Pontifícia Universidade Católica
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Roberto Gomes de Mattos

Insecticide-treated bed nets' supply chain optimization under uncertainty for malaria prevention and control

Dissertação de Mestrado

Dissertation presented to the Programa de Pós-Graduação em Engenharia de Produção of PUC-Rio, in partial fulfillment of the requirements for the degree of Mestre em Engenharia de Produção.

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To my girlfriend and parents, for their unconditional love.

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Abstract

Mattos, Roberto Gomes de; Leiras, Adriana (Advisor); Oliveira, Fabricio (Co-Advisor). **Insecticide-treated bed nets' supply chain optimization under uncertainty for malaria prevention and control.** Rio de Janeiro, 2017. 115p. Dissertação de Mestrado – Departamento de Engenharia Industrial, Pontifícia Universidade Católica do Rio de Janeiro.

In 2015, almost half of the world population lived in areas at risk of malaria transmission. There were around 214 million malaria cases and 438,000 associated deaths. One of the major paths to prevent and reduce malaria transmission is through vector control, especially with the use of insecticide-treated nets (ITN). In this context, ITN distribution campaigns face several challenges, such as uncertainties related to funding, transportation, market and price volatility, which might be effectively tackled through long-term agreements and proper planning. However, that might not be an option for all humanitarian organizations and governments. Besides, considering uncertainties during budgetary planning is particular relevant. In this sense, a robust optimization model, based on Bertsimas and Sim (2004) and Fernandes et al. (2016) frameworks, is proposed to minimize the involved costs or, given a budget constraint, maximize the coverage of priority areas. A literature review on robust optimization applied to humanitarian logistics is conducted, in which aspects with less academic research attention are revealed and considered in the model, such as the simultaneous account of the aforementioned uncertainties and demand prioritization. A United Nations Children's Fund campaign in Ivory Coast is studied, and reveals that, as expected, as the robustness level increases so does the total costs. In return, the robust model generally provides a solution with improved supply chain flexibility, that might minimize efforts, in case it is necessary to adjust procurement and transportation plans when uncertainty is revealed. In addition, robust solutions were assessed through Monte Carlo simulations against several realizations of uncertain parameters values, pointing that, as desired, solution feasibility increases alongside the specified level of conservatism.

Keywords

Malaria; Bed Nets; Humanitarian Logistics; Robust Optimization; Uncertainty.

Resumo

Mattos, Roberto Gomes de; Leiras, Adriana (Advisor); Oliveira, Fabricio (Co-Advisor). **Otimização sob incerteza da cadeia de suprimentos de mosquiteiros utilizados na prevenção e controle da malária.** Rio de Janeiro, 2017. 115p. Dissertação de Mestrado – Departamento de Engenharia Industrial, Pontifícia Universidade Católica do Rio de Janeiro.

Em 2015 quase metade da população mundial vivia em área de risco de transmissão de malária. Neste mesmo ano, estimam-se 214 milhões de casos e 438 mil fatalidades. A principal forma de prevenção e redução da transmissão da malária é através do controle dos vetores, em particular, destaca-se o uso de mosquiteiros impregnados com inseticidas de longa duração (MILD). Neste contexto, os programas de distribuição de MILDS enfrentam desafios relacionados a obtenção de fundos e à gestão da cadeia de suprimentos como, por exemplo, incertezas associadas as atividades logísticas, as variáveis de oferta e demanda, e a volatilidade de preços. À luz destes fatos, esta dissertação propõe um modelo de otimização robusta, fundamentado em extensões dos arcabouços teóricos de Bertsimas e Sim (2004) e Fernandes et al. (2016), capaz de minimizar os custos de um programa de distribuição de mosquiteiros ou, dada uma restrição orçamentária, maximizar a distribuição para áreas prioritárias. Ademais, foi realizada uma revisão da literatura acadêmica acerca de modelos de otimização robusta aplicados no contexto da logística humanitária, onde alguns aspectos ainda pouco explorados foram ressaltados e considerados no modelo proposto. Um estudo de caso real é feito sobre um projeto feito do Fundo das Nações Unidas para crianças na Costa do Marfim. Os resultados apontam que conforme esperado, à medida que o nível de robustez considerado no modelo cresce, os custos totais também aumentam. Em contrapartida, o modelo robusto fornece soluções com maior flexibilidade na cadeia de suprimentos para a eventual necessidade de se ajustar os planos de compras e distribuição. Por fim, as soluções robustas foram avaliadas através de simulações de Monte Carlo, indicando que, conforme desejado, a probabilidade de viabilidade dos planos aumentam junto com nível de conservadorismo da solução.

Palavras-chave

Malária; Mosquiteiros; Logística Humanitária; Otimização Robusta; Incertezas.

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1
Introduction

Malaria is an illness that in 2015 infected approximately 214 million people, killing one child every 2 minutes (World Health Organization; WHO, 2015a). In that same year, United Nations (UN) Member States adopted a new sustainable development agenda, known as Sustainable Development Goals (SDG), as a revision of the Millennium Development Goals (MDG) set in 2000. The SDG consists of 17 goals that must be met by all countries until 2030, including to end poverty, protect the planet and ensure prosperity for all. Particularly, the third goal aims to ensure healthy lives and promote the well-being for all at all ages, with a specific target to end malaria epidemic by 2030 (UN, 2017).

Between 2001 and 2015, more than 663 million malaria cases were averted in sub-Saharan Africa (SSA), the most affected region in the world, due to malaria control interventions, in which insecticide-treated nets (ITN) are the keystone, accounting for 69% of this achievement. In 2014, the global spending in ITNs reached almost $1 billion (63% of the total spending), avoiding $610 million in malaria case management costs (WHO, 2015a). Although more than 177 million ITNs were distributed in SSA in 2015 (Net Mapping Project, 2016), only 55% of the population at risk slept under an ITN and hence annual funding must be increased to meet reduction goals (WHO, 2015a).

In the light of the above, humanitarian organizations (HO) are under increasing pressure to demonstrate transparency and accountability, in other words, that they are efficiently allocating resources and donations while effectively assisting beneficiaries. Since logistics might represent 80% of total disaster relief costs, it is imperative to actively manage humanitarian supply chains (Van Wassenhove, 2006).

Thomas and Mizushima (2005) define humanitarian logistics (HL) as “the process of planning, implementing and controlling the efficient, cost-effective flow and storage of goods and materials as well as related information, from point of origin to point of consumption for the purpose of meeting the end beneficiary's requirements”. Van Wassenhove (2006), summarises this definition as the “processes and systems involved in mobilizing people, resources, skills and knowledge to help vulnerable people affected by disaster”.

According to the International Federation of Red Cross and Red Crescent Societies (IFRC; IFRC 2017a), a disaster is a “sudden, calamitous event that seriously disrupts the functioning of a community or society and causes human, material, and economic or environmental losses that exceed the community’s or society’s ability to cope using its own resources”.

In addition, Van Wassenhove (2006) distinguishes natural and man-made disasters according to the speed that they strike: sudden-onset, which arrives rapidly or even unfolds instantly (e.g. earthquakes, hurricanes, terrorist attacks) and slow-onset that might even be predicted further in advance (e.g. drought, famine and poverty). However, Kovacs and Spens (2009) suggest that complex emergencies might show simultaneously natural and man-made characteristics, and others, depending on which way you look at it, can be seen as slow or sudden-onset disasters. It is worth noting that while sudden-onset disasters usually attract significant media coverage and donations, slow-onset disasters tend to be forgotten and under financed (Van Wassenhove, 2006). Moreover, whereas sudden-onset disasters requires agile supply chains focused on response times, the planning horizon for slow-onset disasters allow humanitarian logisticians to concentrate on cost efficiencies (Oloruntoba and Gray, 2006).

In this respect, IFRC (2017b) classifies disease epidemics like malaria as biological hazards under the natural disasters group. Malaria epidemics, which might be considered as a sudden-onset disaster, may arise when climate and other conditions boost transmission in vulnerable areas where people have insufficient immunity to this particular disease. That is the reason why malaria epidemics might spread as a consequence of a prior disaster, such as floods. On the other hand, it can also occur when people with low immunity move to high transmission areas, as construction sites and refugee camps (WHO, 2016a). However, the vast majority of malaria cases occurs in areas with high endemicity (Malaria Atlas Project, 2017), where malaria transmission is stable, and within this point of view, it can be considered a slow-onset disaster.

In particular, Apte (2009) defines humanitarian relief as “an ongoing process for slow-onset disasters with a long-term need for supplies”, in which “relief requirements are known and relief organizations face relatively long planning lead times”. In this respect, ITN distribution campaigns can be seen as humanitarian relief operations with the aim of reducing malaria transmission.

Since humanitarian logisticians work under the context of a disaster, they face many challenges that are not usually found within the private sector environment (Van Wassenhove, 2006), for instance: complex operations conditions (e.g. poor and over utilized infrastructure, disruptions), politically volatile climate, high level of uncertainty (e.g. demand, supply, assessments), resource scarcity (e.g. human resources, technology, equipment, financial), pressure of time associated with survival rates, high staff turnover due to burn out and a large numbers and diversity of involved stakeholders (e.g. government, donors, beneficiaries, military, HO).

Caunhye et al. (2012) points that these key challenges in HL are often addressed by academic researchers through operations research (OR) methods such as statistical and probabilistic models, queuing theory, simulation, decision theory, fuzzy methods, and more frequently, optimization methods. Despite the uncertainty nature of disaster relief, Leiras et al. (2014) indicate the predominance of deterministic models in mathematical programming papers related to HL. Among 83 reviewed papers by the authors, only 34 used stochastic programming, in which uncertainties are approached through the optimization of an objective function based on the expected value of probabilistic scenarios.

Nevertheless, average-based-values strategies might not be appropriate, since it can hinder proper relief in several scenarios. As an alternative to stochastic programming, the robust optimization framework, in general, uses worst-case perspective to take prudential decisions under uncertain environments. Particularly, in the humanitarian context, this approach seems to be the most appropriate choice, since there is a natural priority in providing the greatest needed amount of aid with resource efficiency, instead of average quantities and costs (Góes and Oliveira, 2015).

Ben-Tal and Nemirosvki (2000) observe that robust optimization (RO) goal is to find a feasible solution for all considered scenarios while optimizing the worst-case one. In addition, Bertsimas and Thiele (2006a) mention that stochastic programming is a powerful modelling framework when probability distributions of uncertain parameters are known. However, in a considerable portion of real-world applications, decision makers do not have this information available, mostly due to the absence of substantial historical data, and hence robust optimization becomes a relevant alternative.

In this connection, Hoyos et al. (2015) reviewed the academic literature regarding OR models with stochastic components in disaster operations management, concluding that among 48 papers only 5 considered a robust approach while the vast majority considered two-stage stochastic programming. This finding confirms the conclusion of the previous literature review of OR models in HL by Galindo and Batta (2013), which highlighted the lack of robust models to treat uncertainties.

With this in mind, a literature review covering 2 thesis, 6 conferences papers and 24 journal papers on RO applications in HL was conducted in this dissertation, and is further discussed on section 3.1. In addition to this specific literature review, only two papers related to malaria commodities' supply chain optimization were found, and both have a deterministic approach (Rottkemper et al. ,2011; Brito et al. 2015).

Rottkemper et al. (2011) develop a deterministic multi-objective transhipment and inventory relocation model for Artemisinin-based Combination Therapy (ACT), to minimize unsatisfied demand and operational costs during a malaria outbreak in areas with sustained humanitarian operations. The model determines the optimal relocation plan from neighbour depots with previous ACT stocks, to compensate the limited stock in the outbreak region, while avoiding future shortage in case the epidemic spreads to neighbour areas. Uncertainty is examined in demand parameter through sensitivity analysis and an example set in Burundi is discussed.

Brito et al. (2015) propose a deterministic transhipment model to define the optimal procurement and distribution plan of 12 million ITNs in Ivory Coast during a mass distribution campaign held by United Nations Children's Fund (UNICEF) in 2014. The authors describe a 7% cost reduction in comparison to UNICEF's original plan.

In this dissertation, the model proposed by Brito et al. (2015) is extended to consider uncertainties related to logistics (infrastructure availability and capacity), market (supplier capacity and demand forecast), price volatility (freight rates, container and ITN acquisition price) and funding unpredictability.

Therefore, this work proposes a robust transhipment network flow model to optimize ITN procurement and distribution plan in the context of malaria control and prevention, under financial, market and logistics uncertainties.

Both robust optimization frameworks of Bertsimas and Sim (2004) and data-driven polyhedral uncertainty sets presented by Fernandes et al. (2016) are considered in the model. In the first framework, a pre-determined number of parameters are allowed to assume their worst-case value, according to decision maker's conservatism level. The second approach uses a dynamic uncertainty set of observed data, within a defined time window, and forecasted values, to create an adaptive convex polyhedral region. The major advantages of this last approach are the ability of capturing the empirical dependence structure between cost parameters, which lead to more plausible uncertain scenarios, and the ease of understanding when setting the robustness parameter (time window).

The proposed model is able to design a supply chain with minimum associated costs, or on the other hand, given a budgetary constraint, to guarantee the maximum achievable coverage of priority areas, according to a composite indicator, which might consider, for instance, malaria incidence and mortality rates per region. A real case of UNICEF's distribution of approximately 12 million LLINs in Ivory Coast in 2014 is studied, in which robust solutions are compared to their deterministic counterpart to highlight the importance of decision-making under uncertainty, notably, through the proposed robust optimization structure. In addition, both deterministic and robust plans' reliability, i.e. the probability of being feasible, are assessed through Monte Carlo simulation.

Among the main contributions to the literature provided in this dissertation, stands out the adjustment of data-driven uncertainty sets framework from a robust financial portfolio dynamic optimization (Fernandes et al., 2016) to a robust multi-period static optimization in the humanitarian logistics context. It is also proposed an extension of Bertsimas and Sim (2004) framework with regard to uncertainties on the independent terms (i.e. right hand side of constraints), based on a hierarchical optimization approach to reduce the burden of setting a particular robustness level for each constraint.

Apart from the previous work of Brito et al. (2015), it is, to the best of our knowledge, the only known academic research related to ITN supply chain design optimization. Other aspects with less academic research attention that were revealed in the conducted literature review are also addressed, such as the lack of studies related to slow-onset disasters, notably an epidemic/endemic disease, the simultaneous account of the aforementioned uncertainties, demand prioritization and multimode transportation.

In particular, the conducted literature review corroborates Leiras et al. (2014) finding, which highlighted that sudden-onset disasters are more studied than slow-onset, even though they can cause more harm to the affected population (Long and Wood, 1995). Although slow-onset disasters allow more time for proper reaction, Kunz and Reiner (2012) state that the difficulty to access areas affected by man-made disasters, due for instance to security issues, may inhibit field research.

On the practical side, the use of such model has a direct impact on human suffering alleviation, since it allows more people to have access to ITN through the efficient and effective usage of financial and logistics resources by humanitarian organization, governments and other stakeholders involved in ITN distribution campaigns. Although many uncertainties and risks related to this supply chain might be effectively tackled by some of these stakeholders through common pool resources, long-term agreements and proper planning, it is important to consider them during annual budgetary planning, when current contracts will be subject to review, or prior to the release of tenders.

This dissertation is organized in the following chapters: chapter 2 presents an overview of Malaria and the logistics and supply chain management of ITN distribution. Chapter 3 presents robust optimization frameworks to support decision making under uncertainty, namely Bertsimas and Sim (2004) interval based polyhedral uncertainty sets and Fernandes et al. (2016) adaptive data-driven polyhedral uncertainty sets. Furthermore, a literature review regarding RO applications in HL is presented, with a particular focus on humanitarian supply chain design. Chapter 4 describes the modelling approach proposed to represent the robust ITN transhipment model. Chapter 5 illustrates the applicability of the proposed model, where one real case is studied. Finally, Chapter 6 concludes this dissertation and discusses future research.

2
Malaria and insecticide-treated bed nets distribution

In this chapter the Malaria burden is presented alongside with the importance of long-lasting insecticidal nets (LLINs) to prevent and control this disease. Next, an overview of LLIN distribution is given and its supply chain features are investigated.

2.1.Malaria overview

Malaria is an acute febrile illness caused by five species of parasites from the *Plasmodium* genus, among which *P. falciparum* is the deadliest one. It spreads among humans by an infected female *Anopheles* mosquito, whose bite introduces the contaminated saliva into the person's blood stream (WHO, 2015a).

In 2000, United Nations member states declared the Millennium Development Goals (MDG), with specific targets to halt and begin the reverse of malaria by 2015 (UN, 2016). Since then, much has been achieved; the target has been met with mortality rates decreasing by 60% and the incidence rates falling by 37% globally and by more than 75% in fifty-seven countries (WHO, 2016a).

However, it is estimated that in 2105, almost half of the world population lived in areas at risk of malaria, with more than 214 million new cases and 438,000 associated deaths, among which almost 70% of children under five years. In this context, the Sub-Saharan Africa carries the heaviest burden, being home for 88% of the cases (mainly by *P. falciparum*) followed by the South-East Asia region with 10% (WHO, 2016a).

Within UN Sustainable Development Goals context, the World Health Organization developed the Global Technical Strategy for Malaria, which provides a technical framework to help countries in their efforts towards a new target for reducing global malaria incidence and mortality rates by at least 90% by 2030. To achieve this goal, the domestic and international annual investment requirement would have to increase from current US$ 2.7 billion to US$ 8.7 billion in 2030 (WHO, 2015b).

In the light of these challenges, the framework states that there are three major cost-effective approaches to prevent and treat malaria:

i. Vector-control, that focus on preventing the parasite transmission from humans to mosquito and back again, with the use of insecticide-treated mosquito nets (ITN), which works as a physical and chemical barrier, and with indoor residual spraying (IRS). Long-lasting insecticidal nets (LLINs) is a highly resistant form of ITN, which can be washed without the need to reimmerse it in the insecticide (Malaria Consortium, 2016). Both ITN and IRS can be supplemented with larval source management approach, which requires specialized capacity that is currently unavailable at most of the areas at risk (WHO, 2015b).
ii. Chemoprevention with the administration of antimalarial drugs to pregnant women, newborn infants, children (only as a seasonal administration on high-risk periods), and travelers. More recently, there has been a major progress towards the RTS,S vaccine development, which had a pivotal phase with children in seven countries in sub-Saharan Africa, and might soon become the first commercially available malaria vaccine for the *P. falciparum* (WHO, 2016b).
iii. Case management, regarding the prompt diagnose with rapid diagnostics test (RDT) and the use of a highly effective treatment with Artemisinin-based combination therapy (ACT).

The large-scale deployment of these three elements are considered key factors for the global malaria incidence and death rates decline in the last fifteen years (WHO, 2016c).

2.2. Insecticide-treated bed nets distribution overview

In 2014, the investment in health commodities of malaria control activities (ITNs/LLINs, ACTs, RDTs and IRS) represented 82% (US$ 1.6 billion) of international malaria spendings, in which ITNs/LLINs accounted for 63% of this amount (WHO, 2015a). In compliance to WHO strategy of maximizing the impact of vector control, LLINs are the recommended form of ITN for public health programs, in which the coverage of the entire population at risk is a highly desirable goal (WHO, 2016a).

Malaria vectors in Africa are the most susceptible to control with ITNs, and therefore this continent is where they have been most used. In 2000, less than 2% of Sub-Saharan Africa population slept under an ITN, and by 2015 this number had a remarkable increase, reaching 55% of global coverage and 68% for children under five years. Despite the advances, it is still 45% far from the universal coverage goal and therefore more than 216 million people still live in a household without an ITN (WHO, 2015a).

Malaria Atlas Project (2016) points to the fact that, as expected, most of the countries with high incident rates are receiving at least reasonable coverage efforts. However, it also reveals a major challenge. At least eight countries are below 30% coverage, including Nigeria, the most populated country in the continent, with 33% of malaria incidence (61,1 million), accounting for more cases and deaths than any other country in the world.

In this context, logistics and supply chain management (LSCM) activities involved in an ITN distribution campaign require considerable effort and must be carefully planned and precisely executed to overcome several challenges that might hinder distribution effectiveness.

As a background for this discussion, it is worth pointing out that in 2009, the Catholic Relief Services (CRS) provided 1 million LLINs for all women and children under five years in Niger, in a period of only four days (CRS, 2014). UNICEF's distribution of 3,5 million LLINs for the entire population of Sierra Leone during six days and within the Ebola outbreak context in 2014 is another example of success, which also involved house-to-house survey for demand planning and voucher issue, the clearance of more than 150 containers in the port and the transportation to thirteen districts (UNICEF, 2014a). The distribution was carried out alongside the biannual Sierra Leone Maternal and Child Health Week, to allow synergies between the programs, and additionally a monitoring campaign was set afterwards to guarantee the proper use of the LLINs.

Many variables account for the decision on how to set an ITN/LLIN distribution strategy and, in this connection, Roll Back Malaria (2011a) proposes a framework, summarized in Table 1, to assess the several available options.

Table 1: Framework for describing bed nets distribution mechanisms

Distribution Mechanism Criterion	Available Options
Supply Modality	Push, Pull
Channel	Community, Outreach, Routine, Retail
Duration	Intermittent, Continuous
Target	General, Vulnerable
Cost to User	Free, Subsidized, Full Cost
Method of Delivery	Direct, Voucher, Coupon
Choice for User	None, Limited, Complete
Sector	Public, Civil Society, Commercial

Source: Roll Back Malaria (2011a)

It is worth observing that distinct sets of options might lead to very different LSCM approaches; as in comparing free large-scale nation-wise campaigns (e.g. a pushed demand, intermittent duration, free of costs, general target, through an outreach channel like a parallel immunization campaign, and direct delivery to beneficiaries) to a subsidized continuous distribution towards vulnerable children (e.g. pulled demand, continuous duration, vulnerable target, with prepositioned stock on schools through voucher delivery).

Initially, bed nets distribution campaign efforts are focused on guaranteeing universal and equitable access, thus large-scale mass community distribution campaigns are set towards this target. However, bed nets must be periodically replaced, and once achieved the universal target, the program goal changes from achieving to sustaining the universal coverage level in the medium and long term.

With this new goal in mind, it is possible to conduct top-up campaigns every couple of years, which needs an updated demand assessment per household to minimize over procurement of the actual required number of nets. On the other hand, repeated universal coverage campaigns can be conducted at longer intervals and are less challenging to implement. Furthermore, continuous distributions schemes employing social marketing, vouchers, and several other approaches, through distinct delivery channels, can be developed to maintain universal target levels (Roll Back Malaria, 2011a).

To illustrate this program progression, it's possible to refer to Tanzania's case, which started in 2004 with a continuous voucher based ITN distribution to pregnant women while attending routine antenatal check-up, and later, in 2007, to infants using the same strategy but during immunization services. Between 2008 and 2011 the country held two massive campaigns that distributed 27 million LLINs, the first aiming children under five years and the next towards the universal coverage target. To subsequently maintain the high coverage levels, the voucher based system was adopted (Roll Back Malaria, 2016).

2.3. Insecticide-treated bed nets supply chain features

Next, some essential features of LLIN's supply chain are presented: (i) supply, (ii) demand, (iii) procurement, (iv) funding, (v) transport, (vi) warehousing, and (v) sustainability.

Supply

LLINs are produced in a wide range of sizes and colours, through thirteen suppliers, that are mainly located in Asia (WHO, 2016d), with a total aggregated capacity of 300 million standard size nets per year (UNICEF, 2016). Despite the recent growth of global supply, some countries have their own pesticide-containing products registration requirements going beyond WHO Pesticide Evaluation Scheme (WHOPES) approval. For instance, Peru and Bolivia only have one registered net, which hinders supply flexibility, availability and market competition. In addition, humanitarian organizations might face unexpected shortage of supply due to suppliers' non-compliance to UN policies. In this context, two suppliers were temporarily suspended in 2014 for misconduct associated with bribery and corruption (UNICEF, 2016).

Up to July 2015, Global Fund placed 48% of its LLINs orders in three suppliers: Vestergaard Frandsen (VF) that has a factory in Vietnam, Disease Control Technologies (DCT) with a production line in India, and Sumitomo, which is based on Tanzania, Vietnam and China (Global Fund et al., 2015).

LLIN production lead-time is high and uncertainty, which deeply affects the planning of subsequent logistics activities. USAid (2010) reveals that, in 2010, the minimum lead-time was 10 days for the procurement of 1.7 million nets from

Sumitomo; however, the acquisition of less than half of this quantity from the same supplier took 74 days. Therefore, no significant correlation between production lead-time and the number of LLINs procured could be found. Besides, the long average lead times for smaller orders (up to 150k nets), 24 days and 50 days for BASF and Vestergaard respectively, shows that humanitarian organizations might face limited-stock availability for short notice procurement. In addition, for three offers received by UNICEF comprising the procurement of one million nets, the production lead-time ranged between 52 to 72 days, which reiterates lead-time volatile nature in this industry UNICEF (2014b)

Demand

LLIN demand is based on financial availability and stability, and in preventive campaign delivery modalities. The optimal allocation per household considered by WHO (2014) is 1 LLIN per 1.8 persons. Annual demand can substantially differ, since large scale projects are implemented in a two- to three-year cycle based on estimated bed net serviceable life (UNICEF, 2016). However, actual bed net durability has been difficult to measure since it depends on products characteristics and on the way household uses it, which is country and culture specific (UNICEF, 2016).

Therefore, demand uncertainty is mianly associated to misjudgements in the LLIN needs assessment, i.e. errors in population or net replenishment forecasts, and to the gap between estimated and obtained funding through the fiscal year (Global Fund et al., 2015).

Finally, with the potential approval of the first commercially available malaria vaccine, RTS,S (WHO, 2016d), programs might switch focus from prevention to eradication, which might question the need for bed nets distribution in the future. On the other hand, Africa’s population is expected to double by 2050, with an increase of 1.3 billion people (UN, 2015). Therefore, in case the vaccine is not approved, there will be a great increase in the population living at risk of transmission, which might leverage the need for LLIN distribution.

Procurement

Humanitarian organizations can procure bed nets through a bidding process for each new order or over long-term agreements (LTA) (USAid, 2010). For instance, UNICEF LTAs are arranged with qualified suppliers with the lowest acceptable prices and the shortest lead-time. However, UNICEF LTAs do not fix the price nor the volume for a given horizon, instead it is an agreement where suppliers cannot charge from UNICEF more than it is charging for other clients, while UNICEF shares its demand forecast and target allocation with suppliers (Global Fund et al., 2015).

The average weighted LLIN price (WAP) declined by 41% over the last five years reaching approximately US$ 3 (UNICEF, 2016). This is partially explained by Global Fund et al. (2015) assessment that bed net prices offered from July 2014 to May 2015 followed oil and derivatives (polyester and high-density polyethylene) prices trends, which are bed nets main production inputs. Price decline was also achieved through humanitarian organizations' collaboration in the reduction of LLIN types (from 44 different colours, sizes and shapes to less than ten) and in the alignment of demand forecasts, which in the end allow supplier capacity increase through better production scheduling (UNICEF, 2016).

Funding

African Leaders Malaria Alliance (ALMA) LLIN funding projection until 2020 (Figure 1) shows that from 2017 onwards there is still a major gap of LLINs to be financed, which clearly reveals the short-range budget environment frequently observed on humanitarian operations.

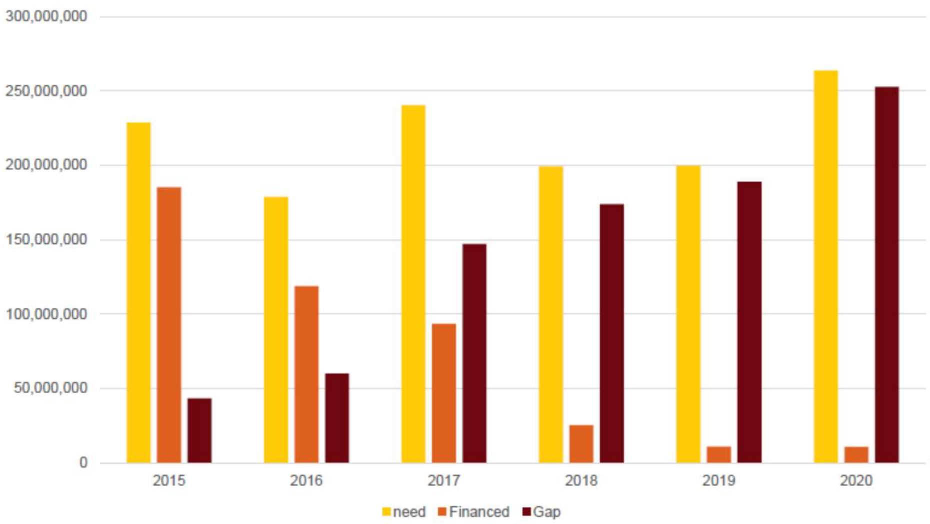

Figure 1: African Leaders Malaria Alliance (ALMA) funding projection shows the gap between already financed and actual need for LLIN procurement.
Source: Global Fund et al. (2015)

Considering LLIN global distribution by humanitarian organization in 2015, Global Fund accounted for 62%, Presidents Malaria Initiative (PMI) 21%, UNICEF 5% and others 12% (Net Mapping Project, 2016).

To improve funding predictability, humanitarian organizations like Global Fund started to synchronize demand forecasts and procurement horizons with country budgeting cycles (UNICEF, 2016). This is particularly relevant to Global Fund, since 95% of its funding comes from the public sector through a three-year-cycle, e.g. in 2016 a pledging conference was held to address financial support for 2017 to 2019 (Global Fund, 2016). In this context, from 2001 until 2013, governments and the private sector pledged 29.4 billion to Global Fund, in which more than 99% was paid.

Transport

A typical flow of ITN/LLIN's through its supply chain it is briefly described by CRS (2014): acquired bed nets from suppliers are shipped to seaports usually used for normal commercial cargo, then the humanitarian organization receives the ITNs/LLINs cargo in the ports of discharge where they are transferred to a central storage area. The bed nets might be dispatched to secondary warehouses before being forwarded to the final distribution points, where they are made available to the beneficiaries. It is worth noting that, due to context specificities, there can be variations of this structure, as in the case of a sufficient in-country stock due to supplier presence in the actual benefited country.

Since the majority of ITN suppliers are located in Asia and almost 90% of the demand is in Africa (WHO, 2015a), ITN distribution usually involves maritime transportation from Asian to African Ports, and inland transportation from suppliers to Asian Ports and from African Ports until local distribution points. Shipping containers from Asia to Africa takes a considerable amount of time, for instance, from Shanghai (China) to Abidjan (Ivory Coast, West Africa) it takes 44 days with MSC Africa Express Service and from 40 to 43 days using Maersk services. On the other hand, to Dar es Salaam (Tanzania, East Africa) it takes about 25 days through MSC and 34 days with Maersk (MSC, 2016 and Maersk, 2016).

Transport activities face many uncertainties and risks that both shippers and carriers must deal with, including, among others, capacity availability, operational delays, disruptions, and freight rate volatility (Thanopoulou and Strandenes).

Shippers can either hire carrier services based on long-term contracts, commonly one to two years, or on the spot market where shipments are handled on a one-time load-by-load basis (Tsai et al, 2011). Spot prices are based on real-time shippers' demands and carrier's capacity, which constitutes a volatile market. Since 2014 the China Containerized Freight Index (CCFI), which tracks contractual and spot-market rates for shipping containers of fourteen trade lanes from ten major ports in China (Shanghai Shipping Exchange, 2016), plunged more than 36% driven by overinvestment in shipping capacity by ocean carriers, decrease of bunker prices, and a downturn in Chinese exports (Petersen, 2016). In addition, container-leasing prices are also responsive to market demand (trade volumes) and asset utilization (Knowler, 2014).

Transportation lead-time can be affected by a number of factors, which can compromise the expected delivery scheduled, such as road conditions, bad weather conditions, capacity bottleneck and operational inefficiencies at ports and terminals.

Unfortunately, developing countries logistic networks usually have limited and constrained infrastructure, inefficient processes and extensive regulations (PricewaterhouseCoopers, 2014). Especially for large volume orders, it is essential to assess container pricing and availability at port of origin and port of discharge capacity to keep up with the predicted schedule and thus avoiding increased costs (UNICEF, 2014b).

In addition, with the decrement of global malaria incidence rates, it tends to concentrate in vulnerable population groups like communities living in difficult access areas, due for instance to infrastructural challenges and security issues (WHO, 2015a). Besides that, malaria transmission is greater in rainy seasons and in the case of intermittent campaigns, bed nets distribution must ideally occur before, but still close, to this period, in which many areas might become inaccessible or costly prohibitive due to flooding or landslides. Moreover, continuous distribution schemes occur in all seasons, and hence they might be more vulnerable to this risk (CRS, 2014).

Warehousing

LLINS are usually packaged in bales of 25, 40, 50 or 100, which are then fitted in containers for sea and inland transportation. There is no need for special storing precautions, since LLINs are non-perishable and they stay well protected within the bales for a reasonable amount of time within normal conditions. However, LLINs are light and voluminous when compared to other humanitarian items like food, and thus require considerable warehouse space (CRS, 2014). In large scale distribution campaigns, there is the possibility to acquire the containers and transport them to hub locations or final distribution points, to use them as a temporary warehouse, and hence reducing handling and storage costs. However, this solution requires roll on/off vehicles or cranes at the final destination, which in the end might become a costly solution in case they are not available in advance (Roll Back Malaria, 2011b).

Sustainability

Large donors like USAid and World Bank have incorporated long-term objectives into their requirements, forcing humanitarian organizations and governments to assess the persistence of programmes impacts to the affected society since their planning phases (Haavisto and Kovacs, 2014).

In this regard, apart from the macroeconomic effects, bed nets distribution programmes should evaluate local environmental aspects, such as reverse logistics and proper disposal of packaging and unusable nets. Additionally, they should raise awareness to avoid misuse, for instance, in fishing activities (Minakawa et al. 2008, McLean et al. 2014), which might cause health issues to the population, ecological deterioration and hence reputational damage to involved organizations in the relief chain.

Local social aspects such as community involvement and capacity building must also be targeted to avoid, among others, program incompatibility towards the beneficiaries, including access inequality to distribution channels like health facilities and schools (Roll Back Malaria, 2011a) and cultural beliefs like population unawareness of LLIN usage importance towards malaria prevention (Sexton, 2011). In addition, erroneous understanding of community's traditions like the possible offensiveness of certain LLINs colours and sleeping arrangements (CRS, 2014) might lead to improper demand forecasting.

3
Robust Optimization

In this chapter, a literature review regarding robust optimization applications in humanitarian supply chain design is conducted to highlight this dissertation contribution to the academic literature. Next, Bertsimas and Sim (2004) robust framework based on interval and polyhedral sets is presented alongside with a proposed hierarchical optimization approach to reduce decision maker's burden of infinite options when setting the robustness parameter in the RHS. Finally, it is presented how Fernandes et al. (2016) adaptive data-driven polyhedral uncertainty sets can be adjusted from a dynamic programming to a static multi-period setting.

3.1.Robust optimization applications in humanitarian supply chain design

In this dissertation, a literature review on the robust optimization approaches in humanitarian logistics was conducted.

The search request was applied in 2016 with no time span restriction and considered the following keywords in the research field: title, abstract and keywords: ((“disaster” OR “emergency” OR “humanitarian logistics”) AND (“supply chain”) AND (“robust optimization”).These keywords were used for the literature search in several academic databases (Scopus, Web of Science, Science Direct, Informs, ProQuest and J-Stage.)

Next, the search was extended to references from the identified studies. It is worth noting that academic research related to risk measures approaches (e.g. shortfall probability, expected shortage, value at risk and conditional value at risk) as a tool to mitigate risks in stochastic programming were disregarded in this literature review.

In total 32 thesis, conference and journal papers exclusively related to robust optimization approaches in humanitarian logistics were reviewed. The studies addressed problems like evacuation planning, emergency vehicles routing, volunteer scheduling, facility location and aid distribution, with the two latest types being more closely related to supply chain design. According to Chopra and Meindl (2004), a supply chain design problem involves decisions concerning manufacturing, storage, or transportation-related facilities' location, capacity allocation, and market allocation within a supply chain network.

Thus, among the 32 studies reviewed, 10 are tied to humanitarian supply chain design, and since they are more relevant to this dissertation, they were classified to observe trends and find literature gaps.

In this regard, Bozorgi-Amiri et al. (2013) presented a multi-objective robust two-stage stochastic approach for disaster relief logistics, based on Mulvey et al. (1995) robust framework, considering uncertainties in supply, demand, procurement costs and transportation costs. The model adds and weights cost variability (known as solution robustness, i.e., close to an optimum solution) and penalties for infeasibility (known as model robustness, i.e., close to a feasible solution) within the objective function, which minimizes financial costs, while minimizing the maximum shortages in the affected areas. The authors present a case study for earthquake preparedness and response plan in Iran.

Also based on Mulvey et al. (1995), Jabbarzadeh et al. (2014) present a multi-objective two-stage robust blood network supply chain design model. The first stage defines permanent facilities location prior to disaster occurrence, while the second stage determines temporary facilities location, allocation, blood collection and inventory level. The objective function minimizes the mean value and variance (solution robustness) of total supply chain costs (permanent facility set up, moving temporary facilities costs, transportation costs and inventory costs) while penalizing the under-fulfilment of blood demand (model robustness). A case study for earthquake response in Tehran, Iran, is presented.

Rezaei-Malek et al. (2016) present a bi-objective two-stage robust stochastic model to determine the optimum warehouses location, the ordering policy for renewing the stocked perishable commodities and aid distribution plan. Uncertainties are considered in demand, supply and logistics infrastructure, which are tackled using Mulvey et al. (1995) robust framework. The objective is to minimize the average of the weighted response times, the total costs, the unmet demand and unused relief items. A real case study is developed for Sadatabad-Shahrakegharb earthquake prone area in Iran.

Similarly, Das and Hanaoka (2013) and Florez et al. (2015) also propose a robust humanitarian supply chain design model considering the aforementioned framework. However, the latter only resembles model robustness, as it considers a penalty in the objective function for the amount of unsatisfied demand above a chosen threshold in each region in order to improve fairness of aid distribution.

Najafi et al. (2013) presents a hierarchical multi-objective, multimode, multi-commodity, multi-period model for relief commodities distribution and injured people transportation in the initial phase of an earthquake response. The authors consider both supply and demand uncertainties that are approached through Bertsimas and Sim (2004) robust framework. The proposed model minimizes the total weighted waiting time of unserved injured persons, the total weighted lead-time of meeting the commodity needs, and the total vehicles utilized in the response.

Zokaee et al. (2016) present a three level relief chain model, consisting of suppliers, relief distribution centres and affected areas. The objective function minimizes total costs and penalizes unmet demand and a real case is developed for the earthquake zone of Alborz, in Iran. Uncertainty is considered in all cost parameters through Bertsimas and Sim (2004) robust framework. On the other hand, demand and supply uncertainties are approached with Bertsimas and Thiele (2006b) framework, which is an extension of the above-mentioned framework for uncertainties that are on the right-hand side (RHS) of constraints. When applying Bertsimas and Sim (2004) framework to RHS uncertain parameters, the decision maker faces the challenge of defining a conservatism parameter (i.e. the budget of uncertainty inside a [0, 1] interval) for each supplier and demand area, which leads to endless possible combinations. In this respect, Bertsimas and Thiele (2006b) apply a single conservatism parameter for all demand areas, with the disadvantage of considering that they have identical independent distributions and are distributed symmetrically in common ranges, which is a strong assumption that might not be suitable for all real-life applications.

Tang et al. (2009) firstly propose a model to forecast the uncertain relief demand after an earthquake. Later, an adjustable robust distribution model is developed, based on the adjustable robust framework introduced by Ben-tal et al. (2004), in which part of the variables must be determined before the realization of the uncertain parameters (nonadjustable variables), while the other part are variables that can be chosen after the realization (adjustable variables). This definition bears similarities to Birge and Louveaux (2011) two-stage stochastic programming framework, where first-stage decisions ("here and now") are made prior to uncertainty revelation, while the second stage ("wait and see") decisions are made after. To keep computational tractability, the adjustable variables (in this case the quantity of commodities transferred from distribution centres to affected areas) are usually defined as affine functions of the uncertain data representing an Affinely Adjustable Robust Counterpart (AARC). The multi-objective function maximizes the satisfaction rate of the relief demand and minimizes distribution costs.

Álvarez-Miranda et al. (2015) present a two-stage robust recoverable facility location and distribution model, based on the recoverable robust framework proposed by Liebchen et al. (2009), in which is possible to modify (recover) the first-stage defined location–allocation policy to make it feasible and/or cheaper once the uncertainty is unveiled in a second stage. The first-stage solution comprises the opening of facilities and their preliminary allocation to costumers, not necessarily reaching full coverage. The uncertainty is considered in demand, supply, logistics infrastructure, and set-up and allocation costs. The recovery actions in the second-stage correspond to the opening of new facilities, the establishment of new allocations and the re-allocation of customers. The objective function minimizes the first-stage costs plus the second-stage robust recovery cost, defined as the worst-case recovery cost over all possible scenarios. The authors present two illustrative case studies related to floods in Bangladesh and Typhoons in the Philippines.

Paul and Hariharan (2012) present a robust facility location and allocation model based on the min max regret criteria addressed by Inuiguchi and Sakawa (1995), which is used to obtain a final solution when a reference solution set is given. In this case, the regret represents the difference between a given solution for the problem and the optimal cost of a specific scenario (reference solution set), and it is used to choose which scenario will be considered for the final solution. Uncertainties are contemplated in the location and magnitude of earthquakes (i.e demand). The objective function minimizes the social cost, which is the sum of the fatality cost, and the cost of maintaining a stock pile at a given facility. A case study in the Northridge area, California, is presented within the context of the United States Strategic National Stockpile (SNS) assistance, which is the USA repository for critical medical equipment and supplies, in the event of national emergencies including major disaster responses.

Tables 2 and 3 summarize the 10 studies related to robust optimization in humanitarian supply chain design and they partially introduce the contributions of this dissertation. After, the criteria (mostly based on Najafi et al., 2013) used to classify the literature and the findings from this review are presented.

Table 2: Summary of the robust optimization papers related to humanitarian supply chain design

	Reference	Year	Type of publication	Modeling				Uncertainties				
				Type of Objective Function	Modeling Technique	Robust Framework	Decision Stages	Supply	Demand	Logistics	Costs	Budget
1	Tang et al.	2009	Conference	C, H	Rob	B	2		x			
2	Bozorgi-Amiri et al.	2013	Journal	C, H	Rob-Sto	M	2	x	x		x	
3	Paul and Hariharan	2012	Journal	C, H	Rob	IS	1		x			
4	Najafi et al.	2013	Journal	C, H	Rob	BS	1	x	x			
5	Das and Hanaoka	2013	Journal	C, H	Rob-Sto	M	2	x	x	x		
6	Jabbarzadeh et al.	2014	Journal	C	Rob-Sto	M	2	x	x	x	x	
7	Álvarez-Miranda et al.	2015	Journal	C	Rob	L	2	x	x	x	x	
8	Florez et al.	2015	Journal	C, H	Rob-Sto	M	2		x	x		
9	Rezaei-Malek et al.	2016	Journal	C, H	Rob-Sto	M	2	x	x	x		
10	Zokaee et al.	2016	Journal	C, H	Rob	BS, BT	1	x	x		x	
11	*This dissertation*	2017	Dissertation	C, H	Rob	BS, F	1	x	x	x	x	x

Type of objective function: C (Cost), H (Humanitarian).

Solution Methodology: Ex (Exact), He (Meta/Heuristics).

Optimization Method: Rob (Robust), Rob-Sto (Robust-Stochastic).

Robust Framework: B (Ben-Tal et al. 2004), BS (Bertsimas and Sim, 2004), BT (Bertsimas and Thiele, 2006b), F (Fernandes et al., 2016), L (Liebchen et al. 2009), IS (Inuiguchi and Sakawa 1995), M (Mulvey et al. 1995).

Table 3: Summary of the robust optimization papers related to humanitarian supply chain design

	Reference	Year	Supply Chain			Disaster				
			Mode of Transport	Products	Demand Prioritization	Application type	Phase	Onset	Origin	Type
1	Tang et al.	2009	SM	SP		I	Prep	Sud	Nat	Ea
2	Bozorgi-Amiri et al.	2013	SM	MP		R	Prep	Sud	Nat	Ea
3	Paul and Hariharan	2012	SM	MP	x	I, R	Prep	Sud	Nat	Ea, Hu
4	Najafi et al.	2013	MM	MP	x	I	Resp	Sud	Nat	Ea
5	Das and Hanaoka	2013	SM	MP		R	Prep	Sud	Nat	Ea
6	Jabbarzadeh et al.	2014	SM	SP		R	Prep	Sud	Nat	Ea
7	Álvarez-Miranda et al.	2015	SM	SP		I	Prep	Sud	Nat	Fl, Ty
8	Florez et al.	2015	SM	SP		R	Prep	Sud	Nat	Ea, Fl
9	Rezaei-Malek et al.	2016	SM	MP		R	Prep	Sud	Nat	Ea
10	Zokaee et al.	2016	SM	MP		R	Prep	Sud	Nat	Ea
11	*This dissertation*	2017	MM	SP	x	I, R	Mit	Slow	Nat	Ed

Mode of Transport: SM (Single Mode), MM (Multi Mode).
Products: SP (Single Product), MP (Multi Product).
Application Type: I (Illustrative), R (Real Case).
Phase: Mit (Mitigation), Prep (Preparedness), Resp (Response), Recov (Recovery).
Onset: Sud (Sudden), Slow.
Origin: Nat (Natural), Man (Man-made),
Type: Ea (Earthquake), Hu (Hurricane), Fl (Flood), Ty (Typhoon), La (Landslide), Ed (Endemic/epidemic disease)

The papers are classified in four classes, which area modelling, uncertainties, supply chain and disaster, spanning seventeen criteria. The first class, modelling, includes type of objective function, modelling technique, robust framework and decision stages. According to the first criterion, papers are categorized into three groups: cost objective function (C), humanitarian objective function (H) based on Holguin-Veras et al. (2013), and both cost and humanitarian (C, H). The second criterion, modelling technique, separates the papers in two groups, the ones with a robust optimization approach (Rob) and those with a robust-stochastic approach (Rob-Stoc), where the stochastic part is related to the optimization of expected values as presented in Birge and Louveaux (2011). The third criterion describes which robust optimization frameworks were applied within the papers: Bertsimas and Sim (BS), Bertsimas and Thiele (BT), Ben-tal et al. (B), Fernandes et al. (F), Liebchen et al. (L), Mulvey et al. (M), Inuiguchi and Sakawa (IS). The fourth criterion describes the number of decision stages considered in the paper: one stage (1), two stages (2) and three or more stages (3+).

The second class, uncertainties, includes binary criteria concerning supply, demand, logistics and budget, in which an (x) represents the presence of uncertainty, and otherwise the field is left empty. The first criterion, supply, cover those papers that consider uncertainties in supply production or distribution centre inventories, due to, for instance, facility disruptions after a disaster. The second criterion, demand, is related to demand uncertainties, due to demand forecast errors, unknown location and magnitude of disasters, among others. The third criterion, logistics, represents uncertainties connected to logistics infrastructure capacity and/or availability, as in the case of congested or destroyed ports and unavailable routes. The fourth criterion, costs, represents uncertainties linked to price volatility, such as procurement costs of relief items and equipment, transportation costs and inventory costs. The fifth criterion, budget, covers the uncertainty of budget availability which might undermine relief efforts.

The third class, supply chain properties, includes mode of transport, products and demand prioritization. According to the first criterion of this group, papers are divided into single mode (SM) and multimode (MM) models. The second criterion describes if the model considers a single product flow (SP) or a multi-product flow (MP) along the supply chain. The third criterion indicates if the model consider demand prioritization, as in the case of different injury levels, in which the more critical cases need to be treated first or in areas where an epidemic disease is spreading faster than others.

Finally, the fourth class shows criteria related to disaster properties: application, phase, onset, origin, and type. The first criterion in this group, application, describes if the paper applied the proposed model in an illustrative (I) or in a real case (R) disaster setting. The second criterion indicates which disaster phase, according to Altay and Green (2006) classification framework, is approached by the model: mitigation (Mit), preparedness (Prep), response (Resp) or recovery (Recov). The third criterion, describes, if the investigated disaster has a sudden (Sud) or slow (Slow) onset. The fourth criterion, origin, indicates if it is a man-made (Man) or natural (Nat) disaster. The last criterion, present which specific type of disaster is studied: endemic/epidemic diseases (Ed) earthquakes (Ea), typhoons (Ty), hurricanes (Hu), floods (Fl) or landslides (La).

The literature review suggests (Table 2) that most of the robust humanitarian supply chain design (RHSCD) papers already consider a humanitarian element within the objective function, such as penalties for unmet demand or fairness of aid distribution. The majority uses a two-stage robust-stochastic model based on Mulvey et al. (1995) solution robustness framework, followed closely by Bertsimas and Sim (2004) framework. However, it is worth noting that six different robust optimization frameworks addressed the RHSCD problem, and thus, there is no unanimity concerning a generally better approach to robust optimization. There is also space for the development of robust models with more than two decision stages and distributionally robust-stochastic models, in which the uncertain data is governed by a probability distribution that is itself subject to uncertainty (Goh and Sim, 2010; Delage and Ye, 2010).

Among five different types of uncertainties, on average, a given paper only considers 2 uncertainties on the model and the majority usually considers only one type. Demand is by far the most approached uncertainty, followed by supply and then by logistics capacity and availability. Despite the volatile nature of prices, only three papers considered this risk and none tackled budgetary uncertainties, which is frequently found on humanitarian organizations due to funding scarcity and unpredictability (Van Wassenhove, 2006). Regarding supply chain properties, only one paper considered a multi-modal approach, which is unexpected, since logistics infrastructure disruptions might hinder the use of usually available assets like trucks and thus leading to the use of more expensive options, such as helicopters. The approach toward single or multi-product supply chain design was equally divided, despite the fact that in the aftermath of a disaster a wide range of relief items and equipment is often needed. Demand prioritization is also a forgotten aspect, since only two papers considered this challenge in their modelling efforts.

Since nearly all papers address the preparedness phase for sudden-onset disasters, there is a lack of research towards other phases and slow-onset disasters that cause more damage to population (Long and Wood, 1995) but are usually forgotten by the media.

In this connection, this dissertation considers several aspects with less academic research attention that were revealed in the conducted literature review, such as the assessment of slow-onset disasters, in particular Malaria, an epidemic/endemic disease, the simultaneous account of supply, demand, logistics, budget and costs uncertainties, demand prioritization and multimode transportation.

3.2. Bertsimas and Sim robust framework

Deterministic models in mathematical programming assume that the input data is accurately known and equal to a nominal value. However, data is susceptible to uncertainties, such as measurement errors, numerical instability, forecast errors and changing environments in long-term decisions (Goerick, 2012). If these uncertainties are not properly addressed, a slight change in the nominal value might render the original optimal solution a suboptimal or even infeasible. In this context, there are several robust optimization frameworks, linked to distinct concepts of robustness, which consider parameter uncertainty to design conservative solutions.

In this work, the approaches proposed by Bertsimas and Sim (2004) and Fernandes et al. (2016) are followed, where both develop models that are relatively immune to data uncertainty given a pre-specified conservatism level.

In this respect, Soyster (1973) originally proposed a linear programming model to build a robust solution that is feasible for all data belonging to a convex uncertainty set. In his approach, the results are too conservative, since it considers the unlikely scenario where all uncertain data assume their worst value simultaneously.

To overcome the problem of over conservatism Ben-Tal and Nemirovski (1998) proposed an ellipsoidal uncertainty set to adjust the conservatism level, which, however, led to a nonlinear robust counterpart model.

Bertsimas and Sim (2004) developed a framework that retains the advantages of the linear framework of Soyster (1973), while allowing the control of the conservatism level of each constraint i.

Bertsimas and Sim (2004) consider the following nominal linear optimization problem:

$$Maximize\ \mathbf{c}'\ \mathbf{x} \tag{1}$$

$$Subject\ to$$

$$\mathbf{Ax} \leq \mathbf{b} \tag{2}$$

$$\mathbf{x} \quad \geq 0 \tag{3}$$

In the above formulation, it assumed that data uncertainty only affects the elements of matrix **A**. Without loss of generality, the objective function coefficient c is assumed to not be subject to uncertainty, since it is possible to rewrite the objective function as $maximize\ z$, add the constraint $z - \mathbf{c}'\ \mathbf{x} \quad \leq\ 0$, and thus include this constraint into $\mathbf{Ax} \leq \mathbf{b}$.

Therefore, in a particular row i of the matrix **A**, let J_i represent the set of coefficients in row i that are subject to uncertainty. Each entry $a_{ij},\ j \in J_i$, is modelled as a symmetric and bounded random variable $\tilde{a}_{ij}, j \in J_i$, that takes values in $[a_{ij} - \hat{a}_{ij}, a_{ij} + \hat{a}_{ij}]$.

For every i, there is a parameter Γ_i, not necessarily integer, that takes values in the interval $[0, |J_i|]$. The role of the parameter Γ_i is to adjust the robustness of the method against the level of conservatism of the solution.

Since it is unlikely that all of the $a_{ij},\ j \in J_i$, will change, the proposed model protects against all cases that up to $\lfloor \Gamma_i \rfloor$ of these coefficients are allowed to change, and one coefficient a_{it} changes by $(\Gamma_i - \lfloor \Gamma_i \rfloor)\hat{a}_{it}$.

The model proposed by Bertsimas and Sim (2004) can be formulated as follows:

$$Maximize_x \;\; \boldsymbol{c}' \;\boldsymbol{x} \tag{1}$$

$Subject\ to$

$$\sum_j a_{ij}\, x_j \; + \; Max_\Omega \left\{ \sum_{j \in S_i} \hat{a}_{ij} x_j \; + \left(\Gamma_i \; - \lfloor \Gamma_i \; \rfloor \right) \hat{a}_{it_i} x_j \right\} \leq b_i \quad \forall i \tag{4}$$

$$\mathbf{x} \geq 0 \tag{3}$$

Where $\Omega = \{S_i \; \cup \{t_i\} | S_i \; \subseteq J_i \;, |S_i \;| = \lfloor \Gamma_i \; \rfloor, t_i \; \in J_i \; \backslash S_i \}$ determines the uncertainty set, in which S_i is associated to uncertainties related to $\hat{a}_{ij}$ and t_i to $\hat{a}_{it_i}$.

Given a solution vector $\boldsymbol{x}^*$ and a conservatism level Γ_i, constraint i is protected by a protection function $\beta_i(\boldsymbol{x}^* , \Gamma_i \;)$ defined as:

$$\beta_i(\boldsymbol{x}^* , \Gamma_i \;) = Maximize_\Omega \left\{ \sum_{j \in S_i} \hat{a}_{ij} x_j^* + \left(\Gamma_i \; - \lfloor \Gamma_i \; \rfloor \right) \hat{a}_{it_i} x_j^* \right\} \tag{5}$$

In addition, the protection function can be stated as the following linear optimization problem:

$$\beta_i(\boldsymbol{x}^* , \Gamma_i \;) = Maximize_u \sum_{j \in J_i} \hat{a}_{ij}\, x_j^* u_{ij} \tag{6}$$

$Subject\ to$

$$\sum_{j \in J_i} u_{ij} \; \leq \Gamma_i \tag{7}$$

$$0 \leq u_{ij} \; \leq 1 \qquad\qquad \forall j \in J_i \tag{8}$$

It is worth noting that $\Gamma_i \; = 0$ implies in $\beta_i(x^* , \Gamma_i \;) = 0$ and the constraints are equivalent to the nominal model. On the other hand, if $\Gamma_i \; = |J_i|$, then $\beta_i(x^* , \Gamma_i \;) = \sum \; \hat{a}_{ij}\, x_{ij}$ the model assumes the robustness level proposed by Soyster (1973).

By strong duality, since the linear form of the protection function is feasible and bounded for all $\Gamma_i \; \in [0, |J_i|]$, then its dual problem is also feasible and bounded and their objective values coincide. The robust counterpart is obtained by substituting the dual form of the protection function in the original problem:

$$Maximize_x \ \boldsymbol{c}' \ \boldsymbol{x} \tag{1}$$

$Subject \ to$

$$\sum_j a_{ij} \, x_j \ + \ z_i \ \Gamma_i \ + \sum_{j \in J_i} p_{ij} \le b_i \qquad \forall i \tag{9}$$

$$z_i \ + p_{ij} \ge \hat{a}_{ij} x_j \qquad \forall i, j \in \ J_i \tag{10}$$

$$p_{ij} \ge 0 \qquad \forall i, j \in \ J_i \tag{11}$$

$$z_i \ \ge 0 \qquad \forall i \tag{12}$$

$$x_j \ \ge 0 \qquad \forall j \tag{13}$$

Where z_i and p_{ij} are dual variables associated to constraints (7) and (8) respectively.

Bertsimas and Sim (2004) also showed that the solution might still be feasible if more than Γ_i uncertain coefficients are perturbed. Assuming that each symmetric and bounded random variable $\tilde{a}_{ij}, j \in \ J_i$ is independent, i.e. the realization of one does not affect the probability distribution of the other, the violation probability of the i^th^ constraint given an optimal solution x^* is:

$$P\left(\sum_j \tilde{a}_{ij} \, x_j^* \ge b_i \right) \le 1 - \Phi\left(\Gamma_i \ - \frac{1}{\sqrt{|J_i|}}\right) \tag{14}$$

Where Φ, is the cumulative distribution function of a standard normal random variable.

3.3. RHS uncertainties

When Bertsimas and Sim (2004) framework is applied to address uncertainty on the independent terms of the constraint (i.e. right hand side, such as demand or supply capacity), the decision maker needs to set a robustness level $\Gamma_i^b \in [0,1]$ for each individual constraint, which might be exhaustive depending on the size of the problem. In this case Bertsimas and Sim (2004) framework might become trivial and with limited applicability, as shown below.

Consider the nominal linear optimization model proposed by Bertsimas and Sim (2004), eq.(1)-eq.(3), and assume that data uncertainty only affects the elements in vector **b**. Let I represent the set of all b_i coefficients (i.e. all rows i), and let $\Omega \subseteq I$ represent the set of b_i coefficients that are subject to uncertainty. Each entry b_i , $i \in \Omega$ in equation (2) is modelled as a symmetric and bounded random variable $\tilde{b}_i$ that takes values in $[b_i - \hat{b}_i , b_i + \hat{b}_i]$. For every $i \in \Omega$, there is a parameter Γ_i^b , that takes values in the interval $[0,1]$. The role of the parameter Γ_i^b is to adjust the robustness of the method against the level of conservatism of the solution. Note that the superscript b in Γ_i^b it is not an index and is used for labelling purpose to avoid confusion to the prior Γ_i used in the context of uncertainties regarding matrix **A**.

The original problem with right hand side uncertainty can be stated as follows:

$$Maximize_x \ \boldsymbol{c}' \ \boldsymbol{x} \qquad (1)$$

$$Subject\ to$$

$$\sum_j a_{ij} x_j \le b_i \qquad \forall i \in I \backslash \Omega \qquad (15)$$

$$\sum_j a_{ij} x_j \le \tilde{b}_i \qquad \forall i \in \Omega \qquad (16)$$

$$\mathbf{x} \geq 0 \qquad (3)$$

To guarantee that inequality (15) holds in the worst-case scenario the problem is reformulated to:

$$Maximize_x \ \boldsymbol{c'} \ \boldsymbol{x} \tag{1}$$

$$Subject \ to$$

$$\sum_j a_{ij} \, x_j \ \leq b_i \qquad \forall i \in I \backslash \Omega \tag{15}$$

$$\sum_j a_{ij} \, x_j \ \leq Min \, \tilde{b}_i \qquad \forall i \in \Omega \tag{17}$$

$$\mathbf{x} \geq 0 \tag{3}$$

Next, the robust counterpart of the above problem (eq.1, 3, 15 and 17) is defined as a bilevel optimization model. In particular, a bilevel model includes two mathematical programs within a single instance, were one of these problems (lower level problem) is part of the constraints of the other one (upper level problem) (Colson et al. 2007). Therefore, some upper level variables are conditioned to the optimal solution of the lower level variables.

$$Maximize_x \ \boldsymbol{c'} \ \boldsymbol{x} \tag{1}$$

$$Subject \ to$$

$$\sum_j a_{ij} \, x_j \ \leq b_i \qquad \forall i \in I \backslash \Omega \tag{15}$$

$$\sum_j a_{ij} \, x_j \ \leq b_i \ - Max_u \hat{b}_i \ u_i \qquad \forall i \in \Omega \tag{18}$$

$$Subject \ to$$

$$u_i \leq \Gamma_i^b \tag{19}$$

$$0 \leq u_i \leq 1 \tag{20}$$

$$\mathbf{x} \geq 0 \tag{3}$$

The objective function of the lower level problem, $Max_u \hat{b}_i \ u_i$, represents the maximum loss in the RHS according to the chosen Γ_i^b . The solution of the lower level problem is given by $u_i = \Gamma_i^b$, and therefore the original problem can be rewritten in a single level:

$$Maximize_x \;\; \boldsymbol{c}' \; \boldsymbol{x} \qquad (1)$$

$$Subject\ to$$

$$\sum_j a_{ij}\, x_j \;\; \leq b_i \qquad \forall i \in I \backslash \Omega \qquad (15)$$

$$\sum_j a_{ij}\, x_j \;\; \leq b_i \;\; - \Gamma_i^b \hat{b}_i \qquad \forall i \in \Omega \qquad (21)$$

$$\mathbf{x} \geq 0 \qquad (3)$$

Overcoming the issue of setting a robustness level $\Gamma_i^b \in [0,1]$ for each individual constraint, Bertsimas and Thiele (2006a) propose a single conservatism parameter, e.g. T , to define the number of demand locations i that might assume their worst-case value, in a single period inventory management problem, but with the drawback that all b_i , $i \in I$ (i.e. the demand of each location) must lie within the same uncertainty set $[b \;\; - \hat{b} \;\; , b \;\; + \hat{b} \;\;]$.

On the other hand, under a multiperiod inventory management problem, in which t represents each time period, Bertsimas and Thiele (2006b) propose an uncertainty budget, e.g. T_{it} , that indicates for each period the number of past periods that the uncertain cumulative demand of a given location i, which appears in the RHS, might assume its worst-case deviation from its nominal value. In addition, they suggest that T_{it} should increase over time to create a reasonable worst-case approach. However, no further propositions are made to overcome the issue of setting the uncertainty budget for each individual demand in each period, which might be challenging for large problem instances.

In this context, the use of a global robustness level, T , is proposed in this dissertation and indicates the maximum number of uncertain right-hand side parameters $\tilde{b}_i, i \in \Omega$, that are allowed to assume their worst-case values, however, unlike Bertsimas and Thiele (2006a), it is considered the original uncertainty set of each $\tilde{b}_i, i \in \Omega$.

Similar to Bertsimas and Thiele (2006b), the idea behind the proposition is an ordering heuristic within an auxiliary problem, that might be based, for instance, on deviation values $\hat{b}_i$, $i \in \Omega$ to choose which $\tilde{b}_i$, $i \in \Omega$ will assume their worst value given a global robustness level Υ set by the decision maker. Despite the arbitrariness in choosing which $\tilde{b}_i$ will assume their worst value; it is a simple and easy to understand approach to set the conservatism levels.

Since Bertsimas and Thiele (2006b) study a constraint with an accumulated uncertain demand on the RHS (similar to $\sum_t \Gamma_{it}^b \hat{b}_{it}$), by strong duality the objective function of the dual formulation from the auxiliary problem, which sets Γ_{it}^b values according to an uncertainty budget Υ_{it} , can replace the RHS uncertainty term in the original problem constraint. However, observe that if the original problem constraint had a non-accumulated demand for each location on the RHS, this reinjection would not be trivial.

In this context, oppositely to Bertsimas and Thiele (2006b) the proposed formulation in this dissertation keeps the auxiliary problem to account for the particular cases in which the dual formulation is not directly applicable. In addition, this proposition allows using other criterion for the ordering heuristic to set the appropriate budget of uncertainty, such as supplier production reliability or the priority of each demand location instead of uncertain parameters deviation values. Moreover, in the proposed formulation there is an explicit concern in reducing the complexity of setting several robustness levels in the RHS (i.e. for each row i) within large problem instances.

To give a practical meaning to the global robustness level, it is worth noting that each $\tilde{b}_i$, $i \in \Omega$ must be classified within a predefined constraint category, such as demand fulfilment, supply capacity or funding availability constraints. Therefore, each constraint category implies in a particular global robustness parameter.

Therefore, it is introduced the set $g \in G$ that represents each uncertain constraint category, and henceforth, global robustness levels are indexed with g, i.e., Υ_g. Besides, let each subset $\Omega_g \subseteq \Omega$ represent the set of b_i uncertain coefficients that falls within the same category g.

The proposed framework results in a hierarchical optimization model, where once given global robustness levels, Υ_g, the lower level defines $\Gamma_i^b, i \in \Omega_g$ values that maximizes or minimizes a given criterion. To illustrate this approach the uncertain parameters deviation values are set as the criterion and thus the lower level problem maximizes the global decrease in the RHS:

$$Maximize_x \ \boldsymbol{c}' \ \boldsymbol{x} \tag{1}$$

$$Subject\ to$$

$$\sum_j a_{ij}\, x_j \ \leq b_i \qquad \forall i \in I \backslash \Omega \tag{15}$$

$$\sum_j a_{ij}\, x_j \ \leq b_i \ - \Gamma_i^b \hat{b}_i \qquad \forall i \in \Omega \tag{21}$$

$$\mathbf{x} \geq 0 \tag{3}$$

$$Maximize_\Gamma \ \sum_{i \in \Omega} \Gamma_i^b \hat{b}_i \tag{22}$$

$$Subject\ to$$

$$\sum_{i \in \Omega_g} \Gamma_i^b \ \leq \mathrm{T}_g \qquad \forall g \in G \tag{23}$$

$$0 \leq \Gamma_i^b \leq 1 \qquad \forall i \in \Omega \tag{24}$$

Given an uncertain constraint category $g \in G$, if $\mathrm{T}_g = 0$ the formulation becomes the nominal problem for that particular category, and if $\mathrm{T}_g = |\Omega_g|$, where $|\Omega_g|$ is the cardinality of the uncertainty set Ω_g,it goes back to Soyster's approach.

To illustrate the ordering heuristic, assume an uncertain constraint category $g = "supply"$ regarding supplier capacity availability, in which i represents an LLIN supplier and $\tilde{b}_i$ its uncertain capacity. Tables 4, 5 and 6 expose an example with three suppliers.

Table 4: Supplier capacity deviation $\hat{b}_i$ from its nominal value $\bar{b}_i$.

$\boldsymbol{i}$	$\hat{\boldsymbol{b}}_{\boldsymbol{i}}$
A	300
B	200
C	500

Table 5: Suppliers are listed in descending order of capacity deviation $\hat{b}_i$ value.

$\boldsymbol{i}$	$\boldsymbol{\hat{b}_i}$
C	500
A	300
B	200

Table 6: Γ_i^b values according to chosen global robustness level T_{supply}.

$\boldsymbol{i}$	$\boldsymbol{\hat{b}_i}$	Global robustness level T_{supply}			
		0	**1**	**2**	**3**
C	500	0	1	1	1
A	300	0	0	1	1
B	200	0	0	0	1

For a global robustness level $\mathrm{T}_{supply} = 1$, a maximum of one supplier is allowed to assume its worst capacity value ($\bar{b}_i - \hat{b}_i$). Thus, on the above example, supplier C is the one that once assuming its worst-case value, represents the greatest decrease in global supply capacity. Therefore, in this case $\Gamma_C^b = 1$ and $\Gamma_A^b, \Gamma_B^b = 0$.

Note that, if $\mathrm{T}_{supply} = 0$, then $\Gamma_A^b, \Gamma_B^b, \Gamma_C^b = 0$ and the model becomes its deterministic counterpart since all nominal values $\bar{b}_i$ are assumed. On the other hand, if $\mathrm{T}_{supply} = |\Omega_{supply}| = 3$, then $\Gamma_A^b, \Gamma_B^b, \Gamma_C^b = 1$ and all suppliers assume their worst capacity value representing the most conservative solution, as proposed by Soyster (1973).

3.4. Fernandes et al. data driven uncertainty sets

Within the context of a robust portfolio dynamic optimization, Fernandes et al. (2016) propose adaptive polyhedral uncertainty sets that are empirically determined using the last K observed data. In this way, the decision maker must choose a window of robustness K (Figure 2), which might be more insightful than setting the number of parameters that are allowed to assume their worst-case value in each implementation period.

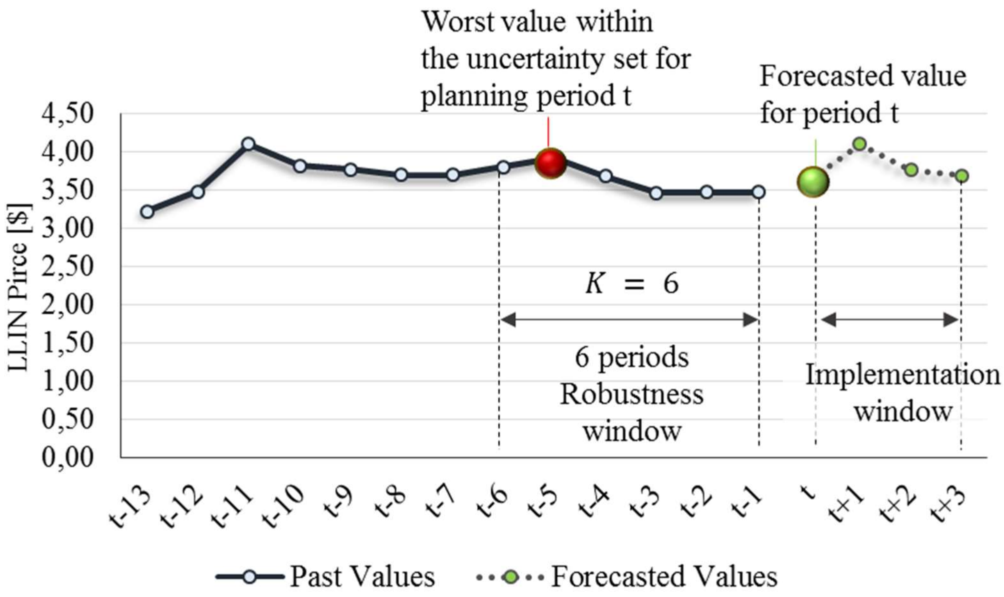

Figure 2: The uncertainty set is adapted for each period inside the implementation window considering the forecasted value for the current period and the k past observed values.

Source: Author

Figure 2 depicts a LLIN price time series of a specific supplier, where, for instance, decisions must be made for an implementation window (i.e. t, $t+1$, $t+2$, $t+3$). Note that the uncertainty set for the current period (e.g. t), considers both the forecasted value for the current period (e.g. t) and the k (e.g. $K=6$) past observed values (e.g. $t-1, \dots, t-6$). Under these assumptions and supposing a minimum costs models, the LLIN price assumed within the objective function for the implementation period t is the observed in $t-5$ (i.e. 3.93), which is the highest among all prices in the uncertainty set, representing an 8% increase on the nominal price for period t (i.e. 3.63). If a higher K is considered, for instance, $K=11$, the worst value is 4.10 related to period $t-11$, which is almost 13% higher than the nominal value. Note that for implementation period $t+1$ and $K=6$, the robustness windows shifts by 1 period and the uncertainty set is now formed by observations $t-5$ until $t+1$. The worst value within the uncertainty set for implementation period $t+1$, is actually the one predicted for period $t+1$ (i.e 4.09) instead of a value inside the robustness window. This instance illustrates the adaptive feature of the aforementioned data-driven uncertainty sets and its ability to adjust the robustness of the method against the level of conservatism of the solution.

Next, the formulation proposed by Fernandes et al. (2016) is adjusted from a dynamic optimization model to a static multi-period model.

First, let $t \in T \subseteq \mathbb{N}$ represent the set of implementation periods where decisions would originally be made with predicted data only.

As previously considered within Bertsimas and Sim (2004) framework, let J_i represent the set of uncertain parameters $a_{ijt}, j \in J_i$ in a particular row i of the constraint matrix **A**. However, no assumptions are made regarding random variable $\tilde{a}_{ijt}, j \in J_i$ boundaries or probability distribution. Besides, the objective function **c** is not subject to uncertainty, since it is possible to use the objective maximize z, add the constraint $z - \mathbf{c}'\,\mathbf{x} \leq 0$, and thus include this constraint into $\mathbf{Ax} \leq \mathbf{b}$.

Let $L \subseteq \mathbb{N}$ represent a set of time series lag operators used to establish the backward periods that set the robustness window and to adjust parameters values in case there is an associated lead-time decision until implementation period t.

Let $\beta \in \mathrm{B} \subseteq L$ represent a subset of lag operators used to define the distance between the implementation period t and a reference period where the problem to be optimized is actually being studied (i.e. $t - \beta$) and from where exists some observed data behind.

Further, other lag operators can be included to account for the time gap between distinct decisions (e.g. LLIN procurement and freight hiring) and the implementation period t, which might arise, for instance, from long lead times (e.g. production and transport lead times).

Therefore, let $G_i \subseteq J$ represents the set of parameters $a_{ijt}, j \in G_i$ in a particular row i of the constraint matrix **A**, that are associated to decision-making processes that occur in periods prior to implementation period t. Thus, for each parameter $a_{ijt}, j \in G_i$ it is introduced $d_j \in \mathrm{D} \subseteq L$, that indicates the lag operator used to represent the distance between the implementation period t and the actual decision-making period for $a_{ijt}, j \in G_i$, i.e. $t - d_j$.

In the context of a LLIN distribution campaign, Figure 3 shows an illustrative example of the distance from a particular implementation period t (i.e. distribution phase) to its planning phase and decision milestones.

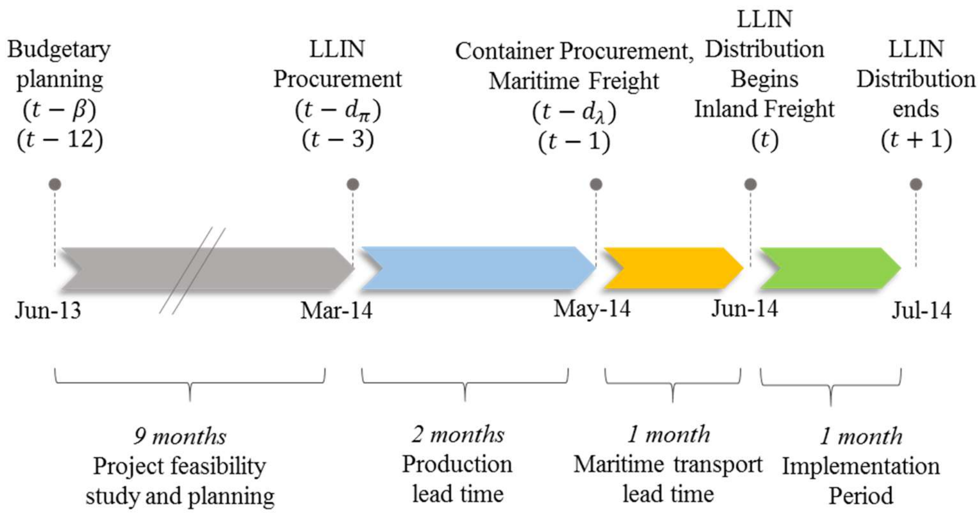

Figure 3: Illustrative time gaps between the actual LLIN distribution period t (Jun/14), to the maritime freight and container procurement period $t - d_\lambda$ (May/14), to the LLIN procurement period $t - d_\pi$ (Mar/14), and to the budgetary planning period $t - \beta$ (Jun/13).

Source: Author

Note that the lag operator $\beta = 12$, sets a one year distance from implementation period t (considered as the beginning of LLIN distribution to districts) to budgetary planning period $t-\beta$ (i.e. the period in which the project feasibility is being studied). Similarly, lag operators $d_\lambda = 1$ and $d_\pi = 3$ are introduced to set the distance from the LLIN distribution period t to the maritime freight $(t-1)$ and LLIN procurement $(t-3)$ decision-making periods respectively.

Further, let $k \in K \subseteq L$ represent the set of lag operators used to define the robustness window for uncertain parameters $a_{ijt}, j \in J_i$, comprised of periods $t - \beta - 1$ until $t - \beta - k$.

Considering the assumptions of the above example (Figure 3) and a LLIN price time series of a specific supplier, Figure 4 depicts, for implementation period t (Jun/14), a 9 months robustness window covering values from periods $t - 15$ (Mar/13) until $t-24$ (Jun/12) and the predicted procurement value $t-3$ (Mar/14). With reference to a minimum cost model, the worst value among predicted and considered past values is represented within the robustness window in period $t - 15$ (Mar/13).

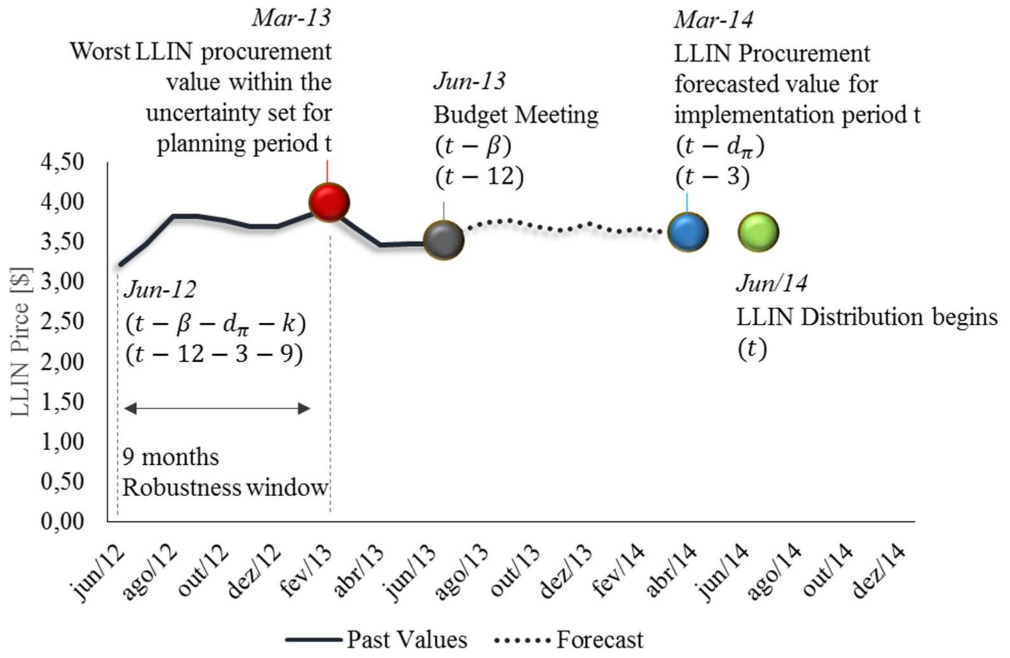

Figure 4: Robustness window comprised of 9 months and the predicted value for a particular LLIN supplier price; considering a production lead time of 3 months ($d_\pi = 3$) and a planning distance of 12 months ($\beta = 12$) to the LLIN distribution period t.

Source: Author

It is worth noting that the robustness window does not necessarily need to be composed by consecutive past values. For instance, observe that in some cases it might be interesting to consider the impact of seasonality, and therefore it is possible to add the lag operator $k = 12$ (i.e. seasonality lag on monthly observations) to more recent past observations, which leads to a non sequential robustness window such as $k \in \{1,2,12\}$, that considers two immediate past observations and the previous year value. However, for the sake of notation simplicity, it is considered, otherwise noted, that a robustness window K is comprised of K consecutive past values.

In the light of the above, for each row i and implementation period $t \in T$ the proposed data-driven uncertainty set hedges the solution against the simultaneous combination of forecasted values (eq. 25) and the values within the robustness window (eq. 26):

$$Maximize_x \ \boldsymbol{c}' \ \boldsymbol{x} \tag{1}$$

$$Subject \ to$$

$$\sum_{j \in J \setminus G_i} a_{ijt} \, x_{jt} + \sum_{j \in G_i} a_{ij,t-d_j} \, x_{jt} \leq b_{it} \qquad \forall i \in I, t \in T \tag{25}$$

$$\sum_{j \in \{J \setminus J_i \cap J \setminus G_i\}} a_{ijt} \, x_{jt} + \sum_{j \in \{J \setminus J_i \cap G_i\}} a_{ij,t-d_j} \, x_{jt} + \sum_{j \in \{J_i \cap J \setminus G_i\}} a_{ij,t-\beta-k} \, x_{jt}$$

$$+ \sum_{j \in \{J_i \cap G_i\}} a_{ij,t-d_j-\beta-k} \, x_{jt} \leq b_{it}$$

$$\forall i \in I, t \in T, k \in K, \beta \in \mathrm{B} \tag{26}$$

$$\mathbf{x} \geq 0 \tag{3}$$

The first term of equation (25) represents the sum over the subset of parameters without an associated decision lag; on the other hand, the second term represents the sum over the subset of parameters with an associated decision lag, and therefore the lag operator d_j is reduced from implementation period t. It is worth mentioning that both subsets are disjoint.

The first term of equation (26) represents the sum over the subset of parameters without uncertainty and without decision lag. Similarly, the second term also denotes the sum over the subset of parameters without uncertainty, but with an associated decision lag. The third term, depicts the sum over the subset of uncertain parameters without an associated decision lag, and thus β (budgetary lag) and k periods are reduced from implementation period t to shape the robustness window. The last term accounts for the sum over the subset of uncertain parameters with an associated decision lag and therefore β, k and d_j are reduced from t. Finally, observe that all subsets are disjoint.

Note that the model is adaptive since the robustness window moves along time, absorbing new patterns and forgetting old ones. In other words, for each period (after the first period) in the implementation horizon, new constraints are added and others are removed. Therefore, the model captures the empirical dependence structure between the uncertain coefficients $a_{ijt}, j \in J_i$, as the uncertainty set changes for each implementation period. Since this idea reflects the dynamics of changing environments (e.g. market conditions) that affect the uncertain parameters, it is a significant enhancement in comparison to Bertsimas and Sim (2004) framework when applied to multi-period or dynamic models.

In this context, suppose an illustrative example of a maximum LLIN demand coverage problem with a procurement budget constraint of \$1,000 (i.e. $b_t = 1{,}000$) and two suppliers, A and B. The variables $x_{A,t}$ and $x_{B,t}$ represent the number of LLNIs procured from each supplier during planning period t. The LLIN procurement prices ($a_{j,t}$) for each supplier are displayed in Table 7. The first implementation period is $t = \tau$, and the robustness window is defined by the last 3 periods, i.e. $k \in \{1,2,3\}$. For the sake of simplicity production lead times and the time distance from implementation period t to budgetary planning period are disregarded, i.e. $\beta, d_A, d_B = 0$.

By using equations (25) and (26) within this illustrative case, it is possible to demonstrate a feasible region for the first implementation period τ (Figure 5).

Table 7: LLIN cost per period and supplier for the illustrative problem.

LLIN Costs per period (\$/LIIN unit)	Robustness Window (Past Values)			Implementation Period (Predicted Values)	
	$\tau - 3$	$\tau - 2$	$\tau - 1$	τ	$\tau + 1$
$a_{A,t}$	0,90	1,10	1,23	1,85	1,53
$a_{B,t}$	0,98	0,85	0,68	0,50	0,51

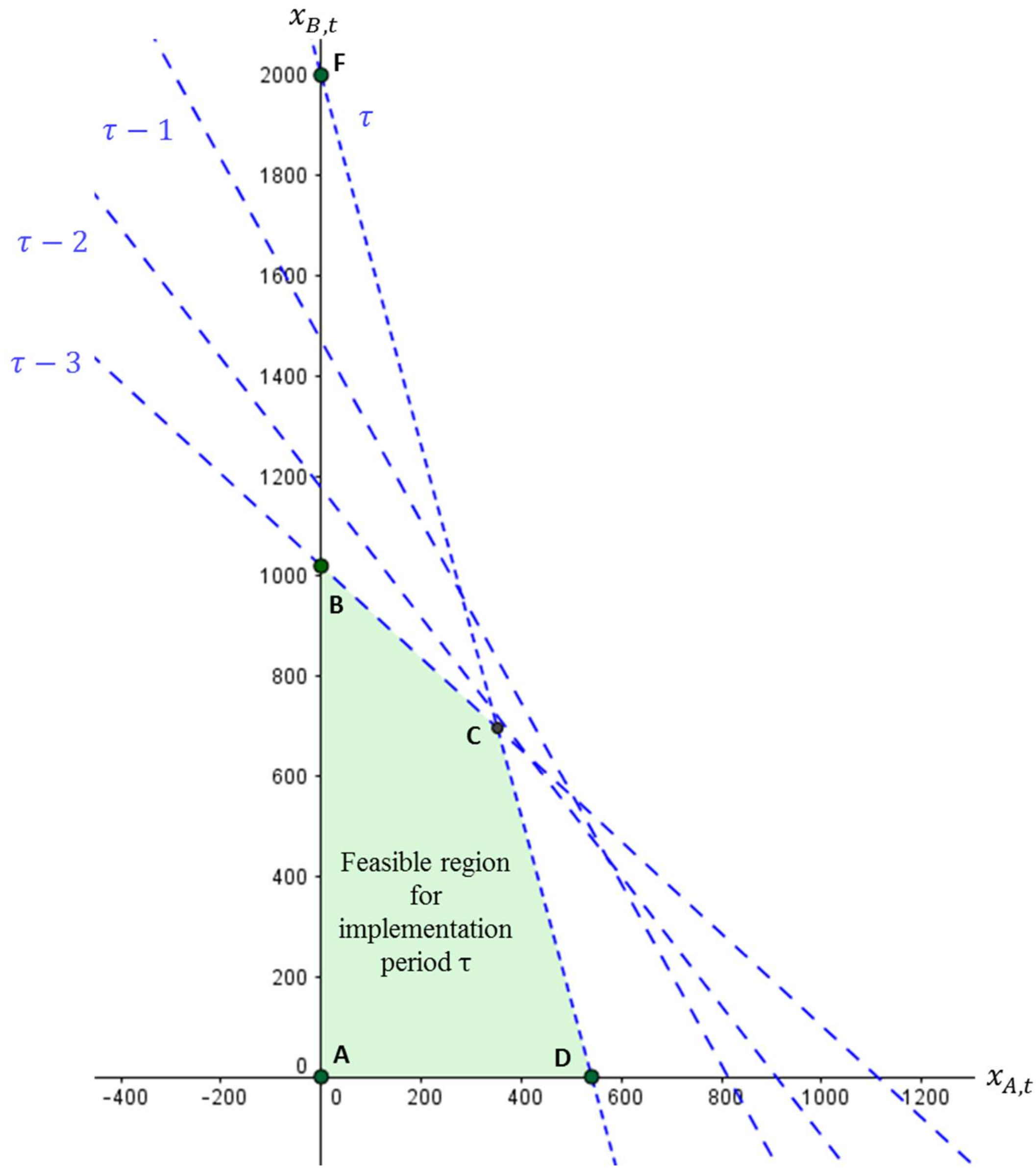

Figure 5: Data driven adaptive feasible region (i.e. green area of ABCD polygon) for implementation period $t = \tau$ built with the example problem of Table 6.

Source: Author

Note in Figure 5 that the feasible region without the proposed robust approach is formed by triangle AFD, which only considers predicted values. As expected, with the data-driven robust framework the feasible region (polygon ABCD) is more conservative but still not as conservative as Soyster's approach (triangle ABD), which would, for instance, take the highest LLIN prices from each supplier from period τ until $\tau - 3$. Although not depicted, the feasible region for planning period $\tau + 1$ is formed by the addition of a new constraint associated to predicted values in $\tau + 1$, and the removal of robustness window's last period constraint, i.e. $\tau - 3$. Finally, it is worth noting that adjustment of Fernandes et al. (2016) framework from a dynamic to a static model, results in robustness windows (e.g. for period $\tau + 1$) that might comprise both predicted (e.g. τ) and observed (e.g. $\tau - 1, \tau - 2$) parameter values.

4 Modelling insecticide-treated bed nets supply chain

This chapter presents the robust transshipment network flow model to optimize LLIN procurement and distribution plan under financial (budget, ITN and container prices, freight rates), market (supply and demand) and logistics (resource/infrastructure availability and capacity) uncertainties. Both robust optimization frameworks of Bertsimas and Sim (2004) and data-driven polyhedral uncertainty sets of Fernandes et al. (2016) are considered in the model.

First, the mathematical model that designs the supply chain with the minimum total procurement, safety stock and distribution costs is developed. After, within a budgetary constraint, a model that guarantees the maximum achievable coverage of priority areas is presented.

Both models represent a five level supply chain, comprised of LLIN suppliers, ports of origin, ports of discharge, hubs and health districts (Figure 6).

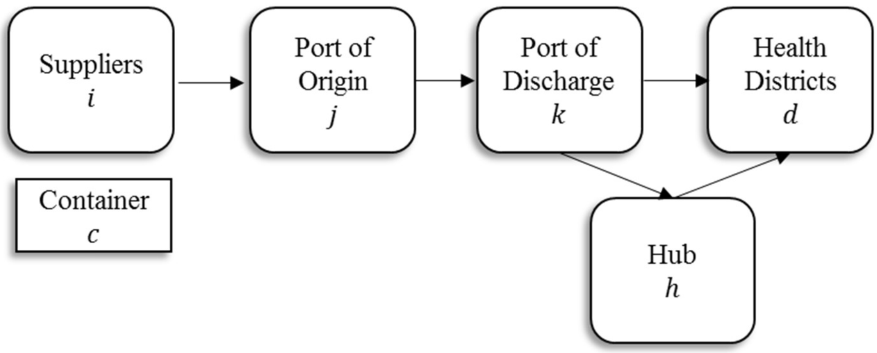

Figure 6: Summarised Model Structure.

Source: Author

Compared to Brito et al. (2015) the proposed models consider additional sets of lag operators, hub and mode of transport. In addition, safety stock costs, unmet demand costs, project budget, capacities of hubs, ports of discharge and mode of transport are also added. Moreover robust parameters, such as the deviation from the nominal value and global robustness levels are introduced. Finally, LLINs and container flows are broken down in separate variables, and both unmet and updated demand variables are included in the maximum demand coverage model.

The sets, variables, and parameters of the model are presented in Table 8.

Table 8: Model sets, parameters and variables.

Sets	
$c \in C$	Container type
$i \in I$	Suppliers
$j \in J$	Ports of origin
$k \in K$	Ports of discharge
$h \in H$	Hubs
$d \in D$	Health districts
$m \in M$	Mode of transport
$t \in T$	Set of periods
$r \in R \subset T$	Project implementation phases (subset of periods)
L	Set of time series lag operators
$\upsilon \in \Upsilon \subset L$	Robustness window (subset of lag operators)
$\pi \in \Pi \subset L$	Production lead time (subset of lag operators)
$\lambda \in \Lambda \subset L$	Maritime transportation lead time (subset of lag operators)
$\beta \in \mathrm{B} \subset L$	Budget planning period (subset of lag operators)
Auxiliary Set	
$p \in P = I$	For LLINs tracking purpose, P is defined as an auxiliary set that is equal to suppliers' set I.

Parameters		**Unity**
Financial Parameters		
cs_{tpcij}	Transportation cost of a container ***c*** with LLINs ***p*** from supplier ***i*** to port of origin ***j*** considered period ***t***.	US$/container
co_{tpcjk}	Transportation cost of a container ***c*** with LLINs ***p*** from port of origin ***j*** to port of discharge/hub ***k*** considered for period ***t***.	US$/container

cp_{tpckdm}	Transportation cost of a container ***c*** with LLINs ***p*** from port of discharge ***k*** to district ***d*** within mode of transport ***m*** considered for period ***t***.	US$/container
ch_{tpckhm}	Transportation cost of a container ***c*** with LLINs ***p*** from port of discharge ***k*** to hub ***h*** within mode of transport ***m*** considered for period ***t***.	US$/container
cd_{tpchdm}	Transportation cost of a container ***c*** with LLINs ***p*** from hub ***h*** to district ***d*** within mode of transport ***m*** considered for period ***t***.	US$/container
pr_{tpi}	LLIN ***p*** procurement cost with supplier ***i*** considered for period ***t***.	US$/LLIN
cc_{tcj}	Container ***c*** procurement cost at port of origin ***j*** considered for period ***t***.	US$/container
ic_{tpi}	LLIN ***p*** safety stock inventory cost with supplier ***i*** considered for period ***t***.	US$/LLIN
bdg_r	Budget during implementation phase ***r***.	US$
$\widehat{bdg}_r$	Maximum allowed deviation from nominal value bdg_r.	US$
Γ^{budget}	Number of implementation phases ***r*** in which the budget might assume its worst-case value.	Phases
Market Parameters		
dm_{rd}	Demand for LLINs at district ***d*** during implementation phase ***r***.	LLINs
$\widehat{dm}_{rd}$	Maximum allowed deviation from nominal value dm_{rd}.	LLINs
uc_d	Unmet demand penalty cost for district ***d***. Also used as a demand prioritization factor.	-
$\Gamma_r^{demmand}$	Quantity of districts ***d*** during implementation phase ***r*** that might assume their highest demand value.	Districts
sc_{rpi}	Capacity of supplier ***i*** to produce LLINs ***p*** during implementation phase ***r***.	LLINs

$\widehat{sc}_{rpi}$	Maximum allowed deviation from nominal value sc_{rpi}.	LLINs
T_r^{supply}	Quantity of suppliers ***i*** during implementation phase ***r*** that might assume their lowest production capacity.	Suppliers
Logistics Parameters		
nq_{pc}	Capacity of LLINs ***p*** inside a container ***c***.	LLINs /Container
pc_{rk}	Capacity of port of discharge ***k*** during implementation phase ***r***.	LLINs
$\widehat{pc}_{rk}$	Maximum allowed deviation from nominal value pc_{rk}.	LLINs
T_r^{port}	Number of ports of discharge that might assume their lowest capacity during implementation phase ***r***.	Ports
hc_{rh}	Capacity of hub ***h*** during implementation phase ***r***.	LLINs
$\widehat{hc}_{rk}$	Maximum allowed deviation from nominal value hc_{rh}.	LLINs
T_r^{hub}	Number of hubs that might assume their lowest capacity during implementation phase ***r***.	Hubs
mp_{rkdm}	Flow capacity between port of discharge ***k*** and district ***d*** under mode of transport ***m*** during implementation phase ***r***.	LLINs
$\widehat{mp}_{rkdm}$	Maximum allowed deviation from nominal value mp_{rkdm}.	LLINs
mh_{rkhm}	Flow capacity between port of discharge ***k*** and hub ***h*** under mode of transport ***m*** during implementation phase ***r***.	LLINs
$\widehat{mh}_{rkhm}$	Maximum allowed deviation from nominal value mh_{rkhm}.	LLINs

md_{rhdm}	Flow capacity between hub ***h*** and district ***d*** under mode of transport ***m*** during implementation phase ***r***.	LLINs
$\widehat{md}_{rhdm}$	Maximum allowed deviation from nominal value md_{rhdm}.	LLINs
T_{rm}^{modal}	Quantity of routes per mode of transport ***m*** that might assume their lowest flow capacity during implementation phase ***r***.	Routes
as_{rpij}	Binary parameter that indicates if a route from supplier ***i*** to port of origin ***j*** is available for LLIN ***p*** during implementation phase ***r***.	-
ao_{rpjk}	Binary parameter that indicates if a route from port of origin ***j*** to port of discharge/hub ***k*** is available for LLIN ***p*** during implementation phase ***r***.	-
ap_{rpkd}	Binary parameter that indicates if a route from port of discharge ***k*** to district ***d*** is available for LLIN ***p*** during implementation phase ***r***.	-
ah_{rpkh}	Binary parameter that indicates if a route from port of discharge ***k*** to hub ***h*** is available for LLIN ***p*** during implementation phase ***r***.	-
ad_{rphd}	Binary parameter that indicates if a route from hub ***h*** to district ***d*** is available for LLIN ***p*** during implementation phase ***r***.	-
Auxiliary Parameters		
$\mathcal{M}$	Big number auxiliary, used to assure that a district is supplied by only one supplier.	-

Decision Variables		
Market Variables		
NP_{rpi}	Quantity of LLINs ***p*** procured from supplier ***i*** for implementation phase ***r.***	LLINs

UD_{rd}	Unmet demand on district ***d*** at the end of implementation phase ***r.***	LLINs
UPD_{rd}	Updated demand on district ***d*** at the beginning of implementation phase ***r.***	LLINs
S_{rpi}	Safety Stock of LLINS ***p*** in supplier ***i*** during implementation phase ***r***, to account for uncertainties related to demand forecast of implementation phase ***r***.	LLINs
Logistic Variables		
TS_{rpcij}	Quantity of containers ***c*** with LLINs ***p*** transferred from supplier ***i*** to port of origin ***j*** for implementation phase ***r***.	Containers
NTS_{rpij}	Quantity of LLINs ***p*** transferred from supplier ***i*** to port of origin ***j*** for implementation phase ***r***.	LLINs
TO_{rpcjk}	Quantity of containers ***c*** with LLINs ***p*** transferred from port of origin ***j*** to port of discharge (or hub) ***k*** for implementation phase ***r***.	Containers
NTO_{rpjk}	Quantity LLINs ***p*** transferred from port of origin ***j*** to port of discharge (or hub) ***k*** for implementation phase ***r***.	LLINs
TP_{rpckdm}	Quantity of containers ***c*** with LLINs ***p*** transferred from port of discharge ***k*** to district ***d*** under mode of transport **m** during implementation phase ***r***.	Containers
NTP_{rpkdm}	Quantity of LLINs ***p*** transferred from port of discharge ***k*** to district ***d*** under mode of transport ***m*** during implementation phase ***r***.	LLINs
TH_{rpckhm}	Quantity of containers ***c*** with LLINs ***p*** transferred from port of discharge ***k*** to hub ***h*** under mode of transport **m** during implementation phase ***r***.	Containers
NTH_{rpkhm}	Quantity of LLINs ***p*** transferred from port of discharge ***k*** to hub ***h*** under mode of transport ***m*** during implementation phase ***r***.	LLINs

TD_{rpchdm}	Quantity of containers ***c*** with LLINs ***p*** transferred from hub ***h*** to district ***d*** under mode of transport **m** during implementation phase ***r***.	Containers
NTD_{rphdm}	Quantity of LLINs ***p*** transferred from hub ***h*** to district ***d*** under mode of transport ***m*** during implementation phase ***r***.	LLINs
RHS robustness variables		
Γ_{rpi}^{supply}	Production capacity decrease of supplier i for LLIN ***p*** during implementation phase ***r***.	%
$\Gamma_{rd}^{demmand}$	Demand increase of district ***d*** during implementation phase ***r*** due to forecast errors.	%
Γ_{rk}^{port}	Port of discharge ***k*** capacity decrease during implementation phase ***r***.	%
Γ_{rh}^{hub}	Hub ***h*** capacity decrease during implementation phase ***r***.	%
Γ_{rkdm}^{modal}	Flow capacity decrease from port of discharge ***k*** to district ***d*** under mode of transport ***m*** during implementation phase ***r***.	%
Γ_{rkhm}^{modal}	Flow capacity decrease from port of discharge ***k*** to hub ***h*** under mode of transport ***m*** during implementation phase ***r***.	%
Γ_{rhdm}^{modal}	Flow capacity decrease from hub ***h*** to district ***d*** under mode of transport ***m*** during implementation phase ***r***.	%
Auxiliary variables		
Z_{rpd}	Binary auxiliary variable that assumes 1 if a district ***d*** is supplied by a LLIN ***p*** and 0 otherwise. It is used to assure that a district is supplied by only one supplier.	-

4.1.Minimum costs model

The suggested model minimizes the total procurement, safety stock and distribution costs involved in a LLIN distribution campaign. Consequently, it also indicates:

i. The number and size of containers to be used in each district;
ii. From which suppliers to purchase and which port to use at origin. This decision also depends on container procurement cost in each port of origin;
iii. The safety stock levels in each supplier;
iv. Which port of discharge should be used;
v. Whether or not to use hubs as consolidation points;
vi. Which modes of transport should be used to reach each district.

Market uncertainties as supply capacity and demand forecast that appear in the RHS, are addressed with the proposed extension of Bertsimas and Sim (2004) robust framework. The same approach is taken regarding logistics uncertainties such as mode of transport and hub/port of discharge capacities.

Financial uncertainties as LLIN and container prices, and transport freights rates are approached through the proposed adaptive data-driven uncertainty sets based on Fernandes et al. (2016).

For the sake of notation simplicity, consider, otherwise noted, summation and constraints' domain equal to their respective indexes domain.

The objective function (eq. 27) minimizes the maximum total procurement, transportation and inventory costs for all implementation phases, considering both predicted (eq. 28) and observed costs within a robustness window defined by the decision maker (eq. 29).

$$Min \sum_{r} \psi_r \tag{27}$$

Equation (28) defines the total procurement, transportation and inventory costs, using predicted costs for each implementation phase (i.e. nominal values that would be used, for instance, in a deterministic model). The lag operators π and λ, both linked to implementation period r, are introduced to account for production lead time and maritime transport lead time respectively.

$$\psi_r \geq \sum_{pi} pr_{r-\pi,p,i} NP_{rpi} + \sum_{pi} ic_{r-\pi,p,i} S_{rpi} + \sum_{pcjk} cc_{r-\lambda,cj} TO_{rpcjk} + \sum_{pcij} cs_{r-\pi,pcij} TS_{rpcij} + \sum_{pcjk} co_{r-\lambda,pcjk} TO_{rpcjk} + \sum_{pckd} cp_{rpckdm} TP_{rpckdm} + \sum_{pckh} ch_{rpck} \quad TH_{rpckh} + \sum_{pchdm} cd_{rpchdm} TD_{rpchdm} \qquad \forall\, r, \pi, \lambda \quad (28)$$

Considering β the budgetary planning period lag, with reference to the implementation period r, and υ the number of backwards periods, with reference to β, equation (29) guarantees that the solution is feasible against the realization of all observed costs within the defined robustness window (e.g. $r - \beta - \upsilon$).

$$\psi_r \geq \sum_{pi} pr_{r-\beta-\pi-\upsilon,p,i} NP_{rpi} + \sum_{pi} ic_{r-\beta-\pi-\upsilon,pi} S_{rpi} + \sum_{pcjk} cc_{r-\beta-\lambda-\upsilon,cj} TO_{rpcjk} + \sum_{pcij} cs_{r-\beta-\pi-\upsilon,pcij} TS_{rpcij} + \sum_{pcjk} co_{r-\beta-\lambda-\upsilon,pcjk} TO_{rpcjk} + \sum_{pckdm} cp_{r-\beta-\upsilon,pckdm} TP_{rpckdm} + \sum_{pckhm} ch_{r-\beta-\upsilon,pckhm} TH_{rpckh} + \sum_{pchd} cd_{r-\beta-\upsilon,pchdm} TD_{rpchdm} \qquad \forall\, r, \pi, \lambda, \beta, \upsilon \quad (29)$$

Constraint (30) assures that demand is met at district *d* during implementation phase r.

$$\sum_{pkm} NTP_{rpkdm} + \sum_{phm} NTD_{rphdm} \geq dm_{rd} \qquad \forall\, r, d \qquad (30)$$

Constraint (31) restricts procurement according to supplier's i production capacity of LLINs p (decreased by a robust parameter Γ_{rpi}^{supply}) during implementation phase r.

$$NP_{rpi} \leq sc_{rpi} - \widehat{sc}_{rpi}\Gamma_{rpi}^{supply} \qquad \forall\, r, p, i \qquad (31)$$

For each implementation phase r constraint (32) limits the number of LLINs transported from each supplier i to all ports of origin j, according to supplier's i production capacity and safety stock of LLINs p.

$$\sum_{j} NTS_{rpij} \leq NP_{rpi} + S_{rpi} \qquad \forall\, r, p, i \qquad (32)$$

For each implementation phase r, constraint (33) defines the minimum safety stock level of LLINs summed in all suppliers as a protection measure against demand uncertainties that are only revealed after the end of each implementation phase (i.e. after campaign evaluation). In this context, the inventory buffer allows a faster humanitarian response in case of LLINs needs misjudgments.

$$\sum_{ip} S_{rpi} \geq \sum_{d} \widehat{dm}_{rd}\Gamma_{rd}^{demmand} \qquad \forall\, r \qquad (33)$$

Equation (34) recursively defines the safety stock of a supplier i during phase r as the difference between procured LLINs and the outbound flow to port of origin j.

$$S_{rpi} = S_{r-1,pi} + NP_{rpi} - \sum_{j} NTS_{rpij} \qquad \forall\, r,p,i \qquad (34)$$

$$S_{rpi} = S_{0,pi} + \sum_{\tau=1}^{R} NP_{\tau pi} - \sum_{j,\tau=1}^{R} NTS_{\tau pij} \qquad \forall\, r,p,i \qquad (34.a)$$

Constraints (35), (36) and (37) guarantee LLIN flow conservation at port of origin j, port of discharge k and at hub h respectively.

$$\sum_{i} NTS_{rpij} = \sum_{k} NTO_{rpjk} \qquad \forall\, r,p,j \qquad (35)$$

$$\sum_{j} NTO_{rpjk} = \sum_{dm} NTP_{rpkdm} + \sum_{hm} NTH_{rpkhm} \qquad \forall\, r,p,k \qquad (36)$$

$$\sum_{hm} NTH_{rpkhm} = \sum_{dm} NTD_{rphdm} \qquad \forall\, r,p,h \qquad (37)$$

Constraints (38), (39) and (40) guarantee container flow conservation at port of origin j, port of discharge k and at hub h respectively.

$$\sum_{i} TS_{rpcij} = \sum_{k} TO_{rpcjk} \qquad \forall\, r,p,c,j \qquad (38)$$

$$\sum_{j} TO_{rpcjk} = \sum_{dm} TP_{rpckdm} + \sum_{hm} TH_{rpckhm} \qquad \forall\, r,p,c,k \qquad (39)$$

$$\sum_{hm} TH_{rpckhm} = \sum_{dm} TD_{rpchdm} \qquad \forall\, r,p,c,h \qquad (40)$$

Constraints (41), (42), (43), (44) and (45) assure that the number of LLINs inside a container c is limited by its capacity.

$$NTS_{rpij} \leq \sum_{c} TS_{rpcij}\, nq_{pc} \qquad \forall\, r,p,i,j \qquad (41)$$

$$NTO_{rpjk} \leq \sum_{c} TO_{rpcjk}\, nq_{pc} \qquad \forall\, r,p,j,k \qquad (42)$$

$$NTP_{rpkdm} \leq \sum_{c} TP_{rpckdm}\, nq_{pc} \qquad \forall\, r,p,k,d,m \qquad (43)$$

$$NTH_{rpkhm} \leq \sum_{c} TH_{rpckhm}\, nq_{pc} \qquad \forall\, r,p,k,h,m \qquad (44)$$

$$NTD_{rphdm} \leq \sum_{c} TD_{rpchdm}\, nq_{pc} \qquad \forall\, r,p,h,d,m \qquad (45)$$

Constraint (46) limits the total flow through a port of discharge (or hub) k according to its capacity (decreased by a robust parameter Γ_{rk}^{port}).

$$\sum_{pj} NTO_{rpjk} \leq \; pc_{rk} - \widehat{pc}_{rk}\Gamma_{rk}^{port} \qquad \forall\, r,k \qquad (46)$$

Constraint (47) limits the total flow through a hub h according to its capacity (decreased by a robust parameter Γ_{rh}^{hub}).

$$\sum_{pkm} NTH_{rpkhm} \leq hc_{rh} - \widehat{hc}_{rh}\Gamma_{rh}^{hub} \qquad \forall\, r,h \qquad (47)$$

Constraint (48) limits the total flow between each port of discharge k and district d by the mode of transport m capacity in that particular route.

$$\sum_{p} NTP_{rpkdm} \leq mp_{rkdm} - \widehat{mp}_{rkdm}\Gamma_{rkdm}^{modal} \qquad \forall\, r,k,d,m \qquad (48)$$

Constraint (49) limits the total flow between each port of discharge k and hub h by the mode of transport m capacity in that particular route.

$$\sum_{p} NTH_{rpkhm} \leq mh_{rkhm} - \widehat{mh}_{rkhm}\Gamma_{rkhm}^{modal} \qquad \forall\, r,k,h,m \qquad (49)$$

Constraint (50) limits the total flow between each hub h and district d by the mode of transport m capacity in that particular route.

$$\sum_{p} NTD_{rphdm} \leq md_{rhdm} - \widehat{md}_{rhdm}\Gamma_{rhdm}^{modal} \qquad \forall\, r,h,d,m \qquad (50)$$

The next ten constraints define route availability due to uncertainties (e.g. security, rainy or harvest season) from supplier i to port of origin j (51 and 52), from port of origin j to port of discharge k (53 and 54), from port of discharge k to district d (55 and 56), from port of discharge k to hub h (57 and 58), and from hub h to district d (59 and 60).

$$TS_{rpcij}as_{rpij} \geq TS_{rpcij} \qquad \forall\, r,p,c,i,j \qquad (51)$$

$$NTS_{rpij}as_{rpij} \geq NTS_{rpcij} \qquad \forall\, r,p,i,j \qquad (52)$$

$$TO_{rpcjk}ao_{rpjk} \geq TO_{rpcjk} \qquad \forall\, r,p,c,j,k \qquad (53)$$

$$NTO_{rpjk}ao_{rpjk} \geq NTO_{rpjk} \qquad \forall\, r,p,j,k \qquad (54)$$

$$TP_{rpckdm}ap_{rpkdm} \geq TP_{rpckdm} \qquad \forall\, r,p,c,k,d,m \qquad (55)$$

$$NTP_{rpkdm}ap_{rpkdm} \geq NTP_{rpkdm} \qquad \forall\, r,p,k,d,m \qquad (56)$$

$$TH_{rpckhm}ah_{rpkhm} \geq TH_{rpckhm} \qquad \forall\, r,p,c,k,h,m \qquad (57)$$

$$NTH_{rpkhm}ah_{rpkhm} \geq NTH_{rpkhm} \qquad \forall\, r,p,k,h,m \qquad (58)$$

$$TD_{rpchdm}ad_{rphdm} \geq TD_{rpchdm} \qquad \forall\, r,p,c,h,d,m \qquad (59)$$

$$NTD_{rphdm}ad_{rphdm} \geq NTD_{rphdm} \qquad \forall\, r,p,h,d,m \qquad (60)$$

To avoid disagreements among beneficiaries, as a result of preferences towards a specific supplier, humanitarian organization might choose to supply each district with only one type of LLIN. Therefore, constraints (61) and (62) are used to determine Z_{pd}, which assumes 1 if a district d is supplied by a LLIN p and 0 otherwise, and equation (63) assures that a district is supplied exclusively by one LLIN p (i.e. exclusively by one supplier). It is worth noting that the big number M is bounded by $\frac{Max\ \{\sum_r dm_{rd}, \forall d\}}{Min\ \{nq_{pc}, \forall p,c\}}$, which is equivalent to highest possible number of containers required to supply the most demanding district.

$$\sum_{rckm} TP_{rpckdm} + \sum_{rchm} TD_{rpchdm} \leq Z_{pd} * M \qquad \forall\, p,d \qquad (61)$$

$$\sum_{rckm} TP_{rpckdm} + \sum_{rchm} TD_{rpchdm} \geq \mathrm{Z}_{pd} \qquad \forall\, p, d \qquad (62)$$

$$\sum_{p} \mathrm{Z}_{pd} = 1 \qquad \forall\, d \qquad (63)$$

Constraint (64) defines binary variables, (65)-(68) real integer variables, and (69) nonnegative real variables.

$$\mathrm{Z}_{pd} \in \{0,1\} \qquad \forall\, p, d \qquad (64)$$

$$TS_{rpcij}, TO_{rpcjk}, TP_{rpckdm}, TH_{rpckhm}, TD_{rpchdm} \in \mathbb{N} \qquad \forall\, r, p, c, i, j,k, h, d, m \qquad (65)$$

$$NTS_{rpij}, NTO_{rpjk}, NTP_{rpkdm}, NTH_{rpkhm}, NTD_{rphdm}, \in \mathbb{N} \qquad \forall\, r, p, i, j, k, h, d, m \qquad (66)$$

$$NP_{rpi}, S_{rpi} \in \mathbb{N} \qquad \forall\, r, p, c, i, j, k, d \qquad (67)$$

$$\psi_r \in \mathbb{R}^+ \qquad \forall\, r \qquad (68)$$

Equation (69) describes the objective function of the lower level, which maximizes the total deviation from uncertain parameters nominal values, given global robustness levels **T** set by the decision maker.

$$Max_{\Gamma} \sum_{pijd} \big(\widehat{sc}_{rpi} \Gamma_{rpi}^{supply} + \widehat{dm}_{rd} \Gamma_{rd}^{demmand} + \widehat{pc}_{rk} \Gamma_{rk}^{port} + \widehat{hc}_{rh} \Gamma_{rh}^{hub} + \widehat{mp}_{rkdm} \Gamma_{rkdm}^{modal} + \widehat{mh}_{rkhm} \Gamma_{rkhm}^{modal} + \widehat{md}_{rhdm} \Gamma_{rhdm}^{modal} \big) \qquad \forall\, r \qquad (69)$$

Constraint (70) limits the number of suppliers i that might assume their lowest production capacity.

$$\sum_{pi} \Gamma_{rpi}^{supply} \leq \mathrm{T}_{r}^{supply} \qquad (70)$$

Constraint (71) limits the number of districts d that might assume their highest demand values.

$$\sum_{d} \Gamma_{rd}^{demmand} \leq \mathrm{T}_{r}^{demand} \tag{71}$$

Constraint (72) limits the number of ports of discharge k that might assume their lowest capacity.

$$\sum_{k} \Gamma_{rk}^{port} \leq \mathrm{T}_{r}^{port} \tag{72}$$

Constraint (73) limits the number of hubs h that might assume their lowest capacity.

$$\sum_{h} \Gamma_{rh}^{hub} \leq \mathrm{T}_{r}^{hub} \tag{73}$$

Constraint (74) limits for each mode of transport m the number of routes that might assume their lowest capacity.

$$\sum_{kd} \Gamma_{rkdm}^{modal} + \sum_{kh} \Gamma_{rkhm}^{modal} + \sum_{hd} \Gamma_{rhdm}^{modal} \leq \mathrm{T}_{rm}^{modal} \qquad \forall\, m \tag{74}$$

Equation (75) defines the variables inside the unit interval.

$$\Gamma_{rpi}^{supply}, \Gamma_{rd}^{demmand}, \Gamma_{rk}^{port}, \Gamma_{rh}^{hub}, \Gamma_{rkdm}^{modal}, \Gamma_{rkhm}^{modal}, \Gamma_{rhdm}^{modal} \in [0,1] \qquad \forall\, r,p,c,i,j,k,h,d,m \tag{75}$$

4.2. Maximum priority demand coverage model with budget constraints

When there are budgetary constraints that hinder the universal coverage goal, stakeholders must set which districts will be part of the LLIN distribution campaign and in this case, it is proposed a model that maximizes the distribution to priority areas

In this context, the objective function (76) maximizes LLINs distribution while penalizing unmet demand. The prioritization of pressing regions is achieved thought the unmet demand cost parameter, uc_d , that can be set as a composite indicator, based, among others, on the number of malaria cases and incidence rate on children under five per district.

$$Max \sum_{rpkdm} NTP_{rpkdm} - \sum_{rd} UD_{rd}\, uc_d \tag{76}$$

Constraint (77) limits project expenditure during implementation period r considering predicted costs (as defined in equation 28), according to available financial resources (decreased by a robust parameter Γ_r^{budget}). In this context, safety stocks are disregarded since it makes no sense to leave people unprotected to hedge against demand forecast uncertainties (i.e. spend money on safety stock at suppliers premises instead of actual LLIN distribution).

$$\begin{aligned}\sum_{pi} pr_{r-\pi,p,i} NP_{rpi} + \sum_{pcjk} cc_{r-\lambda,cj} TO_{rpcjk} \\ + \sum_{pcij} cs_{r-\pi,pcij} TS_{rpcij} + \sum_{pcjk} co_{r-\lambda,pcjk} TO_{rpcjk} \\ + \sum_{pckdm} cp_{rpckdm} TP_{rpckdm} + \sum_{pckhm} ch_{rpckh}\ TH_{rpckhm} \\ + \sum_{pchdm} cd_{rpchd}\ TD_{rpchdm} \le bdg_r - \widehat{bd}g_r\, \Gamma_r^{budget} \\ \forall\, r, \pi, \lambda \quad (77)\end{aligned}$$

Similarly, constraint (78) limits project expenditure during implementation period r, however considering all observed costs within the defined robustness window, to guarantee solution feasibility under a diverse combination of costs (as defined in equation 29).

$$\sum_{pi} pr_{r-\beta-\pi-\upsilon,p,i} NP_{rpi} + \sum_{pcjk} cc_{r-\beta-\lambda-\upsilon,cj} TO_{rpcjk} + \sum_{pcij} cs_{r-\beta-\pi-\upsilon,pcij} TS_{rpcij} + \sum_{pcjk} co_{r-\beta-\lambda-\upsilon,pcjk} TO_{rpcjk} + \sum_{pckdm} cp_{r-\beta-\upsilon,pckdm} TP_{rpckdm} + \sum_{pckhm} ch_{r-\beta-\upsilon,pckhm} TH_{rpckh} + \sum_{pchdm} cd_{r-\beta-\upsilon,pchdm} TD_{rpchdm} \leq bdg_r - \hat{b}dg_r\, \Gamma_r^{budget} \quad \forall\, r,\pi,\lambda,\beta,\upsilon \quad (78)$$

The safety stock is also dropped from constraint (32) becoming constraint (79) that for each implementation phase r limits the number of LLINs transported from each supplier i to all ports of origin j, according to supplier's i production capacity of LLINs p.

$$\sum_{cj} NTS_{rpcij} \leq NP_{rpi} \qquad \forall\, r,p,i \qquad (79)$$

Equation (80) recursively defines the total unmet LLIN demand in health district d until and including the implementation period r.

$$UD_{r,d} = UD_{r-1,d} + dm_{rd} - \sum_{pkm} NTP_{rpkdm} - \sum_{phm} NTD_{rphdm} \qquad \forall\, r,d \qquad (80)$$

Equation (81) recursively defines the updated demand in health district d during implementation period r, as the sum of the actual demand with the total unmet demand until the previous period.

$$UPD_{r,d} = dm_{rd} + UD_{r-1,d} \qquad \forall\, r, d \qquad (81)$$

Constraint (82) links the number of LLINs that can be transported to a health district d to its updated demand during implementation phase r.

$$\sum_{pkm} NTP_{rpkdm} + \sum_{phm} NTD_{rphdm} \leq UPD_{r,d} \qquad \forall\, r, d \qquad (82)$$

Constraint (83) defines the new real integer variables of the problem.

$$UD_{rd}, UPD_{rd} \in \mathbb{N} \qquad \forall\, r, d \qquad (83)$$

Further, equations (31), and (35) to (68) from the previous model are conserved in this approach.

In addition, it is introduced a new hierarchical level to define which implementation periods r will have their nominal budget value decreased to hedge against funding uncertainties. The objective function (84) maximizes the total budget deviation, given a global robustness level $\mathbf{T}^{\boldsymbol{budget}}$ set by the decision maker.

$$Max_{\Gamma} \sum_{r} \hat{b}_r \; \Gamma_r^{budget} \qquad (84)$$

Constraint (85) limit the number of periods r that might assume their lowest funding availability.

$$\sum_{r} \Gamma_r^{budget} \leq \mathrm{T}^{budget} \qquad (85)$$

Equation (86) defines the variable inside the unit interval.

$$\Gamma_r^{budget} \in [0,1] \qquad (86)$$

The previous lower level problem (i.e. equations 69 to 75) presented in the cost minimization model is conserved to treat uncertainties related to supply, demand and logistics resource capacities.

Finally, the proposed model is sufficiently general to directly incorporate other criteria alongside demand prioritization, such as the equity of LLIN distribution that might be achieved, for instance, by adding a minimum percentage demand fulfillment constraint per district, which value must be carefully assessed to avoid model infeasibility. On the other hand, it is also possible to set and weight this particular constraint in the objective function, transforming the problem into a multi-objective model.

5
Case Studies

In this chapter, an illustrative case is introduced to validate the proposed model and to demonstrate the mechanism of uncertainty protection. Next, a UNICEF's distribution in 2014 of approximately 12 million LLIN in Ivory Coast, firstly presented as a deterministic model in Brito et al. (2015), is studied.

The proposed robust optimization model and the described cases were implemented using the software AIMMS 4.30, CPLEX solver 12.5, processor Intel® Core™ i7-4500U @ 2.40 GHz, 8 Gb RAM and the 64-bit operating system Windows10 ®. An optimality gap smaller than 1% was set as the stopping criterion for the minimum cost model, on the other hand, a time limit of one hour was the criterion for the maximum demand coverage model.

5.1. Illustrative Case

An illustrative case is used to validate the proposed model and to demonstrate the mechanism of uncertainty protection. The illustrative case considers a set of two suppliers (S1 and S2), two ports of origin (PO1 and PO2), two ports of discharge (PD1 and PD2), one hub (H1) and three districts (D1, D2 and D3), in which the distribution takes place in a single implementation phase. Figure 7 presents the considered supply chain structure.

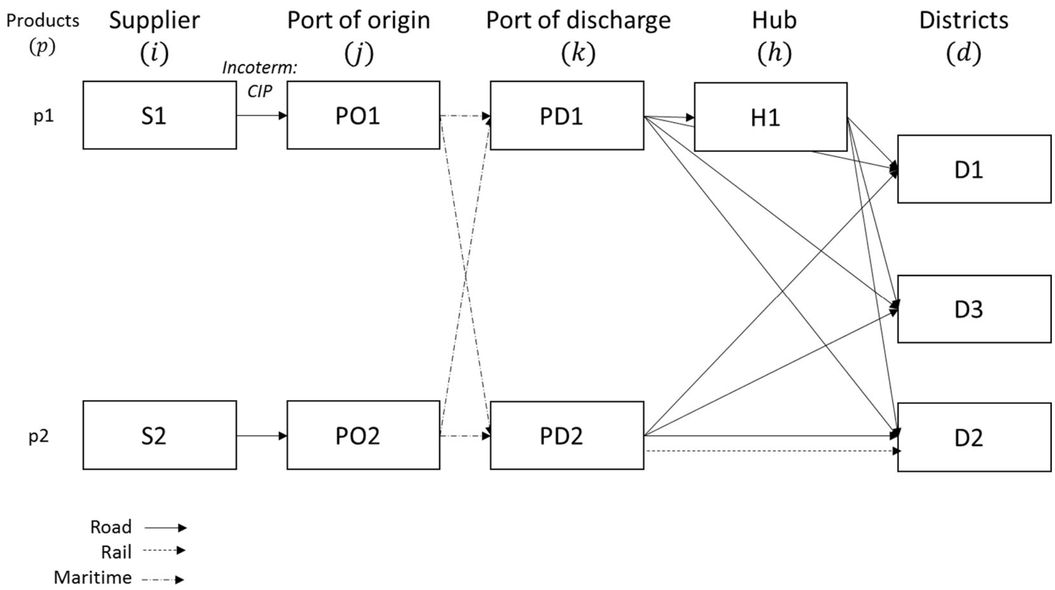

Figure 7: Illustrative case supply chain structure.

Source: Author

Predicted LLIN procurement prices, safety stock costs and supplier nominal capacities with their associated maximum allowed deviations are presented in Table 9.

Table 9: Predicted LLIN procurement prices, safety stock price and supplier's capacity

Supplier	LLIN Price ($)	Safety Stock ($)	Supply capacity (LLIN)	Max capacity deviation
S1	3	0.3	400,000	40,000
S2	4	0.4	1,000,000	20,000

Source: Author

Suppliers are responsible to deliver LLINs until the port of origin, thus transportation costs from suppliers to the available ports of origin equal to zero.

LLINs can be transported in 20 ft. and 40 ft. containers, with a capacity of 20.000 and 40.000 LLINs respectively. The predicted procurement price of a 20 ft. container is $1.000, and a 40 ft. is $1.500. Predicted transportation costs between ports of origin and ports of discharge are presented in Table 10.

Table 10: Predicted transportation costs from port of origin to port of discharge

Transportation Cost ($/20 ft. container)	Port of discharge	
	PD1	PD2
Port of Origin		
PO1	1,000	1,200
PO2	1,200	1,000

Source: Author

In addition to roads that connect port of discharge and hubs to districts, PD2 is connected to district D2 by a railway 50% cheaper than the equivalent route made by road and with a nominal capacity of 10 TEUs (twenty-foot container equivalent unit) and a minimum capacity of 6 TEUs. It is worth noting that road transport capacity is adequate and therefore, it does not represent a restriction to the supply chain planning. Predicted road transportation costs for 20 ft. containers are presented in Table 10, and transportation costs for 40 ft. containers are considered as 65% more expensive than the equivalent route for 20 ft. containers. Table 11 also shows the LLIN nominal demand per district and port of discharge and hubs capacity, with their maximum allowed deviation.

Table 11: Predicted road transport costs, port and hubs capacities and LLIN demand per district

Road Transport Cost ($/20 ft. container)	Hub	Districts			Port and Hub	
	H1	D1	D2	D3	Capacity (TEU)	Max deviation
Port of Discharge						
PD1	400	200	400	510	20	2
PD2	700	400	200	810	50	1
Hub						
H1	-	200	500	100	10	1
Demand (LLIN)	-	200,000	200,000	200,000	-	-
Max deviation	-	20,000	10,000	5,000	-	-

Source: Author

LLIN procurement and maritime lead times are both two months, i.e. $\pi = 4$ and $\lambda = 2$, and for the sake of simplicity, the budget planning lag β is equal to zero. Time series for all financial costs parameters are presented in Appendix 1.

The optimal result from the deterministic minimum cost model reaches approximately \$2.05 million in which LLIN procurement accounts for \$2.00 million (97.4%), container procurement \$22,500 (1.1%), maritime transportation costs \$28,050 (1.4%) and inland distribution costs \$3,300 (0.2%). 400,000 LLINs are procured from supplier S1 and shipped from PO1 in ten 40 ft. containers until PD1. Note that S1 nominal capacity is fully utilized. On the other hand, 200,000 LLINs are procured from supplier S2 (20% of its nominal capacity) and are shipped from PO2 until PD2 in five 40 ft. containers. From PD1, five containers go straight to district D1 while the other five go to hub H1 for further distribution until D3. The five containers that reach PD2 flow to D2 on the available railway route.

Considering the supply robust model, when $T^{supply} = 1$, up to one supplier is allowed to assume its minimum capacity value. According to the proposed hierarchical model to treat RHS uncertainties, when supplier S1 assumes its minimum capacity (i.e. 360,000) it also represents the maximum decrease in global supply capacity (i.e. -40,000) and therefore, in this particular illustrative case, $T^{supply} = 1$ implies in $\Gamma_{p1,S1}^{supply} = 1$ and $\Gamma_{p2,S2}^{supply} = 0$. Consequently, procurement from S1 decreases from 400,000 to 200,000 LLIN, and supplier 2 now provides this difference, increasing total costs in 9.8%.

In the demand robust model, when $T^{demand} = 1$, safety stocks at suppliers must cover the maximum LLIN demand deviation of at least one district. In this case, since D1 represents the district with the highest demand deviation, i.e. 20,000, $\Gamma_{D1}^{demand} = 1$,$\Gamma_{D2}^{demand}, \Gamma_{D3}^{demand} = 0$ and the model allocates 20,000 LLIN in supplier S2, increasing overall costs by 4.3%.

Under port of discharge uncertainties, when $T^{port} = 1$, up to one port of discharge might assume its minimum capacity and since PD1 decreases by 2 TEUs in its worst-value case, while PD2 by only 1 TEU; PD1 represents the maximum loss in global ports of discharge capacity. Therefore, $\Gamma_{PD1}^{port} = 1$ and $\Gamma_{PD2}^{port} = 0$, and the model reallocates one 40f ft. container that previously reached PD1 from PO1 to PD2, increasing overall costs by 0.03%.

Under mode of transport capacity uncertainty, when $T^{rail} = 1$ up to one railway route might assume its lowest capacity value. Since there is only one available route, from PD2 to D2, it assumes its lowest capacity of 6 TEUs and thus from the five 40 ft. containers that flowed through the railway, now two are transported by road, increasing costs in 0.02%. Similarly, under hub capacity uncertainty, when $T^{hu} = 1,$ the only available hub in the model assumes its minimum capacity, falling from 10 to 9 TEUs. Rather than transporting five 40 ft. container from H1 until D3, the model indicates that only four containers transit in H1 and thus one 40 ft. container goes straight from PD1 to D3 increasing total costs by 0.001%.

Under financial costs uncertainties, when considering a one period robustness window, i.e. $K = 1$, the total costs do not change, since predicted LLIN procurement values, which represent the highest impact in total costs, are actually higher than the previous observed values. In other words, even though some observed costs from other parameters are higher within the defined robustness window, the worst total cost is obtained thought predicted costs. The same applies when setting the window to three consecutive periods ($K = 3$).

However, when considering six consecutive periods, $K = 6$, the overall costs increase by 22.12%, and if set to twelve consecutive periods, $K = 12$, total costs increase by significant 65.56%.

Next, the maximum distribution model is investigated. The nominal budget is considered as the total minimum costs obtained from the deterministic model, i.e. \$2.05 million. It is assumed that the budget might deviate up to a maximum of 5% from its nominal values, reaching \$1.95 million in the worst-case scenario (when $\mathrm{T}^{budget} = 1$). Demand prioritization is achieved thought distinct unmet demand costs per districts, i.e. $uc_1 = 10, uc_2 = 20, uc_3 = 30$, in which the highest values indicates the most prioritized region. In this context, when only 95% of the budget is available, 96% of the total demand is fulfilled. In other words, the model fully supplies district D3 and D2, while D1 receives 87% of its nominal LLIN demand.

In the light of the above, the proposed model is able to suggest solutions that properly reflect the decision-maker level of conservatism through procurement and logistics changes within the supply chain. As expected, as the robustness level increases so does the price to be paid for its solution. In particular, regarding the financial costs uncertainties the increased solution value means, above all, the need to consider an additional amount of budget to hedge against price volatility. Finally, notice that, besides prioritizing the coverage of pressing areas, when the maximum distribution model is linked to the optimal solution of the minimum costs model, it is able to assess the impact on demand fulfillment rates due to funding struggles to achieve the minimum required budget.

5.2. UNICEF distribution in Ivory Coast 2014

Between July and December 2013, a large-scale LLIN distribution campaign started in Ivory Coast with two pilot phases, comprising 1.8 million LLINs funded by the World Bank and implemented by CARE. Later, from June until December 2014, UNICEF was responsible for the procurement and distribution of 12 million LLINs within three implementation phases funded by the Global Fund. In this context, Figure 8 depicts the ports of discharge, hubs and demanding regions per distribution phase in Ivory Coast map.

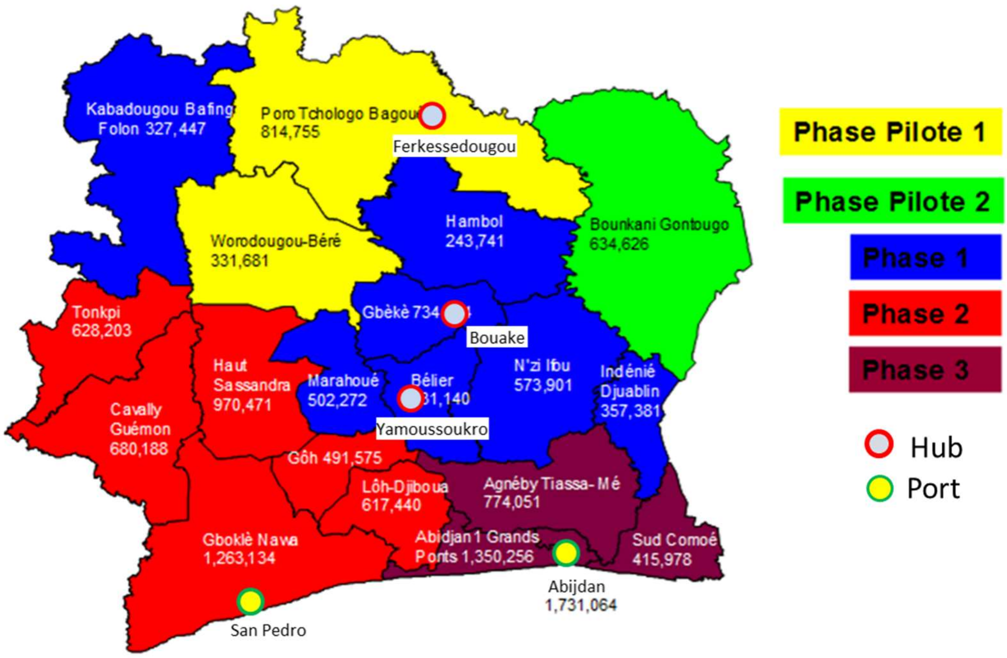

Figure 8: Panorama of UNICEF's large scale distribution campaign in Ivory Coast, 2014.

Source: Brito et al. (2015)

The same assumptions and nominal parameters values described in Brito et al. (2015) are considered in this dissertation and presented below:

LLINs can be procured from distinct suppliers based in Asia and are delivered to the nearest port: Haiphong and Ho Chi Minh (Vietnam), Chennai (India), Bangkok (Thailand), Qingdao, Shanghai and Tianjin (China).

Ivory Coast's two main ports, Abidjan and San Pedro, are considered in the model and three cities, Ferkessédougou, Yamoussoukro and Bouake can be set as hubs to allow the usage of smaller trucks to reach remote areas and to reduce last mile transportation distance and overall transport costs.

From these ports of discharge and hubs, LLINs are distributed to 71 health districts, where they are prepositioned before the distribution takes place. With the exception of Abidjan health district, all other regions have to receive LLINs inside containers to tackle the lack of storage capacity at health district level, which also represents a security concern. Besides, each health district must be supplied entirely by a single supplier to avoid quarrels among beneficiaries, due to preferences towards a specific supplier, once the distribution begins. It is worth noting that hubs are also used to address potential bottlenecks such as insufficient space to accommodate containers at district levels, and the need of proper equipment to handle containers, for instance, forklifts and trucks with cranes.

Suppliers are responsible to deliver LLINs in containers up to the port of origin in Asia. In addition, no transportation costs are introduced when suppliers are located in the same city of port of origin. There are three available container sizes, 20 ft., 40 ft. and 40 ft. HC (high-cube). The freight rates from ports of origin in Asia to ports of discharge and hubs in Ivory Coast were collected through market research and includes local insurance, customs clearance and duties, port storage and offloading costs in Ivory Coast. Transportation costs from the ports of discharge and hubs to the health districts were calculated based on their distance with the linear regression presented in equation (87) that has a coefficient of determination$R^2 = 0.99$ (Brito et al. 2015).

$$Inland\ Cost = 395.60 + 2.45 * Distance \tag{87}$$

Each suppliers has: (i) an specific production capacity; (ii) a variable stuffing capacity according to each container size; and (iii) a LLIN selling price. Demand at each health district was calculated using WHO (2014) recommendation of one

LLIN for every 1.8 persons in the target population. Figure 9 illustrates the entire supply chain structure considered in the model.

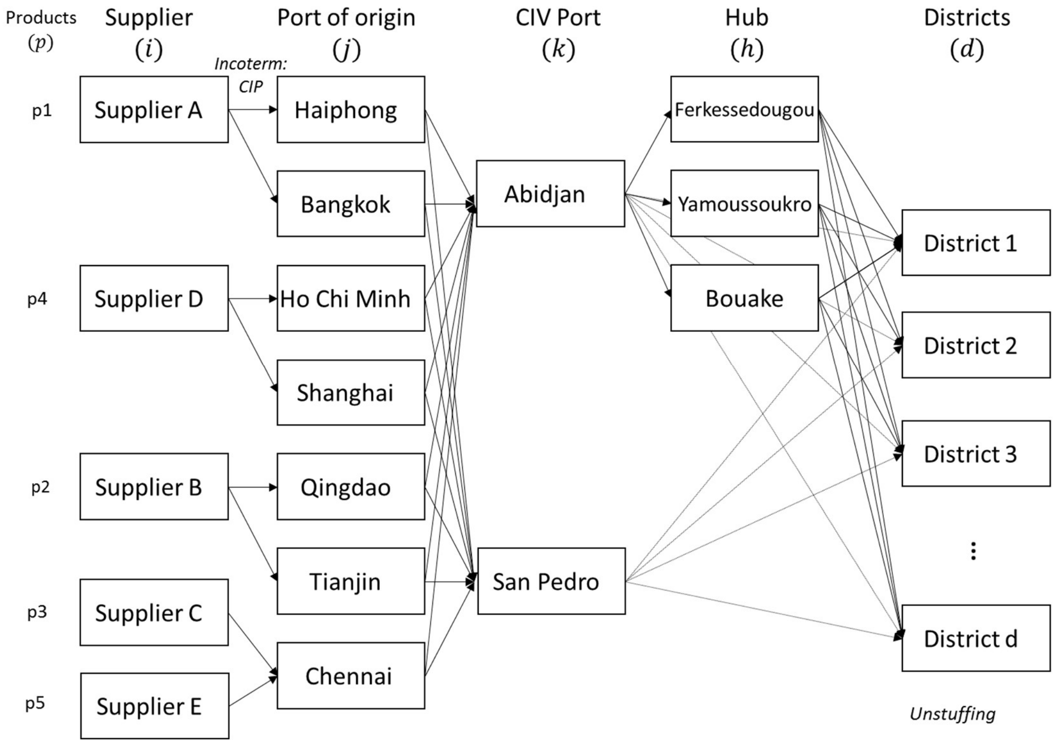

Figure 9: Supply chain structure.

Source: Adapted from Brito et al. (2015)

In addition to Brito et al. (2015), the following assumptions are made.

For the data-driven robust approach implementation, time series were generated for each cost parameter considering their nominal values multiplied by monthly return rates of crude oil price (LLIN procurement price), diesel price (inland freight rates), steel coil price (container procurement price) and the dry Baltic index (maritime freight rates) obtained through Investing (2017) database. It is worth noting that China Containerized Freight Index (CCFI) would be a more adherent proxy, since its specific for container freight, however, unlike the dry Baltic index, it is not public available.

The budgetary planning phase is considered as 12 months prior to actual LLIN distribution phase r, i.e., $\beta = 12$, and the maritime transport and the production lead time are both 2 months, i.e. $\pi = 4$ and $\lambda = 2$. Figure 10 shows the aforementioned time series proxies monthly returns, with reference to the first UNICEF implementation phase, which began in June 2014. Note that, considering a robustness window of one year ($K = 12$), oil price reaches its maximum in March 2012, 15% more expensive than its predicted value, and diesel price peaks in September 2012 (5% increase). In addition, the dry Baltic index, which presents high volatility, has its highest value (24% increase) in April 2012 and steel coil prices are actually lower than forecasted value.

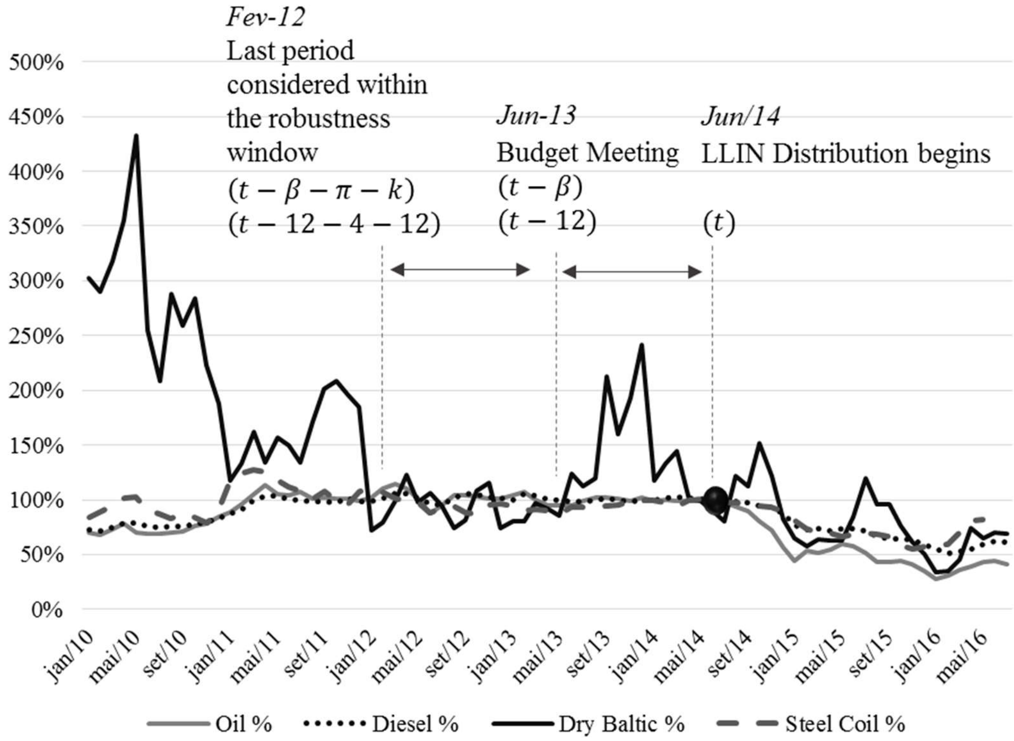

Figure 10: Data-driven robust optimization parameters and time series proxies.

Source: Author

The inventory costs of maintaining a safety stock within supplier facilities are considered as 10% of LLIN procurement costs per LLIN unity stock. Demand and supply worst-case values were assumed as a percentage from their nominal values in Brito et al. (2015), i.e. 105% and 75% for each health district and supplier respectively.

Port of discharge capacities were obtained through Logistics Cluster (2017) Ivory Coast's ports assessment and since their monthly capacity significantly outweigh project's container flow, the model disregards port of discharge robustness parameters. In addition, hub's and road transportation capacities are considered sufficient and since they do not represent a limitation to logistics planning, their robustness parameters were also disregarded in the model.

Towards the development of the maximum priority demand coverage model, the demand prioritization parameter, uc_d , for each health district was estimated based on total malaria cases per Ivory Coast administrative region in 2012, which was obtained through Malaria Atlas Project (2016) data. Considering inc_d the 2012 incidence rate of the administrative region in which district d is located, equation (88) presents uc_d calculation formula.

$$uc_d = \frac{inc_d}{Min_{d \in D}\{inc_d\}} \qquad \forall d \qquad (88)$$

5.2.1. UNICEF minimum cost model results

For the minimum cost model, the impact of each type of uncertainty in the total costs and the overall effect in the supply chain design is assessed through the cases presented in Table 12.

First, the deterministic model (case 1) is used as a reference to the robust models. Next, cases 2.1 to 2.5 investigate financial costs uncertainties within the data-driven robust framework, in which the size of the robustness window ranges from a one month to a one-year of consecutive observed values, with quarterly gaps between each robustness level, i.e. $K = 1,3,6,9,12$. Cases 3.1 to 3.4 discuss supply capacity uncertainties in which up to four suppliers might assume their worst-case capacity. Demand uncertainty is examined with a 20% progressive increase in the number of districts that might assume their highest LLIN needs through cases 4.1 to 4.5. Both supply and demand uncertainties are investigated within the proposed RHS robustness hierarchical framework. Finally, cases 5.1 to 5.5 investigate the gradual and simultaneous increase of each uncertain parameter robustness level.

Table 12: Minimum cost model investigated cases

#	**Uncertainty type**	**Modeling approach**	**Financial costs** (Robustness Window K)	**Demand** $(T_r^{demmand}\forall r$	**Supply** $(T_r^{supply}\forall r)$
1	N/A	Deterministic	0	0	0
2.1	Financial costs	Data-driven uncertainty sets	1	0	0
2.2			3		
2.3			6		
2.4			9		
2.5			12		
3.1	Supply	RHS robustness	0	0	1
3.2					2
3.3					3
3.4					4
4.1	Demand	RHS robustness	0	20%	0
4.2				40%	
4.3				60%	
4.4				80%	
4.5				100%	
5.1	Financial costs, supply and demand	Data-driven uncertainty sets and RHS robustness	1	20%	1
5.2			3	40%	2
5.3			6	60%	3
5.4			9	80%	4
5.5			12	100%	4

Source: Author

As the deterministic approach is insensitive to variability in the uncertain parameters, very often the plans suggested by such models are rendered infeasible once uncertainties are revealed. Since an unfeasible plan cannot be used in practice and it incurs in additional emergency replanning costs, it is useful to measure and compare the reliability of the deterministic and the robust plans, in other words, if they are executable after uncertainties are revealed.

In this context, to assess the feasibility rate of each solution, uncertain parameters values were sampled for each case through 10,000 Monte Carlo simulations, using uniform, triangular and normal (Gaussian) distributions. For a given set of sampled uncertain parameters of a particular simulation, a solution is considered unfeasible if it violates a constraint. Note that the violation probability proposed by Bertsimas and Sim (2004) and previously presented in equation (14), assume that random variables are independent, which is not true for the case under study, and therefore the proposed Monte Carlo simulation is required to assess the feasibility rates.

In the absence of the real probability distributions behind each uncertain parameter, the uniform distribution is used to assess uncertain parameters' extreme values inside the uncertainty interval with constant probability. The triangular distribution is used to investigate a conservative risk profile through a positive (e.g. supplier capacity parameter) or negative (e.g. demand parameter) skewness. Finally, the Gaussian distribution is used to provide an unbiased assessment.

The minimum and maximum values inside a parameter uncertainty interval, e.g. [sc_{rpi}-$\widehat{sc}_{rpi}$, sc_{rpi}+$\widehat{sc}_{rpi}$], were used as input parameters to the uniform distribution. For the normal distribution, nominal parameter's value were considered as the average, e.g. sc_{rpi}, and the standard deviation as one third of the maximum deviation, $\frac{\widehat{sc}_{rpi}}{3}$. For financial cost parameters, the standard deviation was calculated for the monthly return (i.e. first difference) time series within the periods inside the robustness window. The triangular distribution requires and additional parameter, the mode, which was considered as one standard deviation far from the average (nominal) parameter value, e.g. $sc_{rpi} - \frac{\widehat{sc}_{rpi}}{3}$. Note that for financial costs and demand parameters, the standard deviation must be added, instead of being reduced, from the average value to achieve a more conservative distribution than the Gaussian. In this context, Figure 11 illustrates the considered probability distributions for supplier B production capacity (in thousands of LLINs), during the first implementation phase.

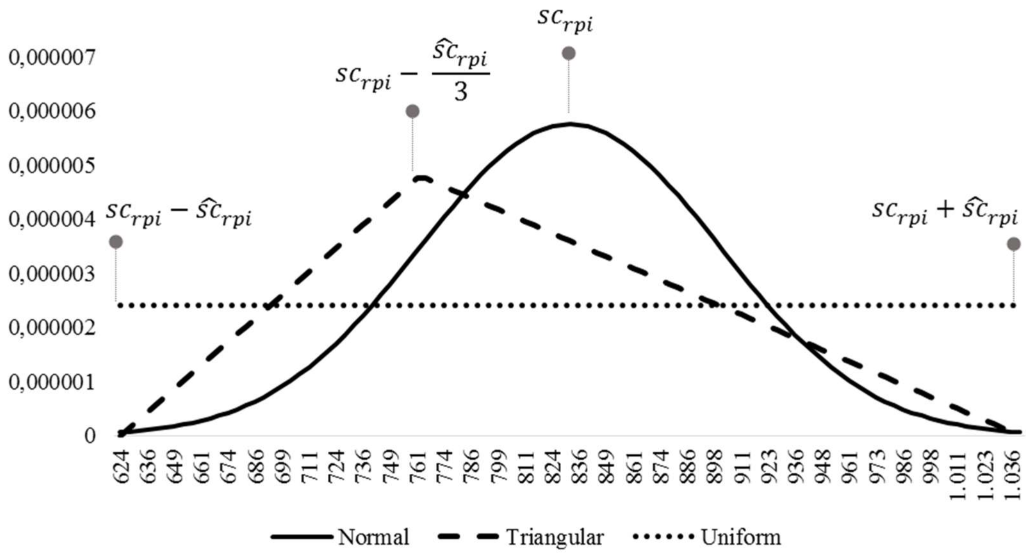

Figure 11: Estimated Normal, Triangular and Uniform probability distributions for supplier B production capacity (in thousands of LLINs)

Source: Author

Financial costs uncertainty

Financial costs uncertainties are evaluated through cases 2.1 to 2.5, in which Table 13 presents the procurement and transportation costs for the deterministic and the data-driven robust model up to a one-year robustness window. In addition, it presents the results from the simulations that evaluated the robust solution feasibility rate.

To give an overall idea of the size of the robust minimum cost problem, note that the data-driven model with a one year robustness window (case 2.5) has 17,405 variables (13,177 integers) and 6,788 constraints.

Table 13: Impact of distinct robustness windows in total procurement, safety stock and transportations costs

Case	**1**	**2.1**	**2.2**	**2.3**	**2.4**	**2.5**	**Rob.**	**Rob.**	**Rob**
Costs (million $)	**Det.**	**K=1**	**K=3**	**K=6**	**K=9**	**K=12**	**Avg.**	**Avg.**	**Dev.**
Procurement									
LLIN	19.45	20.34	20.84	20.84	20.87	22.26	21.03	88.3%	3.4%
Container	0.88	0.80	0.81	0.81	0.80	0.83	0.81	3.4%	1.8%
Safety Stock	0.000	0.002	0.000	0.000	0.000	0.001	0.001	0.0%	141.6%
Transport									
Sup-> PO	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0%	-
PO->PD	1.68	1.60	1.63	1.70	1.69	1.75	1.67	7.0%	3.4%
PD->Hubs->Dis	0.30	0.30	0.30	0.31	0.30	0.29	0.30	1.3%	2.0%
Total	22.31	23.04	23.58	23.66	23.66	25.14	23.82	-	-
Rob.-Det.		0.73	1.26	1.34	1.34	2.83	-	-	-
Rob-Det.(%)		3.3%	5.7%	6.0%	6.0%	12.7%	-	-	-
Opt. Gap (%)	0.57%	0.62%	0.75%	0.58%	0.59%	0.59%	-	-	-
Solv. Time (s)	1,105	513	1,933	1,376	320	2,621	-	-	-
Feasibility Prob.									
Uniform	12.1%	27.6%	41.5%	47.7%	49.1%	90.3%	-	-	-
Normal	13.0%	38.9%	69.3%	80.8%	81.9%	99.5%	-	-	-
Triangular	2.6%	12.9%	27.5%	39.4%	39.0%	94.9%	-	-	-

Det. (deterministic model result), Rob. Avg. (average results from robust models), Rob. Dev. (relative standard deviation from robust models), Sup (supplier), PO (port of origin), PD (port of discharge), Dis (district), Rob.-Det. (difference between robust and deterministic solution, i.e. price of robustness), Opt. Gap (optimality gap), Solv. Time (solving time), Unif. (Chance of the solution being feasible when uncertainty follows a uniform distribution), Norm. (Normal distribution), Trian. (Triangular distribution)

Source: Author

Total costs for the deterministic model sum \$22.31 million, and as the robustness window lag increases, it results on an average of 2.4% increase to the prior robustness level. In the most conservative scenario, spanning a one-year robustness window, the cost increase reaches as far as 12.7% from its deterministic counterpart comprising a total of \$25.14 million. It also becomes clear that LLIN procurement costs represents by far the major cost share (average of 88.3%), followed by maritime transportation costs (7%) and container procurement (3.4%). As the robust window increases, LLIN procurement also has the biggest average impact in total costs, 7.1%. Further, the container and transportation plans in the robust models are, on average, 3.1% cheaper compared to the deterministic case, which indicates a solution that prioritizes LLIN procurement plan to achieve the cheapest solution.

It is worth noting that total transportation costs from suppliers to port of origin are equal to zero, because the dataset only allows production distribution to ports in cities where suppliers are located.

In regard to feasibility rates, when solutions are tested against the several realization of the uncertain financial cost parameters, the deterministic model has the highest chance of exceeding the optimal total costs (e.g. 97.4% under triangular distribution), and thus violating constraints (28) and (29). On the other hand, as the robustness window increases, so does the chance of the robust solution being feasible. Note that when $K = 3$, the robust plan starts to perform reasonably well, with a 69.3% probability of being feasible under normal distribution reaching up to 99.5% when $K = 12$ under the same distribution. As expected, in most cases results from the triangular distribution are more conservative than the uniform, which in turn are more conservative than the normal distribution.

Next, the impact of increasing robustness windows is evaluated on supply chain design features such as supplier utilization, container procurement and logistic infrastructure assessment. Table 14 indicates that LLIN procurement per supplier is almost unaffected by this robust approach, with supplier A representing an average of 53.2% (6.6 million LLIN) of total share, followed by supplier B with 25% (3.1 million), supplier C, 18% (2.2 million) and D, 3.7% (0.4 million).

Table 14: Impact of distinct robustness windows in the number of LLINs procured per supplier.

Supplier proc. (million LLIN)	1 Det.	2.1 K=1	2.2 K=3	2.3 K=6	2.4 K=9	2.5 K=12	Rob. Avg.	Rob. Avg.	Rob Dev.
A	6.66	6.63	6.61	6.61	6.52	6.61	6.60	53.2%	0.7%
B	3.09	3.10	3.09	3.10	3.10	3.11	3.10	25.0%	0.2%
C	2.22	2.27	2.24	2.21	2.21	2.20	2.23	18.0%	1.4%
D	0.43	0.39	0.36	0.47	0.56	0.49	0.45	3.7%	17.3%
E	0.00	0.00	0.09	0.00	0.00	0.00	0.02	0.1%	223.6%
Total	12.40	12.40	12.40	12.40	12.40	12.40	12.40	-	-

Source: Author

Table 15 indicates the average supplier capacity utilization (among the three implementation phases) in which on average suppliers A, B and C are almost fully utilized, while supplier D only uses 14.6% of its capacity, with no substantial changes between distinct robustness windows.

Table 15: Impact of distinct robustness windows on the average supplier capacity utilization.

Supplier capacity utilization (%)	1 Det.	2.1 K=1	2.2 K=3	2.3 K=6	2.4 K=9	2.5 K=12	Rob Avg.	Rob Dev.
A	99.7%	99.3%	99.0%	99.0%	97.7%	99.0%	98.8%	0.6%
B	99.0%	99.0%	99.0%	99.3%	99.3%	99.3%	99.2%	0.2%
C	96.0%	99.3%	97.3%	94.7%	97.7%	94.7%	96.7%	2.0%
D	13.7%	13.0%	12.0%	15.0%	17.3%	15.7%	14.6%	2.1%
E	0.0%	0.0%	0.3%	0.0%	0.0%	0.0%	0.1%	0.1%

Source: Author

Table 16 indicates that on average 40 ft. HC containers represent 72.6% (354 units) of procurement efforts on the robust models, followed by 40 ft. with 25.1% (124 units) and 20 ft., 3.3% (16 units), which makes sense since 40ft HC represents the best marginal value per capacity. However, no straightforward conclusion can be extracted from the high relative standard deviation values, which might be actually related to the fact that procurement and transportation costs are the same for 40ft and 40ft HC in Brito et al. (2015) dataset.

Table 16: Impact of distinct robustness windows in the amount of container procurement per size.

Container Procurement	1 Det.	2.1 K=1	2.2 K=3	2.3 K=6	2.4 K=9	2.5 K=12	Rob. Avg.	Rob. Avg.	Rob Dev.
20ft	15	15	25	12	14	16	16	3.3%	30.7%
40ft	138	197	98	125	98	101	124	25.1%	34.3%
40ftHC	341	286	377	355	376	375	354	72.6%	11.0%
Total	494	498	500	492	488	492	494	-	-

Source: Author.

Table 17 represents the amount of containers, in twenty-foot equivalent units (TEU), transported from ports of origin in Asia, which is deeply affected by the previously presented supplier utilization results. Once more, the difference between the deterministic result and the robustness approach for all considered lags are spurious. On average, Haiphong port in Vietnam moves an average of 536 TEUs (55.2%) coming from supplier A, followed by Qingdao port in China with 208 (21.4%) coming from supplier B, Chennai port in India with 202 TEUs (20.8%) coming from supplier C and E, and Shanghai port in China with 24 TEUs (2.5%) coming from supplier D.

Table 17: Impact of distinct robustness windows in the amount of TEUS in transit per port of origin in Asia.

Port of Origin Flow Share (TEUs)	1 Det.	2.1 K=1	2.2 K=3	2.3 K=6	2.4 K=9	2.5 K=12	Rob. Avg.	Rob. Avg.	Rob Dev.
China: Qingdao	210	210	208	208	206	210	208	21.4%	0.8%
China: Shanghai	24	20	20	25	30	25	24	2.5%	17.4%
China: Tianjin	0	0	0	1	0	0	0	0.0%	223.6%
India: Chennai	201	207	208	202	197	197	202	20.8%	2.6%
Thailand: Bangkok	0	2	0	0	0	0	0	0%	223.6%
Vietnam: Haiphong	538	542	539	536	529	536	536	55.2%	0.9%
Vietnam: Ho Chi Min	0	0	0	0	0	0	0	0%	-
Total	973	981	975	972	962	968	972	-	-

Source: Author

Table 18 represents the quantity of TEUs dispatched from ports and hubs in Ivory Coast directly to health districts. Most TEUs are dispatched or unstuffed in Abidjan port (average of 488 TEUS, 50.5%), since Abidjan district alone accounts for almost 23% of the total LLIN demand under UNICEF project scope. On the other hand, San Pedro port dispatches an average of 348 TEUs (35.7%). Hubs are used almost entirely during phase 1 to supply the less populated central and northern region that account for approximately 25% of project's demand. Yamoussoukro hub, 236 km far from Abidjan port, consolidates an average of 72 TEUs (6.4%) with a relative standard deviation of 25.3% (e.g. for $k = 6$ it moves only 48 TEUs). Bouake is the second most used hub, with an average of 58 TEUs (6%) followed by Ferkessedougou with a tiny fraction of the outbound flow (7 TEUs, 0.6%) to districts.

Table 18: Impact of distinct robustness windows in the amount of TEUS transported from port of discharge and hubs to health districts in Ivory Coast

Port Discharge and Hub flow Share (TEUs)	1 Det.	2.1 K=1	2.2 K=3	2.3 K=6	2.4 K=9	2.5 K=12	Rob. Avg.	Rob. Avg.	Rob Dev.
Port: Abidjan	484	473	484	512	508	478	491	50.5%	3.6%
Port: San Pedro	338	359	337	355	336	347	347	35.7%	3.0%
Hub: Yamoussoukro	85	83	86	48	53	76	69	7.1%	25.3%
Hub: Bouake	56	56	57	57	65	57	58	6.0%	6.4%
Hub: Ferkessedougou	10	10	11	0	0	10	6	0.6%	91.5%
Total	973	981	975	972	962	968	972		0.7%

Source: Author

In the light of the above, it is concluded that despite the considerable impact in financial aspects, the data-driven robust approach imposed marginal influence on the supply chain design. In this context, robustness can be understood as the proper budget buffer, in other words, an additional amount of money on top of the original budget, to hedge against the impact of price volatility on procurement and distribution plans.

Supply Uncertainty

Next, supply uncertainties are evaluated through cases 3.1 to 3.4. In this context, Table 19 illustrates for each supplier and implementation phase, its average and minimum capacities, the difference between them, i.e. the deviation from the nominal value, and the lower level problem solution from the proposed hierarchical approach to deal with supply uncertainty. In other words, given a supply robustness level $\mathrm{T}_r^{supply} \in \{0,1,2,3,4\}$ that represents the number of suppliers that might assume their minimum capacity value in each implementation phase, Γ_{rpi}^{supply} values are chosen in such a manner that the maximum decrease in global supply capacity is achieved. Note that supplier E is disregarded from the robustness analysis because it is actually a standby supplier, which represents a capacity buffer to avoid model infeasibility and whose LLIN price is 42% above the cheapest supplier.

Table 19: Supplier nominal and minimum capacities per phase, and Γ_{rpi}^{supply} value for each robustness level T_r^{supply}.

Supplier	Phase	Supplier Capacity (million LLIN)			Γ_{rpi}^{supply} for each T_r^{supply}				
		Min	Average	Δ (Avg - Min)	0	1	2	3	4
A	1	1.128	1.505	0.376	0	1	1	1	1
	2	1.568	2.090	0.523	0	1	1	1	1
	3	2.311	3.081	0.770	0	1	1	1	1
B	1	0.624	0.832	0.208	0	0	0	1	1
	2	0.915	1.220	0.305	0	0	0	0	1
	3	0.841	1.121	0.280	0	0	1	1	1
C	1	0.819	1.092	0.273	0	0	1	1	1
	2	0.947	1.263	0.316	0	0	0	1	1
	3	0.581	0.774	0.194	0	0	0	1	1
D	1	0.430	0.574	0.143	0	0	0	0	1
	2	0.973	1.298	0.324	0	0	1	1	1
	3	0.312	0.416	0.104	0	0	0	0	1
E	1	10.000	10.000	0.000	0	0	0	0	0
	2	10.000	10.000	0.000	0	0	0	0	0
	3	10.000	10.000	0.000	0	0	0	0	0

Source: Author

Table 20 presents the procurement and transportation costs for the deterministic and the robust model with supply uncertainties. On average, the gradual increment in supply robustness level, T_r^{supply}, represents a 1.2% increase in total costs. The worst case-scenario, equivalent to Soyster's approach where all suppliers assume their lowest capacity values, reaches \$ 23.44 million, or 5.1% above the deterministic model. Since LLIN procurement represent the highest share in project's costs (88.1%), these findings confirm the expected significant impact of supply uncertainties on total expenses.

In addition, Table 20 presents solutions' feasibility probability in regard to constraint (31), that restrict procurement according to supplier's i uncertain production capacity. For the deterministic plan chances are virtually zero and when $T_r^{supply} = 1$, they are still limited (3.5% under normal distribution). Even when $T_r^{supply} = 3$, the plan has a modest performance (42.3% under normal distribution).

In contrast, when $T_r^{supply} = 4$, the probability is almost 100% for all distributions, which is actually the expected outcome since for this particular case the protection function is equivalent to Soyster's formulation. Such behavior might be explained by the fact that suppliers A, B and C have their production capacity nearly fully utilized in all cases. Note that, results from the triangular distribution are more conservative than the uniform, which in turn are more conservative than the normal distribution.

Table 20: Impact of distinct supply robustness levels in total procurement, safety stock and transportations costs

Case **Costs (million $)**	**1** **Det.**	**3.1** T_r^{supply} **=1**	**3.2** **2**	**3.3** **3**	**3.4** **4**	**Rob.** **Avg.**	**Rob.** **Avg.**	**Rob** **Dev.**
Procurement								
LLIN	19.45	19.93	20.24	20.36	20.68	20.30	88.1%	1.6%
Container	0.88	0.83	0.83	0.85	0.84	0.84	3.6%	1.1%
Safety Stock	0.000	0.000	0.000	0.000	0.000	0.00	0.0%	200.0%
Transport								
Sup-> PO	0.00	0.00	0.00	0.00	0.00	0.00	0.0%	-
PO->PD	1.68	1.62	1.60	1.64	1.62	1.62	7.0%	0.8%
PD->Hubs->Dis	0.30	0.28	0.28	0.29	0.29	0.29	1.2%	2.4%
Total	22.31	22.66	22.96	23.15	23.44	23.05	-	-
Rob.-Det.	-	0.34	0.64	0.83	1.13	-	-	-
Rob-Det.(%)	-	1.5%	2.9%	3.9%	5.1%	-	-	-
Opt. Gap (%)	0.57%	0.70%	0.84%	0.99%	0.81%	-	-	-
Solv. Time (s)	1,105	1,600	1,797	1,600	1,513	-	-	-
Feasibility. Prob.								
Unif.	0.3%	2.1%	4.1%	26.0%	100.0%	-	-	-
Norm.	0.6%	3.5%	8.8%	42.3%	98.9%	-	-	-
Trian.	0.1%	0.5%	1.9%	21.9%	100.0%	-	-	-

Source: Author

Table 21 indicates LLIN procurement per supplier. Note that as T_r^{supply} increases, suppliers that assume their minimum capacity value now represent a smaller share compared to the deterministic solution. For instance, supplier A accounts for 53.7% of LLIN procurement in the deterministic model, and when $T_r^{supply} = 1$, it represents only 39.6%, increasing procurement costs by 2.4%.

Further, note that in the deterministic model 96.6% of LLIN supply comes from three distinct suppliers (A, B and C). As supply robustness level increases more suppliers are used, up to the point that when three suppliers are allowed to assume their worst case value, i.e. $T_r^{supply} = 3$, all five suppliers are used, including the standby supplier E, which in this case represents 4.6% of supply share.

In this context, robustness can be translated as supply chain flexibility, which is defined as the ability to change or react with little penalty in time, effort, cost or performance (Toni and Toncha, 2005). In other words, to minimize the negative impact of supply shortage, the robust solution involves extra costs by using more suppliers to ease the reallocation from the original procurement plan.

Table 21: Impact of distinct supply robustness levels on the number of LLINs procured per supplier.

Supplier proc. (million LLIN)	**1 Det.**	**3.1 T_r^{supply} =1**	**3.2 2**	**3.3 3**	**3.4 4**	**Rob. Avg.**	**Rob. Avg.**	**Rob Dev.**
A	6.66	4.92	4.98	4.92	5.00	4.95	39.9%	0.9%
B	3.09	3.09	2.27	2.30	2.30	2.49	20.1%	16.1%
C	2.22	2.25	2.26	2.28	1.68	2.12	17.1%	13.7%
D	0.43	2.14	2.91	2.33	2.27	2.41	19.4%	14.0%
E	0.00	0.00	0.00	0.58	1.14	0.43	3.5%	127.4%
Total	12.40	12.40	12.41	12.40	12.40	12.40	-	-

Source: Author

The overall effect of supply robust solutions on the rest of the supply chain is a direct result from procurement plan changes. As UNICEF becomes more averse to supply shortage risk, Haiphong (Vietnam) and Qingdao (China) ports are less used since supplier A and B share decreases. On the other hand, with supplier D and E share growth, Shanghai (China) and Chennai (India) ports are preferred. However, no significant changes occurs on Ivory Coast port of discharge and hubs distribution plan.

Demand Uncertainty

Demand uncertainty is investigated in cases 4.1 to 4.5 and are tackled through the procurement of safety stocks that are stored at supplier's facilities, and might be sent to districts after program evaluation results. Within the adopted demand forecast errors and warehousing cost assumptions, the progressive increase in demand robustness levels represent an average growth of $ 0.35 million in total costs. In respect to the deterministic model, the worst-case scenario, in which UNICEF hedges against forecast errors in all 71 districts, i.e. $T_r^{demmand} = 100\%$, represents a significant increase of $ 0.41 million on overall costs (Table 22).

In addition, Table 22 presents solutions' feasibility probability in regard to constraint (33), that defines the minimum required safety stock for a given budget of uncertainty $T_r^{demmand}$. The simulation shows that when $T_r^{demmand} = 20\%$, the robust plan performs well with a 36.9% chance of feasibility under normal distribution, and from $T_r^{demmand} = 40\%$ onwards chances are already 100% for the same distribution. This sudden increase in the feasibility rates might be explained by the fact that 40% of the most demanding districts ($T_r^{demmand} = 40\%$) represent considerable 67% of total demand. In addition, constraint (33) simultaneously consider all health districts and thus sampled high demand values that would hinder feasibility, might be counterbalanced by other districts' sampled values. Therefore, even for lower levels of conservatism, the constraint does not have a significant chance of being violated. Note that, unlike previous results, instead of the triangular distribution, the uniform distribution produces the most conservative results.

Table 22: Impact of distinct demand robustness levels in total procurement, safety stock and transportations costs

Case	1	4.1	4.2	4.3	4.4	4.5	Rob.	Rob.	Rob
Costs (million $)	**Det.**	**20%**	**40%**	**60%**	**80%**	**100%**	**Avg.**	**Avg.**	**Dev.**
Procurement									
LLIN	19.45	19.67	19.74	19.80	19.82	19.82	19.77	87.2%	0.3%
Container	0.88	0.87	0.87	0.87	0.87	0.87	0.87	3.8%	0.4%
Safety Stock	0.000	0.051	0.066	0.082	0.092	0.097	0.08	0.3%	24.4%
Transport									
Sup-> PO	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0%	-
PO->PD	1.68	1.66	1.66	1.66	1.66	1.65	1.66	7.3%	0.3%
PD->Hubs->Dis	0.30	0.29	0.30	0.29	0.29	0.29	0.29	1.3%	0.9%
Total	22.31	22.55	22.64	22.69	22.73	22.73	22.67	-	-
Rob.-Det.		0.24	0.32	0.38	0.41	0.41	-	-	-
Rob-Det.(%)		1.1%	1.4%	1.7%	1.8%	1.8%	-	-	-
Opt. Gap (%)	0.57%	0.38%	0.45%	0.38%	0.38%	0.30%	-	-	
Solv. Time (s)	1,105	1,511	1,389	1,564	2,264	1,602	-	-	
Feasibility Prob.									
Unif.	-	0.0%	59.2%	97.4%	100.0%	100.0%	-	-	-
Norm.	-	36.9%	100.0%	100.0%	100.0%	100.0%	-	-	-
Trian.	-	0.4%	99.6%	100.0%	100.0%	100.0%	-	-	-

Source: Author

Note in Table 23 that as the robustness grows, the total number of LLINs procured rises up to 1.8% in the worst-case scenario, to protect against the 5% demand forecast error. It is also possible to observe that supplier's D share increases from a 3.4% baseline to a maximum of 4.3%, whereas others suppliers are almost kept constant compared to the deterministic plan.

Table 23: Impact of distinct demand robustness levels on the number of LLINs procured per supplier.

Supplier proc. (million LLIN)	**1 Det.**	**4.1 20%**	**4.2 40%**	**4.3 60%**	**4.4 80%**	**4.5 100%**	**Rob. Avg.**	**Rob. Avg.**	**Rob Dev.**
A	6.66	6.66	6.62	6.64	6.65	6.67	6.65	52.8%	0.3%
B	3.09	3.13	3.13	3.13	3.13	3.13	3.13	24.9%	0.0%
C	2.22	2.29	2.28	2.29	2.29	2.29	2.29	18.2%	0.1%
D	0.43	0.45	0.53	0.54	0.54	0.53	0.52	4.1%	7.2%
E	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0%	0.0%
Total	12.40	12.53	12.56	12.60	12.61	12.62	12.58	100%	0.3%
Rob. - Det.	-	0.14	0.17	0.20	0.21	0.22	0.19	-	18.2%
Rob. -Det.(%)	-	1.1%	1.3%	1.6%	1.7%	1.8%	1.5%	-	-
Supplier D share	3.4%	3.6%	4.2%	4.3%	4.3%	4.2%	4.1%	-	-

Source: Author

Although procurement from supplier D increases, its production is almost entirely shipped to districts instead of being part of the safety stock. Therefore, the robust model tends to hold part of suppliers original procurement plan to build the stock. In this context, supplier's safety stock tend to be spread among suppliers A (average of 9.3%), B (21.2%) and C (68,5%), as seen on Table 24.

Table 24: Impact of distinct demand robustness levels in safety stock levels per supplier.

Safety stock (LLIN*1000)	**1 Det.**	**4.1 20%**	**4.2 40%**	**4.3 60%**	**4.4 80%**	**4.5 100%**	**Rob. Avg.**	**Rob. Avg.**	**Rob Dev.**
Supplier A	0	30	33	87	70	7	46	9.3%	71.2%
B	0	50	67	76	122	253	113	21.2%	72.4%
C	0	237	325	363	393	379	338	68.5%	18.2%
D	0	12	0	0	10	0	4	1.1%	138.5%
E	0	0	0	0	0	0	0	0.0%	0.0%
Total safety stock	0	329	425	526	594	632	501	-	-
Uncertain Demand	0	274	415	509	578	620	479	-	-

Source: Author

Concerning supply chain design revisions, the robust model needs to increase Shanghai port utilization to ship supplier D additional production.

Under demand uncertainty, robustness can also be understood as supply chain flexibility, since the preposition of safety stock in several suppliers before uncertainty is revealed, allows a more timely reaction with less financial burden compared to the release of a new tender.

Financial costs, supply and demand uncertainties

Next, financial costs, supply and demand uncertainties are simultaneously considered to investigate their combined effect (cases 5.1 to 5.5). When robustness is gradually increased in this model, each level accounts, on average, for a 4% growth in total costs, almost entirely due to LLIN procurement costs growth. In the worst-case scenario, total costs reach up to $ 27.03 million, representing a substantial 21.1% surplus upon the deterministic model (Table 25). Regarding the probability of the robust solution being feasible (i.e. not violating constraints (28), (29), (31) and (33)), only after case 5.4 the robust plan performs reasonably well, with a 90.0% chance under normal distribution, but on the other hand, under more conservative distribution the performance is still modest (e.g. 50.3% for triangular distribution). Such behavior is explained by the uncertain production capacity constraints, that produce similarly to results when assessing supply uncertainties alone (cases 3.1 to 3.4). Note that, as expected the triangular distribution renders the most conservative results, followed by the uniform and normal distribution.

Table 25: Impact of distinct global robustness levels in total procurement, safety stock and transportations costs ($ million)

	Det.	**Costs, Supply and Demand uncert.**					**Rob. Avg.**	**Rob. Avg.**	**Rob. Dev.**
Case	**1**	**5.1**	**5.2**	**5.3**	**5.4**	**5.5**			
Rob. Window (k)	**0**	**1**	**3**	**6**	**9**	**12**			
T_r^{supply}	**0**	**1**	**2**	**3**	**4**	**4**			
$T_r^{demmand}$	**0**	**20%**	**40%**	**60%**	**80%**	**100%**			
Procurement									
LLIN	19.45	21.07	21.92	22.16	22.57	24.10	22.37	89.1%	5.0%
Container	0.88	0.73	0.74	0.77	0.78	0.80	0.76	3.0%	3.8%
Safety Stock	0.000	0.054	0.068	0.099	0.105	0.151	0.096	0.4%	39.3%
Transport									
Sup-> PO	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0%	-
PO->PD	1.68	1.50	1.52	1.65	1.66	1.70	1.61	6.4%	5.6%
PD->Hubs->Dis	0.30	0.27	0.28	0.29	0.29	0.28	0.28	1.1%	3.7%
Total	22.31	23.63	24.52	24.98	25.41	27.03	25.11	100%	5.0%
Rob.-Det.	-	1.32	2.20	2.66	3.09	4.72	2.80	-	44.9%
Rob.-Det. (%)	-	5.9%	9.9%	11.9%	13.9%	21.1%	12.5%	-	-
Opt. Gap (%)	0.57%	0.38%	0.39%	0.54%	0.65%	0.59%	-	-	-
Solv. Time (s)	1,105	1,351	1,043	1,087	1,054	1,108	-	-	-
Feasibility. Prob.									
Unif.	-	0.0%	0.4%	8.3%	62.5%	97.3%	-	-	-
Norm.	-	0.6%	5.3%	10.7%	90.0%	98.4%	-	-	-
Trian.	-	0.0%	0.4%	2.6%	50.3%	98.6%	-	-	-

Source: Author

Regarding supply chain design alterations, the impact of combining all uncertainties is similar to the sum of their previously described individual contributions. In particular, the combined uncertainties model adopts a LLIN procurement plan (supplier utilization) and transportation plan (port of origin, discharge and hubs utilization) very similar to the supply uncertainty robust model. On the other hand, safety stock results show an average increase of 21.9% in supplier A share, 3.9% in supplier C and 2.5% in supplier D, whereas supplier B and C decrease by 4.0% and 24.3% respectively.

5.2.2. UNICEF maximum priority demand coverage model results

In particular, for UNICEF's mass distribution campaign, the main idea behind the maximum priority demand coverage model is to investigate the impact on demand fulfillment, in case a budget buffer is not properly adjusted to hedge uncertainties or even when a project does not meet its bottom funding goals.

In this context, the minimum cost model result from the deterministic case 1 is considered as the reference budget. Table 26 displays the cases used to evaluate the model, in which the validation case 6 uses the reference budget disregarding uncertainties, to check if the model distributes the entire nominal demand. Next, cases 7.1 to 7.3 investigate budget uncertainties, in which up to all three distribution phases might assume their worst budget, which is considered as 95% of the reference value. Similar to the minimum cost models, cases 8.1 to 8.5 investigate financial costs uncertainties with the data-driven robust framework and cases 9.1 to 9.4 discuss supply capacity uncertainties. Finally, cases 10.1 to 10.5 investigate the gradual and simultaneous increase of each uncertain parameter robustness level.

Table 26: Maximum priority demand coverage model investigated cases

#	**Uncertainty type**	**Modeling approach**	**Financial costs** (Robustness Window K)	**Budget** (T^{budget})	**Supply** ($T_r^{supply} \forall r$)
6	N/A	Deterministic	0	0	0
7.1	Budget	RHS robustness	0	1	0
7.2				2	
7.3				3	
8.1	Financial costs	Data-driven uncertainty sets	1	0	0
8.2			3		
8.3			6		
8.4			9		
8.5			12		
9.1	Supply	RHS robustness	0	0	1
9.2					2
9.3					3
9.4					4
10.1	Budget, Financial costs, Supply and demand	RHS robustness and Data-driven uncertainty sets	1	1	1
10.2			3	1	2
10.3			6	2	3
10.4			9	2	4
10.5			12	3	4

Source: Author

First, note that with an optimality gap of 0.03% from the best linear programming bound, i.e. the actual total LLIN demand, after one hour of solving time, the deterministic model (case 6) spent 100% of the budget covering 99.99% of the demand, leaving 2 districts not fully met.

Budget uncertainty is evaluated through cases 7.1 to 7.3, in which the total expenditure and the total demand coverage are analyzed for each budget robustness level $T^{budget} \in \{1,2,3\}$ that allows the model to gradually decrease by 5% the deterministic financial plan, from the highest to the lowest resourceful phase (Table 27).

To give an overall idea of the size of the robust maximum priority demand coverage problem, observe that case 7.3 has 17,753 variables (13,528 integers) and 7,175 constraints.

As the budget robustness levels gradually increases the available financial resources are always entirely spent, and the unmet demand grows by 1.5% on average. Therefore, in the worst-case scenario when the total budget is reduced to 95% (case 7.3), 10 districts are not fully met and total demand fulfillment rate is 95.6%.

Table 27: Impact of budget uncertainties on total expenditure and demand fulfillment

	Det,	**Budget Uncertainty**			**Rob. Avg.**	**Rob. Dev.**
Case	**6**	**7.1**	**7.2**	**7.3**		
$\mathbf{T}^{budget}$	**0**	**1**	**2**	**3**		
Financial Indicators ($ million)						
Deterministic Budget	22.31	22.31	22.31	22.31	22.31	0.0%
Reduced Budget	22.31	21.89	21.50	21.20	21.53	1.6%
Final Budget (%)	100.0%	98.1%	96.3%	95.0%	96.5%	1.5%
Spent Budget	22.31	21.89	21.50	21.20	21.53	1.6%
Spent Budget (%)	100.0%	100.0%	100.0%	100.0%	100.0%	
Demand Fulfillment Indicators (LLIN million)						
Nominal Demand	12.40	12.40	12.40	12.40	12.40	0.0%
LLIN Delivered	12.40	12.18	11.98	11.85	12.00	1.4%
Demand fulfillment (%)	99.9%	98.3%	96.7%	95.6%	96.8%	
Fully Covered Districts	69	67	60	61	63	6.0%
Fully Covered Districts (%)	97.2%	94.4%	84.5%	85.9%	88.3%	
Opt. Gap (%)	0.03%	0.73%	0.51%	1.09%	-	-
Solv. Time (s)	3,600	3,600	3,600	3,600	-	-

Det.: Deterministic
Fully covered districts (FCD): Number of fully covered districts

Source: Author

Under financial costs uncertainties (cases 8.1 to 8.5), procurement prices and transportation freight rates are subject to a maximum of a one-year robustness window with quarterly gaps. As the window size gradually increases, the entire budget ($ 22.31 million) is always spent and the unmet demand grows by an average of 2.1%. In the worst-case scenario (8.5), 15 districts are not fully met and total demand fulfillment rate drops to 89.5% (Table 28).

Table 28: Impact of financial cost uncertainties on demand fulfillment (in millions of LLINs)

	Det,	Financial Costs Uncertainty					Rob. Avg.	Rob. Dev.
Case	**6**	**8.1**	**8.2**	**8.3**	**8.4**	**8.5**		
Rob. Window (k)	**0**	**1**	**3**	**6**	**9**	**12**		
Nominal Demand	12.40	12.40	12.40	12.40	12.40	12.40	12.40	0.0%
LLIN Delivered	12.40	12.08	11.83	11.78	11.78	11.09	11.71	3.1%
Demand fulfillment (%)	99.9%	97.4%	95.4%	95.0%	95.0%	89.5%	94.5%	-
Fully Covered Districts	69	61	59	60	60	56	59	3.2%
FCD (%)	97.2%	85.9%	83.1%	84.5%	84.5%	78.9%	83.4%	-
Opt. Gap (%)	0.03%	1.23%	1.24%	1.14%	1.06%	2.45%	-	-
Solv. Time (s)	3,600	3,600	3,600	3,600	3,600	3,600	-	-

Rob. Window (k) = Robustness window (k)

Source: Author

Next, under supply uncertainties (cases 9.1 to 9.4), up to four major suppliers might assume their lowest capacity. In this context, as robustness levels increase the entire budget ($ 22.31 million) is always spent and the unmet demand grows by an average of 0.9%. In the worst-case scenario (9.4), 13 districts are not fully met and total demand fulfillment declines to 96.4% (Table 29).

Table 29: Impact of supply capacity uncertainties on demand fulfillment (in millions of LLINs)

	Det,	Supply Uncertainty				Rob. Avg.	Rob. Dev.
Case	**6**	**9.1**	**9.2**	**9.3**	**9.4**		
T_r^{supply}	**0**	**1**	**2**	**3**	**4**		
Nominal Demand	12.40	12.40	12.40	12.40	12.40	12.40	0.0%
LLIN Delivered	12.40	12.27	12.13	12.10	11.95	12.11	1.1%
Demand fulfillment (%)	99.9%	98.9%	97.9%	97.6%	96.4%	97.7%	-
Fully Covered Districts	69	61	61	63	58	61	3.4%
Fully Covered Districts (%)	97.2%	85.9%	85.9%	88.7%	81.7%	85.6%	-
Opt. Gap (%)	0.03%	1.37%	1.52%	1.66%	3.39%	-	-
Solv. Time (s)	3,600	3,600	3,600	3,600	3,600	-	-

Source: Author

When budget, financial costs and supply uncertainties are simultaneously considered in the model (cases 10.1 to 10.5) it still spends the entire available budget in all cases. As the global robustness level gradually increases, the unmet demand grows by an average of 3.3%, and in the worst case-scenario (10.5) 23 districts are not fully met and demand fulfillment plunges to its lowest investigated value, 83.3% (Table 30).

Table 30: Impact of distinct global robustness levels on demand fulfillment

	Det,	**Budget, Financial Costs and Supply uncertainties**						
Case	**6**	**10.1**	**10.2**	**10.3**	**10.4**	**10.5**	**Rob. Avg.**	**Rob. Dev.**
$\mathbf{T}^{budget}$	**0**	**1**	**1**	**2**	**2**	**3**		
Rob. Window ($\boldsymbol{k}$)	**0**	**1**	**3**	**6**	**9**	**12**		
$\boldsymbol{T}_r^{supply}$	**0**	**1**	**2**	**3**	**3**	**4**		
Financial Indicators ($ million)								
Deterministic Budget	22.32	22.32	22.32	22.32	22.32	22.32	22.32	0.0%
Reduced Budget	22.32	21.89	21.89	21.50	21.50	21.20	21.71	1.4%
Final Budget (%)	100%	98.1%	98.1%	96.3%	96.3%	95.0%	96.8%	
Spent Budget	22.32	21.89	21.89	21.50	21.50	21.20	21.71	1.4%
Spent Budget (%)	100%	100%	100%	100%	100%	100%	100%	
Demand Fulfillment Indicators (LLIN million)								
Nominal Demand	12.40	12.40	12.40	12.40	12.40	12.40	12.40	0.0%
LLIN Delivered	12.40	11.72	11.36	11.12	11.03	10.33	11.11	4.6%
Demand fulfillment (%)	99.9%	94.5%	91.6%	89.7%	89.0%	83.3%	89.6%	-
FCD	69	61	57	52	50	48	54	9.9%
FCD (%)	97.2%	85.9%	80.3%	73.2%	70.4%	67.6%	75.5%	-
Opt. Gap (%)	0.03%	1.47%	1.91%	1.99%	4.35%	22.49%		
Solv. Time (s)	3,600	3,600	3,600	3,600	3,600	3,600		

Source: Author

In the light of the above, is possible to deduce for this specific UNICEF case, that, in particular, the financial costs uncertainty causes the highest growth on unmet demand rates. It is also worth noting that, although not depicted, all cases satisfactorily met the demand priority requirement. In other words, the districts not fully covered were always among the least priority ones.

6
Conclusion

With increased efforts in prevention and control measures, the malaria burden has significantly been reduced in many countries. In this context, long lasting insecticide treated nets provide a protection against mosquito bites, and their distribution through large scale campaigns are one of the most effective ways to control and prevent malaria transmission.

However, mass distribution campaigns also represent a challenge since they require careful financial and logistic planning, under several constraints and uncertainties that might hinder their effectiveness. In this respect, Brito et al. (2015) introduced the relevance of considering an optimization model, which in the case was approached through deterministic inputs, to reduce the total costs of a LLIN distribution campaign, in particular, for a UNICEF project that in 2014 delivered approximately 12 million LLINs in Ivory Coast. Among others, their work revealed useful logistic insights of the problem and, above all, that the modelling process achieved a 7% cost reduction compared to UNICEF's original supply and distribution plan.

As an extension of Brito et al. (2015), this dissertation proposes a robust optimization approach to the LLIN mass distribution problem, based on customizations of Bertsimas and Sim (2004) framework, to account for uncertainties on constraints' independent terms, such as logistics and supply capacities. In addition, to consider financial costs uncertainties, the data-driven dynamic model with adaptive uncertainty sets of Fernandes et al. (2016) was adjusted to a static multi-period setting. Notably, in the last framework the decision maker must choose a window of robustness, comprised of past-observed data, which might be an intuitive way of setting a robustness parameter.

Under the same uncertain environment, two modelling objectives are independently set; the first minimizes the total costs of a campaign, while the other maximizes the distribution to priority demand areas when the available budget is insufficient to guarantee universal coverage.

To achieve the proposed goal, first a literature review in robust optimization models within the context of humanitarian supply chain design is conducted, in which elements with less academic research attention were revealed for future research suggestions. With this in mind, some were actually considered in the proposed model, such as the simultaneous account of supply, demand, logistics, budget and costs uncertainties, demand prioritization and multimode transportation.

To validate the mechanism of the proposed model and illustrate its features, at first, an illustrative and reproducible case is set. Further, the model is applied to the same UNICEF case presented by Brito et al. (2015), in which some assumptions and adjustments were made to accommodate the robust framework. In both instances, the robust model properly suggests procurement and logistics changes, according to the chosen level of conservatism towards uncertainties.

In particular, UNICEF case revealed that, as expected, robust solutions might increase total costs (i.e. the price of robustness) from marginal 1.1% (total of $22.55 million) up to significant 21% ($27.03 million) compared to its deterministic counterpart ($22.31 million). This cost increase might be interpreted as the required budget buffer to hedge against a pre-defined level of uncertainty. In return, the robust model generally provides a solution with improved supply chain flexibility by reallocating suppliers and logistic infrastructure utilization. In other words, the robust model gives a solution that might least penalize time, effort, cost or performance in case there is a need to adjust procurement and transportation plans when uncertainty is revealed (e.g. supply shortage risk). In addition, the robust solutions were assessed through Monte Carlo simulation against several realizations of uncertain parameters values, pointing that, as desired, solution feasibility increases with the level of conservatism. However, in some cases, such as under supply uncertainty alone, the robust plan does not perform reasonably well until a high level of conservatism is set, and therefore considering uncertainties independently does not necessarily leads to a much better performance and, additionally, it also shows the importance of considering uncertainties simultaneously. In this context, the trade-off between extra costs and improved reliability in the robust plan must also be evaluated in light of the fact that the deterministic plan usually has a small chance of feasibility, and therefore, its optimality must be questioned.

On the other hand, the maximum coverage model indicates that disregarding the recommended budget buffer (to hedge against uncertainties), might lead to solutions in which demand fulfilment rates drops from 98.9% (i.e. 237.7 thousand people unassisted) in the least conservative case, up to a very reduced performance of 83.2% (i.e. 3.7 million people unassisted) in the worst-case scenario.

Under other circumstances, when the distribution campaign does not cover the entire population at risk, the maximum priority demand coverage model is able to set the procurement and distribution plan according to a demand prioritization criterion formula, that might consider, for instance, the number of children under five and at risk of transmission, mortality rates, total incidence rates, among others.

It is worth noting that, under the scarce and competitive funding environment that usually surrounds humanitarian operations, setting and approving an appropriate budget buffer to hedge against price volatility in addition to other unforeseen expenses is a difficult task. In addition, the introduction of a new corporate or public administration culture oriented to risk aversion decision, might represent significant, and even unpopular short-term trade-offs such as changes in current project portfolio (e.g. withdrawing a mass campaign project within a less priority country to redistribute its budget to foster robust solutions in priority countries). Nevertheless, in a strategic long-term vision, robust solutions are required to guarantee reliable campaigns and humanitarian aid continuity.

For further research related to this work, it is suggested the addition of hub location decisions within the robust model that, although not frequently mentioned in the LLIN distribution campaign context, might bring useful logistics insights. In addition, it is recommended the inclusion of a multi-product set, to account for several LLIN sizes and other health commodities associated to the forward supply chain of LLIN distribution campaigns. With this in mind, it is also suggested the inclusion of the reverse supply chain of LLIN and other malaria commodities. This idea comes from a USAID pilot project at Madagascar in 2010, which examined the viability of recycling as an option for retired LLINs that might pose environmental and health risks to communities (Nelson et al. 2011). The study reveals that although challenging, the collection of retired LLIN from households during a mass distribution campaign is logistically possible.

It is also suggested the development of a further adjustment on the data driven adaptive uncertainty set of Fernandes et al. (2016) to better account for robustness under time series with a monotonic trend component. For instance, suppose a time series with a monotonic upwards trend in which the decision maker wants to hedge against its increasing values. Note that in this particular case, observed values within the robustness window might actually not protect against uncertainty, and the forecasted value will most likely be used, which in the end is almost equivalent to a deterministic model.

Finally, driven by the simulation results that pointed to a high chance of constraints violation under lower levels of conservatism within the proposed robust model; it is recommended the addition of an adjustable or recoverable robust framework to minimize the involved costs in redesigning the procurement and distribution plan in case the revealed uncertainty results in an unfeasible plan.

7
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8
APPENDIX

8.1. Financial costs time series for the illustrative case

Table 31: Predicted and observed LLIN procurement costs

Product (p)	Supplier (i)	(t-16)	(t-15)	(t-14)	(t-13)	(t-12)	(t-11)	(t-10)	(t-9)	(t-8)	(t-7)	(t-6)	(t-5)	(t-4)
P1	S1	4.29	4.57	4.96	4.79	4.29	3.61	3.63	3.70	3.42	2.90	2.37	2.55	3.00
P2	S2	5.71	6.08	6.61	6.38	5.72	4.81	4.84	4.93	4.55	3.86	3.15	3.40	4.00

Since LLIN production lead time is 4 months, predicted procurement prices occur in period (t-4)
Safety stock costs are 10% of the LLIN procurement price

Source: Author

Table 32: Predicted and observed container procurement prices

Container (c)	(t-14)	(t-13)	(t-12)	(t-11)	(t-10)	(t-9)	(t-8)	(t-7)	(t-6)	(t-5)	(t-4)	(t-3)	(t-2)
20ft	962.42	1,307.19	1,848.04	1,475.50	1,470.59	1,178.11	954.25	781.05	517.98	537.59	700.99	1,148.70	1,000.00
40ft	1,443.63	1,960.79	2,772.06	2,213.24	2,205.89	1,767.16	1,431.38	1,171.57	776.97	806.38	1,051.48	1,723.04	1,500.00

Procurement prices are the same for ports PO1 and PO2
Since maritime lead time is two months, predicted container procurement prices occur in period (t-2)

Source: Author

Table 33: Predicted and observed maritime freight rates for 20 ft. containers

Prod.	PO	PD	Cont.	(t-14)	(t-13)	(t-12)	(t-11)	(t-10)	(t-9)	(t-8)	(t-7)	(t-6)	(t-5)	(t-4)	(t-3)	(t-2)
P1	PO1	PD1	20ft	962.42	1,307.19	1,848.04	1,475.50	1,470.59	1,178.11	954.25	781.05	517.98	537.59	700.99	1,148.70	1,000.00
P1	PO1	PD2	20ft	1,154.91	1,568.63	2,217.65	1,770.59	1,764.71	1,413.73	1,145.10	937.26	621.57	645.10	841.18	1,378.44	1,200.00
P2	PO2	PD1	20ft	1,154.91	1,568.63	2,217.65	1,770.59	1,764.71	1,413.73	1,145.10	937.26	621.57	645.10	841.18	1,378.44	1,200.00
P2	PO2	PD2	20ft	962.42	1,307.19	1,848.04	1,475.50	1,470.59	1,178.11	954.25	781.05	517.98	537.59	700.99	1,148.70	1,000.00

Prod. (Product), PO (port of origin), PD (port of discharge), Cont. (container)

Since maritime lead time is two months, predicted freight rates occur in period (t-2)

Freight rates for 40 ft. container are 65% more expensive than for 20 ft. containers

Source: Author

Table 34: Predicted and observed inland freight rates for 20 ft. containers

Mod.	PD/H	Dist./H	(t-12)	(t-11)	(t-10)	(t-9)	(t-8)	(t-7)	(t-6)	(t-5)	(t-4)	(t-3)	(t-2)	(t-1)	t
Rail	PD2	D2	115.93	107.91	104.16	104.75	102.58	96.05	89.11	83.08	86.91	89.49	96.26	100.75	100.00
Road	PD1	HUB	384.97	522.88	739.22	590.19	588.24	471.24	381.70	312.42	207.19	215.03	280.39	459.47	400.00
Road	PD2	HUB	673.70	915.04	1,293.63	1,032.84	1,029.41	824.67	667.98	546.73	362.58	376.30	490.68	804.08	700.00
Road	HUB	D1	231.86	215.81	208.32	209.49	205.16	192.10	178.22	166.16	173.81	178.97	192.52	201.50	200.00
Road	HUB	D2	579.63	539.51	520.80	523.71	512.89	480.25	445.54	415.39	434.52	447.41	481.29	503.75	500.00
Road	HUB	D3	115.93	107.91	104.16	104.75	102.58	96.05	89.11	83.08	86.91	89.49	96.26	100.75	100.00
Road	PD1	D1	231.86	215.81	208.32	209.49	205.16	192.10	178.22	166.16	173.81	178.97	192.52	201.50	200.00
Road	PD1	D2	463.71	431.61	416.64	418.97	410.32	384.20	356.43	332.31	347.61	357.93	385.04	403.00	400.00
Road	PD1	D3	591.22	550.30	531.21	534.18	523.15	489.86	454.45	423.70	443.21	456.35	490.92	513.82	510.00
Road	PD2	D1	463.71	431.61	416.64	418.97	410.32	384.20	356.43	332.31	347.61	357.93	385.04	403.00	400.00
Road	PD2	D2	231.86	215.81	208.32	209.49	205.16	192.10	178.22	166.16	173.81	178.97	192.52	201.50	200.00
Road	PD2	D3	939.00	874.00	843.68	848.40	830.89	778.01	721.76	672.93	703.91	724.80	779.69	816.07	810.00

Prices do not differ from product P1 to product P2, and freight rates for 40 ft. container are 65% more expensive than for 20 ft. containers
Mod. (modal), PD/H (port of discharge or hub), Dist./H (district or hub)