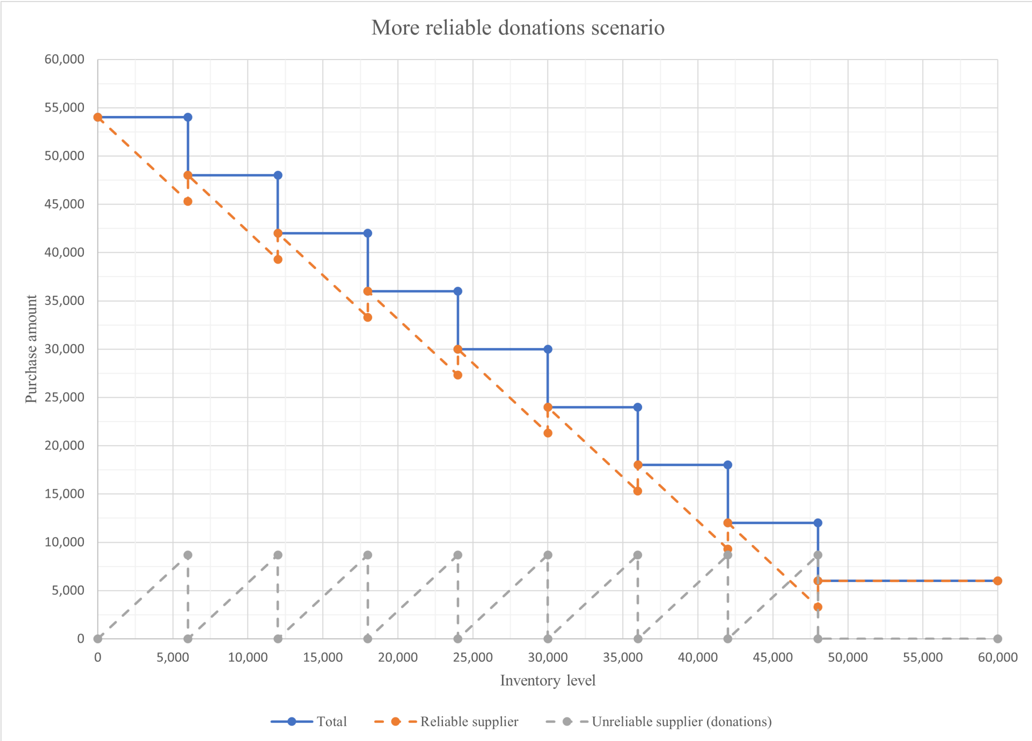

Figure 4.25: Acquisition variation per supplier for A_1 action set with more reliable donations ($\mathcal{B}(3, 0.6)$) - West Java case

Table 4.18 summarises the average costs for each of the 3 reliability experiments studied, where we observe that the less reliable scenario indeed offers a greater average cost for the operation, whereas both baseline and more reliable scenario present similar costs, as presented before.

Table 4.18: Average costs ($) for different levels of reliability of donations, assuming A_1 action set - West Java case

	Less reliable scenario	Baseline scenario	More reliable scenario
Average costs	534,583.49	533,451.09	533,451.09

Although, differently from the Petrópolis case, the amount acquired from unreliable supplier never really surpasses the amount acquired from the reliable supplier, returning to 0 when the total acquisition drops. This is explained by the scenario demands and its probabilities. For the West Java experiment, the scenario with biggest demands has a very high probability, whilst scenarios with smaller demands have low probabilities, which implies that relying on donations to support the operation can lead to high shortage volumes in the most likely scenario. To exemplify this behavior, we propose another experiment, where we arbitrarily change the demand scenario probabilities for a more equitable distribution, as displayed in table 4.19, keeping the same parameters for the experiment and assuming action set A_1 and baseline probabilities for donations received.

Table 4.19: Probability for each demand scenario - Equitable experiment

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Probability	0.15	0.35	0.20	0.30

In the equitable distribution experiment the amount acquired from the unreliable supplier is able to overtake the amount obtained from the reliable supplier, as displayed by Figure 4.26.

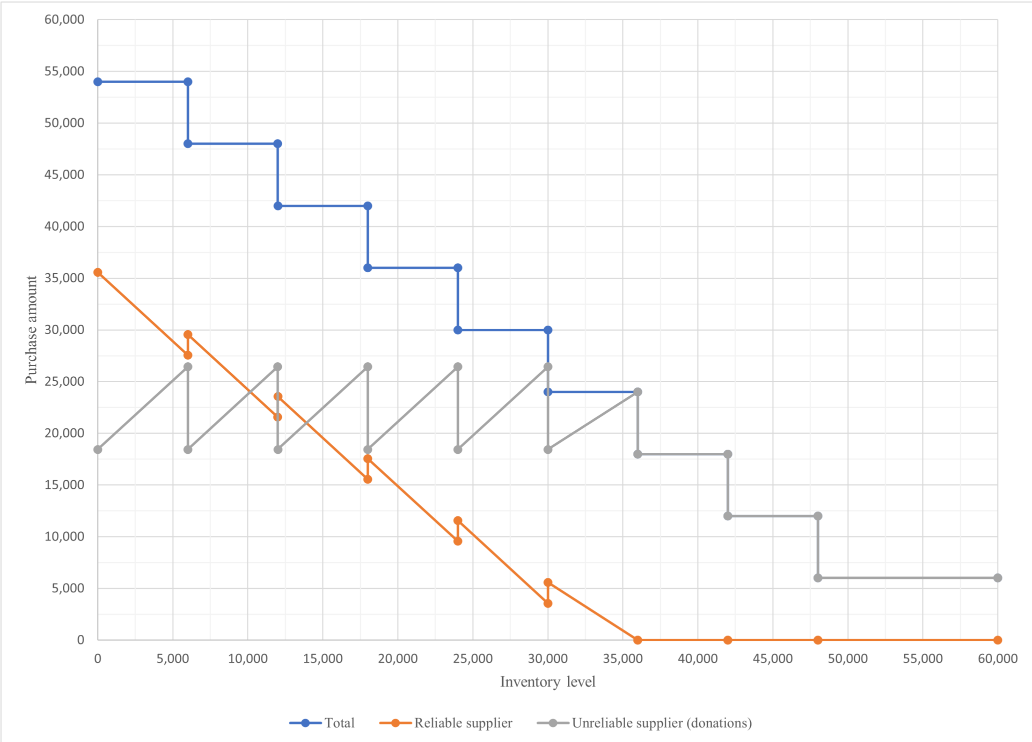

Figure 4.26: Acquisition variation per supplier for A_1 and equitable demand probabilities - West Java case

Finally, the distribution policies for all 23 municipalities, in each scenario, is determined by the TSSP, as demonstrated by figures 4.27, 4.28, 4.29 and 4.30, that present amount of units distributed for each percentage of demand plea met, for each one of the four demand scenarios, assuming A_1.

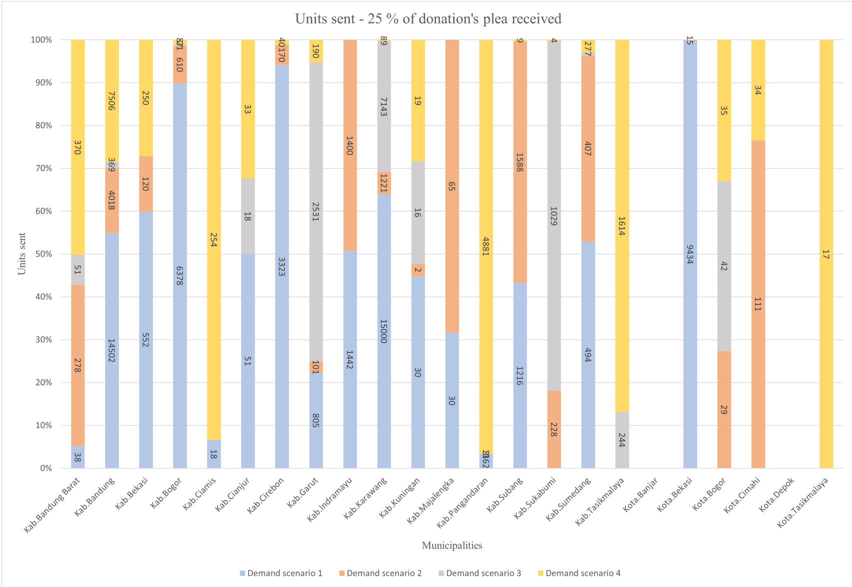

Figure 4.27: Units distributed to each municipality assuming 25% of demand plea met - West Java case

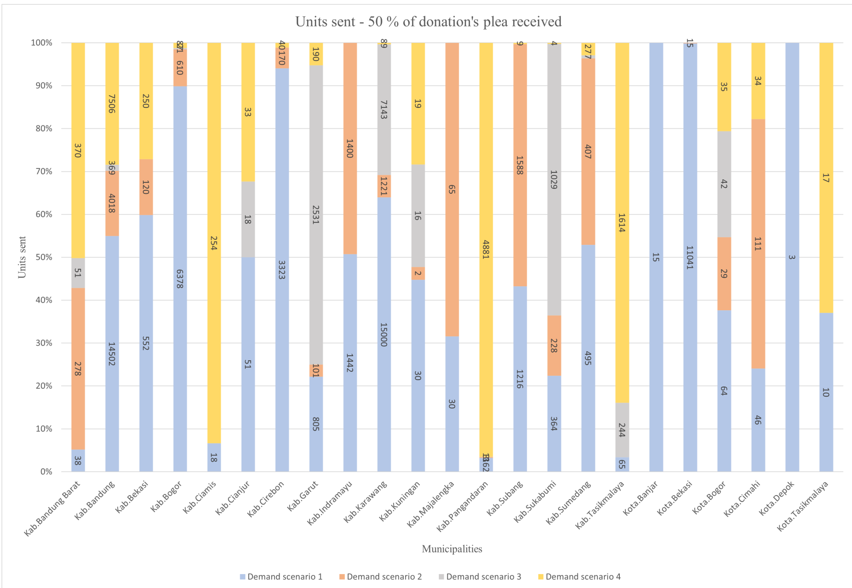

Figure 4.28: Units distributed to each municipality assuming 50% of demand plea met - West Java case

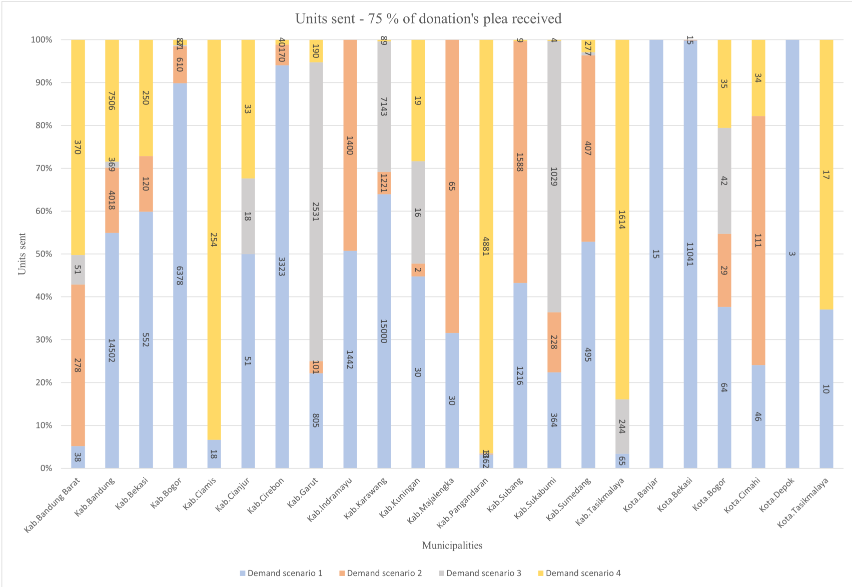

Figure 4.29: Units distributed to each municipality assuming 75% of demand plea met - West Java case

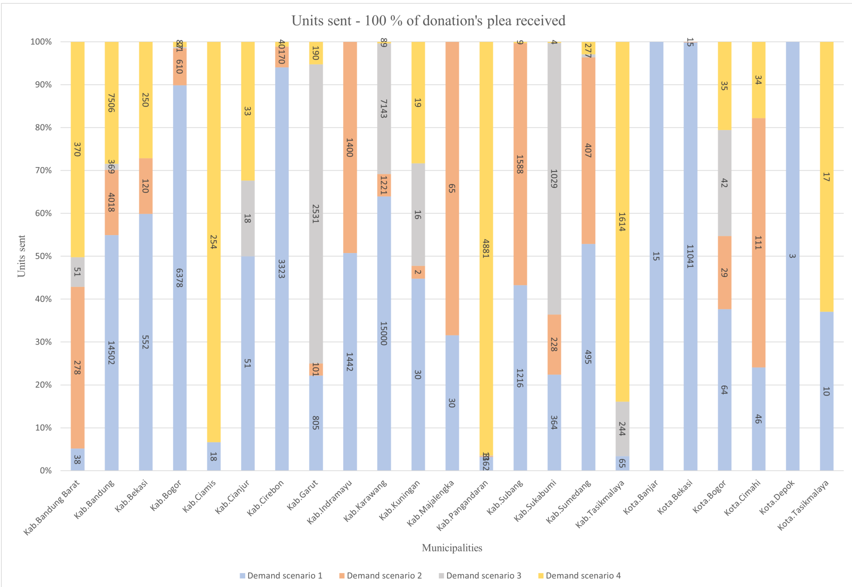

Figure 4.30: Units distributed to each municipality assuming 100% of demand plea met - West Java case

It is noteworthy that the first demand scenario has a much higher probability, and also a higher overall demand among municipalities. Hence, it pulls the amount acquired from the Command center up, having a much greater impact in the acquisition policies, once the shortages would have a much greater impact. Therefore, scenario 1 impacts the amount acquired enough to ensure that the demand of all municipalities are covered for the other 3 demand scenarios, which implies that only demand scenario 1 is affected by shortage of supplies, for the 4 different donation request scenarios, as exemplified by figure 4.31.

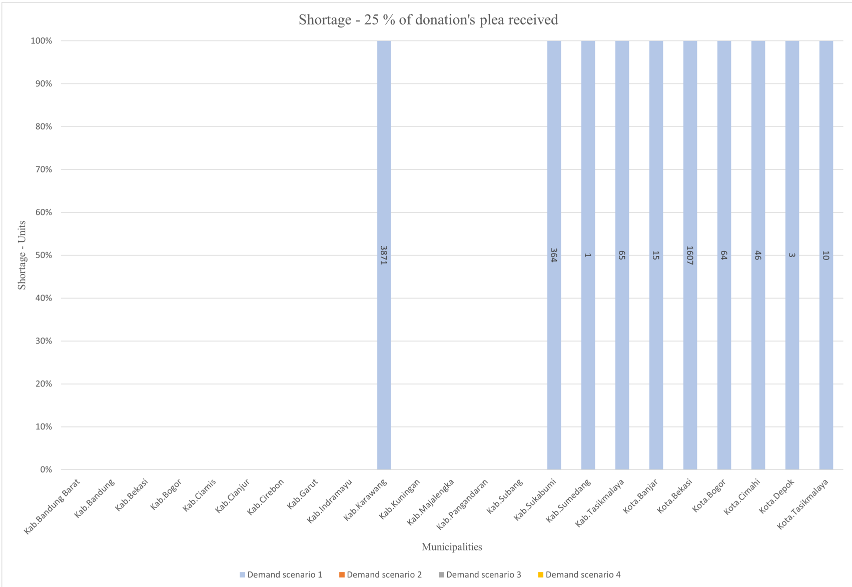

Figure 4.31: Shortage allowed to each municipality assuming a 25% demand plea met - West Java case

Furthermore, we can identify that the municipality of *Kab.Karawang* has a total demand of 18,871 units for demand scenario 1. Although, as explained in section 4.2.3, all the Municipal-Level Disaster Management Agencies have the same storage capacity of 15,000 units. This explains the high shortage for the municipality, 3,871 units, shown in figure 4.31. This also informs the decision maker that this municipality needs infrastructure intervention to improve its capacity, otherwise it will not be capable of meeting its demand, even if it could have all the resources available.

Implementation and Computational remarks - Java case

A summary of the computational results for the West Java case is presented in table 4.20, displaying both execution times (in seconds) and amount of physical memory (RAM, in megabytes) required to execute the proposed framework, for each action set studied.

Table 4.20: Computational results - West Java case

KPI	11 actions			21 actions			41 actions		
	TSSP	MDP	Total	TSSP	MDP	Total	TSSP	MDP	Total
Time (s)	2254.1	35.768	2289.868	4224.469	46.47	4270.939	8032.581	74.581	8107.162
RAM (MB)	1072	116	1383	2039	196	2235	3975	311	4091

Once again we can observe that the TSSP carries the heaviest burden of the framework, for both execution times and amount of memory consumed, since it is directly impacted by the number of actions being considered and the number of states. And that the MDP runs relatively fast even for a greater number of actions: 59 seconds for 41 actions and 60,000 states of the system.

It is very important to highlight that the Petrópolis case and the West Java case have different setups, with distinct number of demand points, number of scenarios and inventory levels, due very different sources of information, and especially, location necessities. So any comparison between the two cases must be handled carefully.

With that in mind, analysing the results of the execution of both cases provided in tables 4.13 and 4.20, we can observe that the MDP runs faster for the West Java case than it does for the Petrópolis one, even though the West Java cases consider almost 5 times more locations being supplied.

On the other hand, the Petrópolis case has 24 total scenarios (demand scenarios multiplied by donation's reliability scenarios), whilst West Java assumes 16 total scenarios. This suggests that the amount of organizations or supply points being considered has little impact on the MDP execution. That is indeed expected, since it is known that the MDP execution is much more affected by the action sets and the space state being considered.

Furthermore, the same can be observed for the TSSP, where the algorithm runs in average 31% faster for the West Java case than for Petrópolis case, for all action sets. Also an expected result, once the amount of executions of the TSSP is directly proportional to the amount of states and actions in the system. Whereas the amount of supply points increases the amount of constraints in the model, making a single run slightly longer. But this increase is offset in the fairly simple Stochastic Model, as the number of executions of the TSSP is greatly increased with the number of states.

However, we can observe that the amount of physical memory used by the West Java case is higher, for both MDP and TSSP. This is easily explained by the way we implemented our model. We keep the results for all inventory levels and actions in memory, to increase the information retrieval speed, focusing on reducing the overall executions times. Hence, the West Java case keeps data for 60,000 inventory levels, 23 organizations and 16 scenarios in memory, which ends up being much larger than the Petropolis case.

An implementation approach to reduce the amount of memory being used is to store the results of the MDP and TSSP in a Database (DB), and only retrieve the necessary values when required, not only for the MDP execution, but also to present the results to the decision maker. This would slightly increase the execution times of both MDP and TSSP, due connections to a DB, but significantly decreased the amount of physical memory used.

The DB approach is the suggested implementation approach for a real life operation. Since the framework only needs to be executed once during the lifetime of the operation, the gain in processing times is not relevant enough when compared to the amount of memory a computer is using, which enables less powerful computers to run the framework successfully. Moreover, it allows decision makers to install the DB in a different machine, such as a DB server, which has a much greater storage capacity.

All in all, we can observe that the framework suggested in this research runs relatively fast and with modest computing resources, even for large instances of the problem, especially when considering it needs to be executed only once during the lifetime of the operations, unless a key parameter is changed during the course of the response.

Chapter 5

Concluding remarks

In this work, we develop two different inventory management frameworks, the first focused on the management of perishable items in long term operations with uncertain demand and uncertain supply/donations. The second studies the distribution of goods in a dual sourcing system with unreliable suppliers and uncertain demands for multiple organizations/actors, both using novel approaches to tackle known constraints of both humanitarian and commercial logistics.

We use humanitarian logistics examples in our experimentation because they present highly complex environments, suitable for exploring new optimisation models. Moreover, although humanitarian logistics is a focus of growing interest from the academy, it still greatly lacks behind commercial logistics. Our research intents to shorten this gap.

The intent behind this research was to develop a novel robust framework which would be comprised of both core ideas: an inventory management model that assumes perishability of items and multi sourcing with unreliable suppliers, that could be used not only for humanitarian operations but also in commercial logistics. Hence, we leave it as a direction for future researches, to enclose both constraints into a single inventory management framework.

For the first core idea, we developed an inventory management model for perishable items as a Markov Decision Process (MDP) with stochastic demand and stochastic donations (offer of goods) and deterministic deterioration rates, where the goal is to minimise the average operational costs for a continuous aid operation in a humanitarian crisis environment.

Utilising a MDP allowed us to determine the optimal ordering policy for perishable items based on the inventory level (states) of the system, preventing shortage of sensitive goods in disaster response. Furthermore, as the model decides whether a new batch of items is accepted to the stock based on the probability of that batch expiring before being demanded, our model is able to consider deterioration without explicitly keeping track of the expiration dates of all items in stock. That greatly simplifies the analysis and enables us to explicitly account for deterioration costs in the model, which seeks a compromise between long-term storage and deterioration costs, while also accounting for logistics and transportation costs.

The experiment presented in this work explores the impact of different shelf lives of the products in the inventory and the results suggest that smaller shelf lives greatly lower the number of items collected (or purchased), even when the inventory levels are low. The intuition here is simple: there is no point in collecting items if the probabilities that they will expire is very high. This is reinforced when the disposal costs are high due to the difficulty of properly disposing deteriorated items, especially goods such as blood and medicines that can impose health threats if not handled correctly.

To sum up, the model contributes to the theory by providing and MDP model that accounts for stochastic demands and donations, while also directly considering the perishability of the donated items. The MDP allows for a simple treatment of long-term operations while also enabling a simple, easy to implement solution strategy based solely on the storage level. This works also contributes to the practice by shortening a gap in the literature with respect to minimising the impact of disasters over a vulnerable community in long term operations, such as plagues, where perishable items, such as vaccines and food, play a critical role in assisting people in need. The proposed tool is easy to use and implement by practitioners.

The experiment also allows us to realise that the proper choice of cost parameters (or functions) is essential when modelling the inventory management of humanitarian operations. In many cases shortage or disposal of goods is not an option, due the sensitivity of the item or lack of donations or local retailers. The costs of the model must be carefully selected based on the main goal of a humanitarian operation: to save and protect lives.

As an expansion of the first model, the second part of this research focuses on an inventory management framework, which aims to minimise the expected operational costs for a DC that acquires and distributes supplies in a disaster relief operation. We assume a dual-sourcing system, with one reliable and one unreliable supplier, and multiple HOs with stochastic demands that receive goods from the DC. To the best of our knowledge, this is the first attempt to assume unreliability of a supplier as a constraint in humanitarian operations.

The framework is comprised of a Markov Decision Process and a parameter evaluation algorithm with a two-stage stochastic optimisation model. The MDP allowed us to determine the optimal ordering/acquisition policy based on the inventory level of the system. The parameter evaluation algorithm is responsible for identifying the amount of goods to be acquired from each supplier, based on the ordering policy identified, and the amount of goods to be distributed for each HO. The proposed framework is easy to implement and the results can be readily analysed by practitioners.

Assuming a dual-sourcing system allows us to select a local supplier, in order to help reestablish the local economy, without compromising the operations in the event of the local (unreliable) supplier being unable to provide the solicited goods. Furthermore, by assuming a centralised decision making structure, where the DC coordinates with suppliers and humanitarian organizations, we implement both horizontal and vertical coordination mechanisms. This allows organizations, acting on different levels of the supply chain, to improve information and resource sharing and to avoid overlap, thus leading to a more reliable decision making process.

The experiments presented in this study analyse the impact of different demand probabilities for each demand point (SP or Municipalities) being supplied by the DC, and the results suggest that disasters with high probabilities of high demands (such as the West Java case) have a large impact on the amount of goods acquired from the reliable supplier. This implies that for disaster situations with a huge number of victims, shortages have a much bigger toll on the total operations costs than transportation or inventory holding costs, especially when realising that shortage costs are usually implemented as a manner of alleviating the suffering of the affected population. Therefore, a more stable and reliable source of goods is required.

The experiment also explores the impact of different actions sets available to the decision maker, and finds that with more available options the decision maker can take more precise actions, reducing the overall costs the operations and avoiding overstocking while keeping a safe inventory level to avoid shortages. However, the study suggests that the number of available actions has a smaller impact on the average expected costs than the reliability of supplies.

The proposed framework can be applied for both long-term and short-term operations and is flexible enough to be applied in a wide range of operations, as demonstrated by the different numerical experiments presented. Moreover, it provides a large amount of information to the decision maker, allowing a more precise and coordinated decision making process.

Besides, it is comprised of a stochastic programming model, that despite being clearly defined, can be altered to include new constraints, decisions and/or operational costs, such as routing decisions, if required by specific situations. Providing a flexible tool for disaster preparation and response.

5.1 Future research directions

The models presented have room for improvement. In our first model we assume lead-times only as a tool to lower the shelf life of perishable goods. Hence, the model could be extended in order to consider lead-times as a constraint, especially considering the several particular characteristics of the supply chains of specific perishable items (e.g. cold supply chains for medicine or blood packs).

Moreover, the perishability model does not consider individual expiration dates for each item in the inventory, however, several authors Holguín-Veras et al. (2014) discuss the difficulty and the importance of donation's management in humanitarian organizations, including managing donations from different donors with different expiration dates that arrive at the disaster site at the same time. Therefore, our model could be improved by assuming multiple sources of goods, raising the possibility of goods with different shelf lives arriving in the disaster site at the same decision epoch, in order to better represent the challenges and needs of humanitarian organizations.

Finally, humanitarian crisis are often responded by multiple organizations with the same goal. Hence, multiple warehousing and coordination between organizations could be considered in posterior extensions of the model, aiming for an equitable distribution of resources donated (and/or purchased) and optimising the total operation costs. Besides, warehouse capacity should also be considered when multiple warehouses are used in the model. These objectives are tackled in the second framework presented in this research.

The second model seeks to improve on the first model by including centralized decision maker and multiple organizations and suppliers in the supply chain. However, it can also be improved. We assume that both reliable and unreliable supplier have no lead-times, and the difference between them is only in the supply costs. Hence, the model can be extended to incorporate lead-times from both suppliers as a constraint, especially assuming that both suppliers can be in very different locations, and could have different lead-times.

Furthermore, our model assumes an unreliable supplier, which may not deliver the products in a specific decision epoch. Hence, DC must also decide how much shortage is allowed for each organization when the inventory is insufficient to supply all the demand, considering only the impact of shortage in the overall costs. However, we do not assume an equitable distribution of goods across the demand points. Therefore, the model can be improved by assuming equity constrains, to ensure that all demand points receive similar amounts of goods.

Finally, we assume an arbitrary value for the probability of the unreliable supplier failing to deliver the procured goods. We do not focus on identifying the actual reliability of suppliers. Therefore, our framework could be improved by identifying a more realistic measure of the reliability of individual suppliers to incorporate it to proposed solution.

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