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Published in:
Annals of Operations Research

DOI:
10.1007/s10479-018-3015-8

Published: 01/12/2019

Document Version
Peer-reviewed accepted author manuscript, also known as Final accepted manuscript or Post-print

Please cite the original version:
Gomes de Mattos, R., Oliveira, F., Leiras, A., Baptista de Paula Filho, A., & Gonçalves, P. (2019). Robust optimization of the insecticide-treated bed nets procurement and distribution planning under uncertainty for malaria prevention and control. *Annals of Operations Research*, *283*(1-2), 1045-1078. https://doi.org/10.1007/s10479-018-3015-8

Robust optimization of the insecticide-treated bed nets procurement and distribution planning under uncertainty for malaria prevention and control

Roberto Gomes de Mattos[1*], Fabricio Oliveira[2], Adriana Leiras [1], Abdon Baptista de Paula Filho[1] and Paulo Gonçalves[3]

[1] *Industrial Engineering Department, Pontifical Catholic University of Rio de Janeiro - PUC-Rio, Rio de Janeiro, Brazil*

[2] *Department of Mathematics and System Analysis, Aalto University, Finland*

[3] *Facoltà di Scienze Economiche, Università della Svizzera Italiana, Lugano, TI - Switzerland*

Department of Industrial Engineering, Pontifical Catholic University of Rio de Janeiro
Rua Marquês de São Vicente, 225 Ed. Cardeal Leme - 9° floor - Gávea
22453-900 - Rio de Janeiro, RJ - Brazil
Telefone: (+55 21) 35271285

** roberto.gmattos@gmail.com*

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Abstract

Vector control, particularly distribution of insecticide-treated bed nets (ITNs), constitutes one of the major pathways to prevent and reduce malaria transmission. ITN distribution campaigns face several challenges, such as inadequate funding, budgetary constraints, hard-to-reach areas, limited transportation, and market and price volatility. While long-term agreements and proper planning can effectively overcome such challenges, those options may not be available for all humanitarian organizations and governments. To gain a better understanding of such tradeoffs we develop a robust optimization model that minimize ITN distribution costs while taking into consideration protection against financial, market and logistical uncertainties. The simultaneous account of such uncertainties is rarely seen on the humanitarian supply chain design literature. The proposed robust model explores data-driven adaptive uncertainty sets that capture the dependence structure among procurement and distribution costs, leading to plausible uncertain scenarios. In addition, we develop a hierarchical optimization approach to ease the burden of setting a specific robustness level for each constraint, when uncertainties are related to the independent terms. We study a United Nations Children's Fund (UNICEF) ITN distribution campaign in Ivory Coast, observing that (1) total costs increase with campaign robustness, as expected, and (2) campaign robustness comprises of improved supply chain flexibility, which might minimize efforts if it becomes necessary to adjust procurement and transportation plans when uncertainty arises. In addition, assessing robust solutions through Monte Carlo simulations against several realizations of uncertain parameter values indicates that, as desired, robust plan feasibility increases with the specified level of conservatism.

Keywords

Malaria; Insecticide Treated Bed Nets; Distribution Campaigns; Humanitarian Operations; Robust Optimization

1. Introduction

In 2105, almost half of the world population lived in areas at risk of malaria, with more than 212 million new cases and 429,000 associated deaths, disproportionately (almost 70%) afflict children younger than five years old. Sub-Saharan Africa (SSA) carries the heaviest burden, being home to 90% of the cases and 92% of the malaria deaths (WHO, 2016a).

The United Nations (UN) Member States adopted in 2015 a new sustainable development agenda with 17 broad goals that must be met by all countries until 2030. 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 (UN, 2017).

Malaria spreads among humans by infected mosquitoes. Vector control is a cost-effective approach to curb malaria. It focuses on preventing parasite transmission from humans to mosquitoes and back again, using insecticide-treated nets (ITNs), which work as physical and chemical barriers, and indoor residual spraying (IRS). The World Health Organization (WHO) estimates that malaria control interventions averted more than 663 million malaria cases in SSA between 2001 and 2015, with ITNs being the keystone and accounting for 69% of this achievement (WHO, 2015a). For instance, ITN coverage in SSA increased from less than 2% in 2000 to more than 55% in 2015, with 68% for children younger than five years old.

Long-lasting insecticidal nets (LLINs) are a highly resistant form of ITN, which can be washed without the need to re-immerse them in insecticide (Malaria Consortium, 2016). In compliance with the WHO strategy of maximizing the impact of vector control, LLINs are the recommended form of ITN for public health programs, for which coverage of the entire population at risk is a highly desirable goal (WHO, 2016a).

In 2014, the global spending on ITNs reached almost $1 billion (63% of total spending on vector control commodities), avoiding $610 million in malaria case management costs (WHO, 2015a). About 177 million ITNs were distributed to 36 countries in SSA in 2015 (Net Mapping Project, 2016), in which Global Fund accounted for most of the deliveries (61%), followed by President's Malaria Initiative (PMI; 23%) and UNICEF (5%). However, more than 216 million people still lived in households without an ITN in 2015; hence, annual funding must be increased to meet the needs (WHO, 2015a).

Humanitarian organizations, in cooperation with governments, are responsible for carrying out ITN distribution campaigns within their humanitarian operations to reduce malaria transmission. However, planning ITN campaigns capable of effective distributing over tens of millions ITNs in multiple countries spanning large geographical areas pose significant challenges that might hinder distribution effectiveness. Such planning challenges arise mostly from the uncertainties that surround the involved logistics and supply chain management (LSCM) activities in an ITN distribution campaign such as uncertainty in the planning environment, including uncertainty in logistics infrastructure/capacity availability, supplier capacity, freight rates, LLIN prices, among others".

Our research develops a robust optimization model that minimizes ITN procurement and distribution plan costs, while considering uncertainties in logistics (infrastructure availability, capacity, multimode transport), market (supplier capacity and demand forecast), and price (freight rates, container and ITN acquisition price).

Given this uncertain supply chain environment that surrounds ITN distribution, a robust optimization approach is imperative to avoid project scope narrowing, delay, cancellation or going over budget due to incorrect forecast of planning parameters. Ultimately, the consequence of improper planning has a direct impact on those who are at risk of contracting malaria. In this sense, the research question addressed by the paper is whether (and, if so, how) robust optimization can improve ITN procurement and distribution planning when compared to the traditional (i.e., deterministic) approach that does not consider the uncertainties associated with the problem.

Apart from the previous work of Brito et al. (2014), this study is, to the best of our knowledge, the only known academic research related to ITN supply chain design optimization. This paper also considers several aspects with less academic research attention, such as the simultaneous accounting of supply, demand, logistical, and cost uncertainties and multimodal transportation.

Our research also contributes to the literature by adapting the robust optimization frameworks of Bertsimas and Sim (2004) and the data-driven polyhedral uncertainty sets presented by Fernandes et al. (2016) to our problem. In the first framework, a pre-determined number of parameters are allowed to assume their worst-case values, according to the 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 second approach are the ability to capture the empirical dependence structure between cost parameters, which leads to more plausible uncertain scenarios, and the ease of understanding when setting the robustness parameter (time window).

We apply our robust optimization model to the real case of UNICEF's distribution of 12 million LLINs in Ivory Coast in 2014. We compare the robust solutions to their deterministic counterparts to highlight the importance of decision making under uncertainty. Since an infeasible plan cannot be used in practice, and it incurs additional emergency re-planning costs, it is useful to measure and compare the reliability of the deterministic and robust plans. In other words, it is critical to understand whether plans are executable after uncertainties are realized. In this context, Monte Carlo simulation help us assess the reliability of both deterministic and robust plans.

On the practical side, the use of such a robust model has a direct impact on the alleviation of human suffering since it allows more people to have access to ITNs through the efficient and effective use of financial and logistical resources by humanitarian organizations, governments and other stakeholders involved in ITN distribution campaigns. Although many uncertainties and risks related to this supply chain might be effectively overcome 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 paper is organized as follows: Section 2 reviews the relevant literature and situates our robust optimization model. Section 3presents an overview of the logistics and supply chain management of ITN distribution. The following section describes robust optimization frameworks to support decision making under uncertainty, namely Bertsimas and Sim's (2004) and Fernandes et al.'s (2016). In Section 5, we define the mathematical model to represent the robust ITN transshipment problem. In Section 6, we illustrate the applicability of the proposed model with a real case. Finally, we conclude this paper and discuss future research.

2. Literature Review

ITN distribution campaigns can be seen as humanitarian operations with the aim of reducing malaria transmission. Caunhye et al. (2012) noted that humanitarian operations' key challenges are often addressed by academic researchers through operations research (OR) methods. Despite the uncertain nature of humanitarian operations, Leiras et al. (2014) indicated the predominance of deterministic models in mathematical programming papers. Among 83 papers reviewed 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, a stochastic programming approach based on average value 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 perspectives to make prudent decisions in uncertain environments. In particular, in the humanitarian context, this approach seems to be a more 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 Nemirovski (2000) observed that the robust optimization (RO) goal is to find a feasible solution for all considered scenarios while optimizing the worst-case scenario. In addition, Bertsimas and Thiele (2006a) mentioned that stochastic programming is a powerful modeling 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; hence, robust optimization becomes a relevant alternative.

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

In our literature searches for robust optimization approaches to supply chain design in humanitarian operations (with facility location and aid distribution being closer to the focus of our research), demand has been by far the most commonly addressed uncertainty (Tang et al. 2009; Paul and Hariharan 2012; Bozorgi-Amiri et al. 2013; Najafi et al. 2013; Das and Hanaoka 2013; Jabbarzadeh et al. 2014; Álvarez-Miranda et al. 2015; Florez et al. 2015; Rezaei-Malek et al. 2016; Zokaee et al. 2016), followed by supply (Bozorgi-Amiri et al. 2013; Najafi et al. 2013; Das and Hanaoka 2013; Jabbarzadeh et al. 2014; Álvarez-Miranda et al. 2015; Rezaei-Malek et al. 2016; Zokaee et al. 2016), and then by logistics capacity and availability (Das and Hanaoka 2013; Jabbarzadeh et al. 2014; Álvarez-Miranda et al. 2015; Florez et al. 2015; Rezaei-Malek et al. 2016). Despite the volatile nature of prices, only four papers have considered this type of risk (Bozorgi-Amiri et al. 2013; Jabbarzadeh et al. 2014; Álvarez-Miranda et al. 2015; Zokaee et al. 2016), and none have tackled budgetary uncertainties, which are frequently found in humanitarian organizations due to funding scarcity and unpredictability. Only one paper (Najafi et al. 2013) considered a multi-modal approach, which is unexpected since logistics infrastructure disruptions might hinder the use of usually available assets, such as trucks, leading to the use of more expensive options, such as helicopters.

Only two papers related to malaria commodities' supply chain optimization were found in our literature searches, and both had deterministic approaches (Rottkemper et al.

2011; Brito et al. 2014). Rottkemper et al. (2011) developed a deterministic multi-objective transshipment 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 determined the optimal relocation plan from neighboring depots with previous ACT stocks to compensate for the limited stock in the outbreak region, while avoiding future shortages in case the epidemic spread to neighboring areas. Uncertainty was examined as a demand parameter through sensitivity analysis, and an example from Burundi was discussed.

Brito et al. (2014) introduced the relevance of considering an optimization model, which in their case was approached through deterministic inputs to reduce the total costs of an LLIN distribution campaign for a UNICEF project that in 2014 delivered approximately 12 million LLINs in Ivory Coast. Among others, their work revealed useful logistic insights into the problem, above all that the modeling process achieved a 7% cost reduction, compared to UNICEF’s original supply and distribution plan. In this paper, the transshipment network flow model proposed by Brito et al. (2014) is extended to consider uncertainties related to logistics, market, and price volatility.

We adapt the data-driven uncertainty set framework from robust financial portfolio dynamic optimization (Fernandes et al., 2016) to robust multi-period static optimization in the humanitarian context. We also present an extension of Bertsimas and Sim’s (2004) framework regarding uncertainties in 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

3. LLIN Supply Chain

LLINs are produced in a broad range of sizes and colors by thirteen suppliers that are mainly located in Asia (WHO, 2016d). LLIN production lead time is high and uncertain, deeply affecting the planning of subsequent logistics activities. USAid (2010) revealed 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 required 74 days. Therefore, no significant correlation between production lead time and the number of LLINs procured could be found. In addition, the long average lead times for smaller orders (up to 150k nets), 24 days and 50 days for two distinct suppliers, showed that humanitarian organizations might face limited stock availability for short notice procurements.

Since several distribution campaigns occur at the same time, not all humanitarian organizations and governments are able to have a clear visibility of each suppliers' production capacity availability for their projects until the release of an invitation to tender. In this sense, the supply context is uncertain since it may shift considerably from the project planning phase until the tender release.

LLIN demand is based on financial availability and stability and on preventive campaign delivery modalities. The optimal allocation per household considered by the 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 product characteristics and on the manner in which the household uses it, which is country and culture specific (UNICEF, 2016).

Demand uncertainty is mainly associated with misjudgments in LLIN needs assessments and with the disparity between estimated and obtained funding over the fiscal year (Global Fund et al., 2015). For instance, since bed net durability varies widely, net replenishment forecast uncertainties affect demand planning of top-up campaigns. In addition, malaria occurs in remote areas in which the population census might not be accurate and thus, a margin of error is considered to avoid stock-outs and unmet demand. Moreover, from the period of planning until the project implementation, regional malaria incidence rates can vary drastically, shifting coverage priority to more pressing regions and hence changing initial demand planning of non-universal distribution campaigns.

Humanitarian organizations can procure bed nets through a bidding process for each new order or by long-term agreements (LTAs) (USAid, 2010). The average weighted LLIN price decreased by 41% over the last five years, reaching approximately US$3 (UNICEF, 2016). This decrease was partially explained by Global Fund et al.'s (2015) assessment that bed net prices offered from July 2014 to May 2015 followed oil and derivatives (polyester and high-density polyethylene) price trends, which are the bed nets' main production inputs. The price decrease was also achieved through humanitarian organizations' collaboration in the reduction of LLIN types (from 44 different colors, sizes and shapes to fewer than ten) and in the alignment of demand forecasts, which in the end allow supplier capacity to increase through better production scheduling (UNICEF, 2016).

The African Leaders Malaria Alliance (ALMA) LLIN-funding projection through 2020 shows that, from 2017 onward, there remains a major gap of LLINs to be financed, clearly revealing the short-range budget environment frequently observed with humanitarian operations (Global Fund et al., 2015).

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 to local distribution points. Transport activities face many uncertainties and risks that both shippers and carriers must manage, including, among others, capacity availability, operational delays, disruptions, and freight rate volatility (Thanopoulou and Strandenes, 2017).

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 compared to other humanitarian items, such as food, and thus require considerable warehouse space (CRS, 2014). In large-scale distribution campaigns, there is the possibility of acquiring the containers and transporting them to hub locations or final distribution points to use them as a temporary warehouse, 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 if they are not available in advance (Roll Back Malaria, 2011b).

4. Robust Optimization Frameworks

Soyster (1973) originally proposed a linear programming model to build a feasible robust solution for all data belonging to a convex uncertainty set. With his approach, the results were too conservative since the model considers the unlikely scenario in which all uncertain data assume their worst values 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's (2004) propose a robust formulation that is able to adjust the conservatism of the solution in term of probabilistic bounds of constraint violations, whilst rendering a linear optimization problem. However, when Bertsimas and Sim's (2004) framework is applied to address uncertainty on the independent terms of the constraint (i.e., the right-hand side, such as demand or supply capacity), the framework may become trivial and have limited applicability.

Overcoming this issue, Bertsimas and Thiele (2006a) proposed the use of a single conservatism parameter, e.g. T , to define the number of demand locations i that might assume their worst-case values 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 $[b \quad - \hat{b} \quad , b \quad + \hat{b} \quad]$.

Conversely, with a multiperiod inventory management problem, in which t represents each time period, Bertsimas and Thiele (2006b) proposed 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 on the RHS, might assume its worst-case deviation from its nominal value. In addition, they suggested that T_{it} should increase over time to create a reasonable worst-case approach. However, no further propositions were made by the authors to overcome the issue of setting the uncertainty budget for each individual demand in each period, which might be challenging for large problem instances.

4.1 Robust hierarchical optimization approach for uncertainties on the RHS

The use of a global robustness level, T , is proposed in this paper and indicates the maximum number of uncertain right-hand side parameters $\tilde{b}_i, i \in \Omega$, that can assume their worst-case values; however, unlike Bertsimas and Thiele (2006a), it is considered the original uncertainty set of each $\tilde{b}_i, i \in \Omega$. 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 its worst value given a global robustness level T set by the decision maker.

Since Bertsimas and Thiele (2006b) studied a constraint with an accumulated uncertain demand on the RHS (similar to $\sum_t \Gamma_{it}^b \hat{b}_{it}$) under a similar strong duality argument, the objective function of the dual formulation from the auxiliary problem, which sets Γ_{it}^b values according to an uncertainty budget T_{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 contrast to Bertsimas and Thiele (2006b), the proposed formulation maintains the auxiliary problem to account for the particular cases in which the dual formulation is not directly applicable. In addition, this proposition allows for using other criteria 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 parameter deviation values. Moreover, in the proposed formulation, there is an explicit concern with reducing the complexity of setting several robustness levels on the RHS (i.e., for each row i) within large problem instances.

To provide a practical meaning for 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, the set $g \in G$ is introduced, which represents each uncertain constraint category, and henceforth, global robustness levels are indexed with g, i.e., T_g. In addition, let each subset $\Omega_g \subseteq \Omega$ represent the set of b_i of uncertain coefficients that fall within the same category g.

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

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

$$Subject\ to$$

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

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

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

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

$$Subject\ to$$

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

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

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.

4.2 Data-driven uncertainty sets

Within the context of a robust portfolio dynamic optimization, Fernandes et al. (2016) proposed adaptive polyhedral uncertainty sets that are empirically determined using the last K observed data. In this manner, the decision maker must choose a window of robustness K, which might be more insightful than setting the number of parameters that can assume their worst-case values during each implementation period. 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. Once again, 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 the boundaries or probability distribution of random variable $\tilde{a}_{ijt}, j \in J_i$.

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 parameter values in case there is an associated lead-time decision until the 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, when the problem to be optimized is actually being studied (i.e., $t - \beta$) and from which there 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 $G_i \subseteq J$ represent the set of parameters $a_{ijt}, j \in G_i$ in a particular row i of the constraint matrix **A**, which are associated with decision-making processes that occur in periods prior to implementation period t. Thus, for each parameter $a_{ijt}, j \in G_i$, $d_j \in \mathrm{D} \subseteq L$ is introduced, which 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 an LLIN distribution campaign, Figure 1 shows an illustrative example of the distance from a particular implementation period t (i.e., distribution phase) to its planning phase and decision milestones.

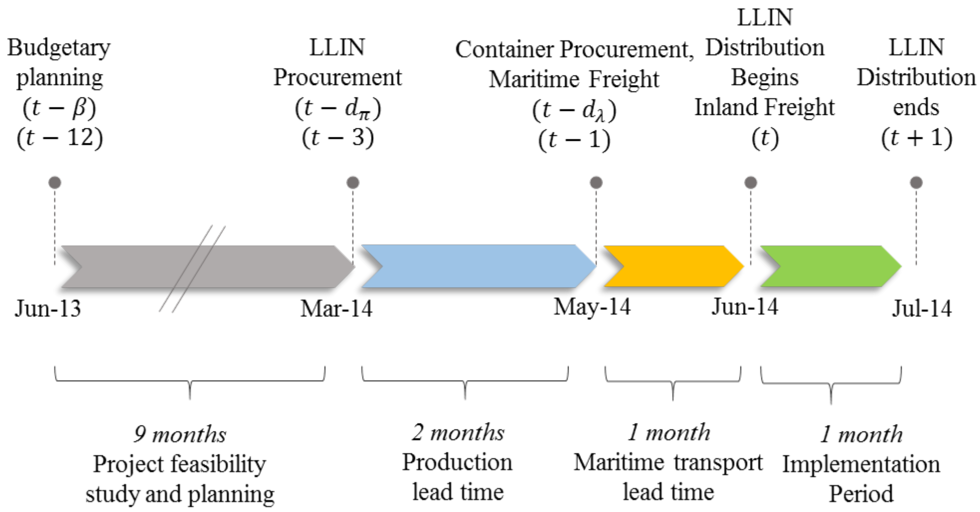

Figure 1: Illustrative time gaps between the actual LLIN distribution period t (Jun/14) and its planning phase and decision milestones.

Note that the lag operator $\beta = 12$, sets a one-year distance from implementation period t (considered 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 1) and an LLIN price time series of a specific supplier, Figure 2 depicts, for implementation period t (Jun/14), a 9-month 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 the predicted and considered past values is represented within the robustness window in period $t-15$ (Mar/13).

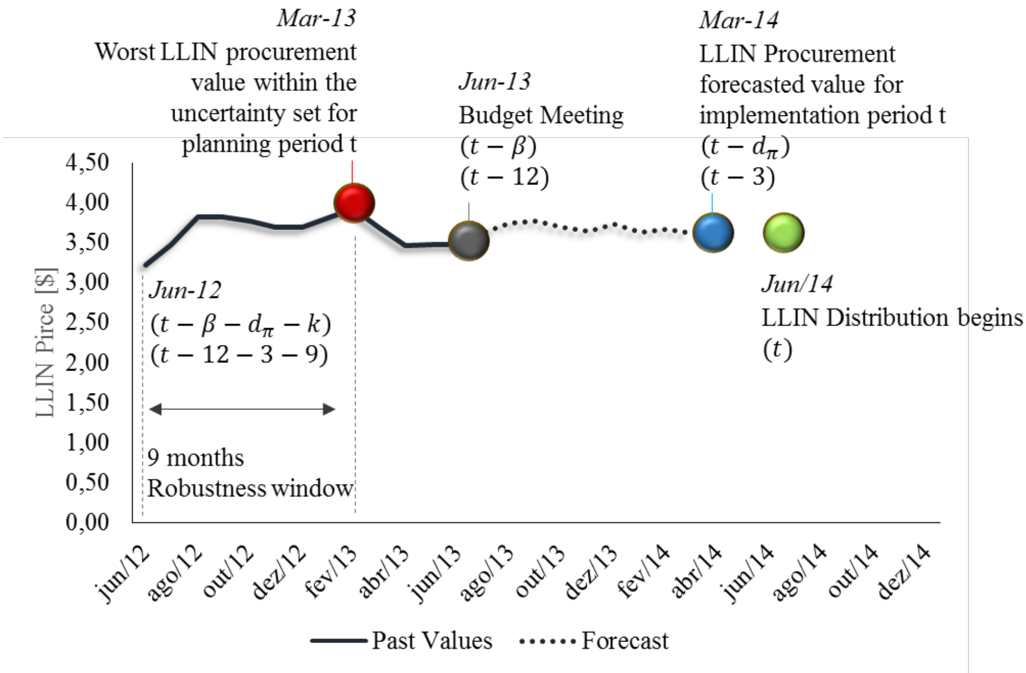

Figure 2: Robustness window comprised of 9 months and the predicted value for a particular LLIN supplier price.

It is worth noting that the robustness window does not necessarily need to be composed of consecutive past values. For instance, observe that, in some cases, it might be interesting to consider the impact of seasonality; therefore, it is possible to add the lag operator $k = 12$ (i.e., seasonality lag on monthly observations) to more recent past observations, leading 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, and otherwise noted, that a robustness window K is comprised of K consecutive past values.

In 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)):

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

$$Subject\ to$$

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

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

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

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

$$\mathbf{x} \ge 0 \quad (3)$$

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

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; 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; therefore, β, k and d_j are reduced from t. Finally, observe that all of the subsets are disjointed.

Note that the model is adaptive since the robustness window moves over 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 those that become obsolete 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 uncertain parameters, it is a significant enhancement over Bertsimas and Sim's (2004) framework when applied to multi-period or dynamic models.

5. Mathematical Model

The proposed model represents a five-level supply chain, comprised of LLIN suppliers, ports of origin, ports of discharge, hubs and health districts (Figure 3).

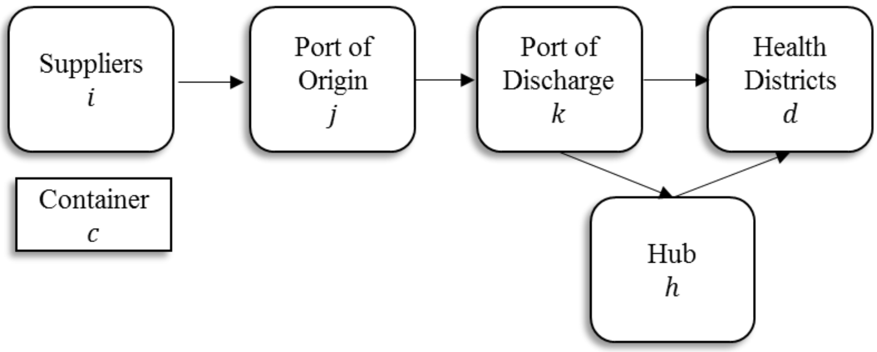

Figure 3: Summarized model structure.

Compared to Brito et al. (2014), the proposed model considers additional sets of lag operators, robust parameters, hubs and modes of transport. In addition, safety stock costs, capacities of hubs, ports of discharge and modes of transport are also added. Finally, LLINs and container flows are broken down into separate variables. The sets, variables, and parameters of the model are presented in Appendix 1.

The model minimizes the total procurement, safety stock and distribution costs involved in an 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 the origin (this decision also depends on container procurement costs at each port of origin);
iii. The safety stock levels at each supplier;
iv. Which port of discharge should be used;
v. Whether to use hubs as consolidation points; and
vi. Which modes of transport should be used to reach each district.

Market uncertainties, such as supply capacity and demand forecast, which appear on the RHS, are addressed with the proposed extension of Bertsimas and Sim's (2004) robust framework. The same approach is taken regarding logistics uncertainties, such as mode of transport and hub/port discharge capacities. Financial uncertainties, such as LLIN and container prices and transport freight rates, are approached through the proposed adaptive data-driven uncertainty sets based on Fernandes et al. (2016).

For the sake of notation simplicity, consider, unless otherwise noted, that the summation and constraint domains are equal to their respective index domains.

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

Subject to

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

The objective function of the upper level problem (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)).

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.

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

Constraint (30) assures that demand is met at district d during implementation phase r. Constraint (31) restricts procurement according to the supplier's i production capacity of LLINs p (decreased by a robust parameter Γ_{rpi}^{supply}) during implementation phase r.

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.

For each implementation phase r, constraint (33) defines the minimum safety stock level of LLINs totaled among 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 for a faster humanitarian response in case of LLIN needs misjudgment. 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.

Constraints (35)-(37) guarantee LLIN flow conservation at port of origin j, port of discharge k and at hub h, respectively. Constraints (38), (39) and (40) guarantee container flow conservation at port of origin j, port of discharge k and hub h, respectively.

Constraints (41)-(45) assure that the number of LLINs inside a container c is limited by its capacity. 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}). Constraint (47) limits the total flow through a hub h according to its capacity (decreased by a robust parameter Γ_{rh}^{hub}). Constraint (48) limits the total flow between each port of discharge k and district d by the mode of transport m capacity along that particular route. Constraint (49) limits the total flow between each port of discharge k and hub h by the mode of transport m capacity along that particular route. Constraint (50) limits the total flow between each hub h and district d by the mode of transport m capacity along that particular route.

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).

To avoid disagreements among beneficiaries, as a result of preferences for a specific supplier, a humanitarian organization might choose to supply each district with only one type of LLIN. Therefore, discretionary constraints (61) and (62) are used to determine Z_{pd}, which assumes 1 if a district d is supplied by an 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 large number M is bounded by $\frac{Max\ \{\sum_r dm_{rd}, \forall d\}}{Min\ \{nq_{pc}, \forall p,c\}}$, which is equivalent to the largest possible number of containers required to supply the most demanding district.

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

Next, the lower level problem is presented that defines the uncertainty budget variable Γ_i^b of each constraint according to the global robustness level parameters T_g set by the decision maker.

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

Subject to

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

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

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

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

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

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

Equation (69) describes the objective function of the lower level, which for each implementation phase r maximizes the total deviation from uncertain parameters' nominal values, given global robustness levels T_{g}.

Constraint (70) limits the number of suppliers i that might assume their lowest production capacity. Constraint (71) limits the number of districts d that might assume their highest demand values. Constraints (72) and (73) limit the number of ports of discharge k and the number of hubs h that might assume their lowest capacity, respectively. Similarly, constraint (74) limits for each mode of transport m the number of routes that might assume their lowest capacity. Finally, equation (75) defines the variables inside the unit interval.

6. Case Study

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 to 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 4 depicts the ports of discharge, hubs and demanding regions per distribution phase on an Ivory Coast map.

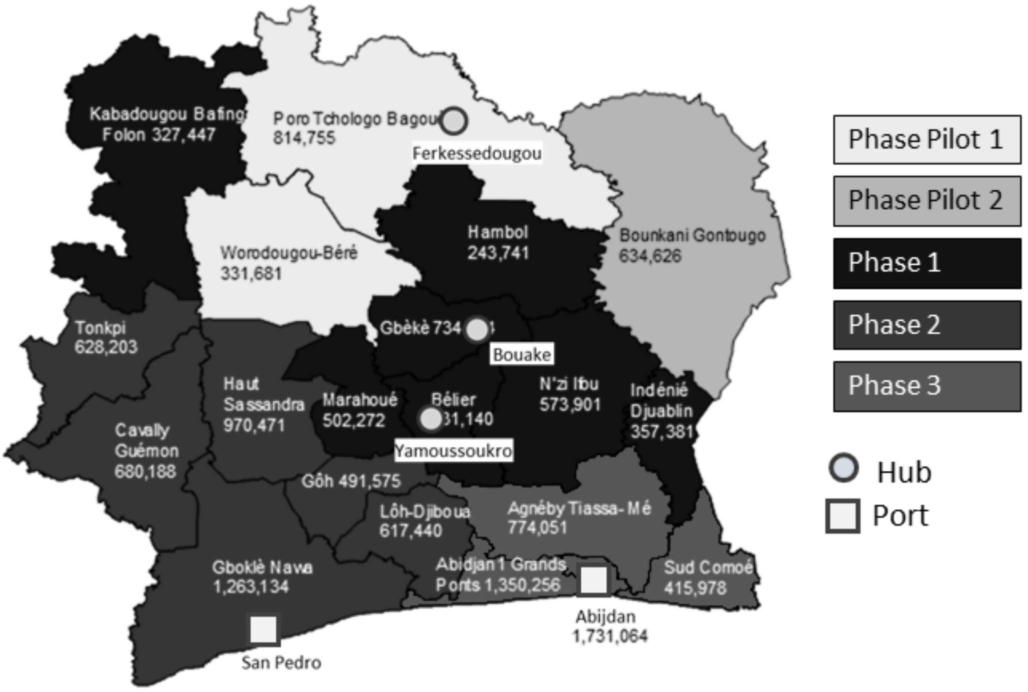

Figure 4: Panorama of UNICEF's large-scale distribution campaign in Ivory Coast, 2014.
Source: Adapted from Brito et al. (2014)

LLINs can be procured from distinct suppliers based in Asia, and they 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 for 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 occurs. With the exception of Abidjan health district, all of the other regions must receive LLINs inside containers to overcome the lack of storage capacity at the health district level, which also represents a security concern. In addition, each health district must be supplied entirely by a single supplier to avoid quarrels among beneficiaries, due to preferences for 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 for proper equipment to handle containers, for instance, forklifts and trucks with cranes.

Suppliers are responsible for delivering LLINs in containers to the port of origin in Asia. In addition, no transportation costs are introduced when suppliers are located in the same city as the 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 they include 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 (76), which has a coefficient of determination of $R^2 = 0.99$ (Brito et al. 2014).

$$Inland\ Cost = 395.60\ + 2.45 * Distance \qquad (76)$$

Each supplier has: (i) a specific production capacity; (ii) a variable stuffing capacity according to each container size; and (iii) an LLIN selling price. Demand in each health district was calculated using the WHO (2014) recommendation of one LLIN for every 1.8 persons in the target population. Figure 5 illustrates the entire supply chain structure considered in the model.

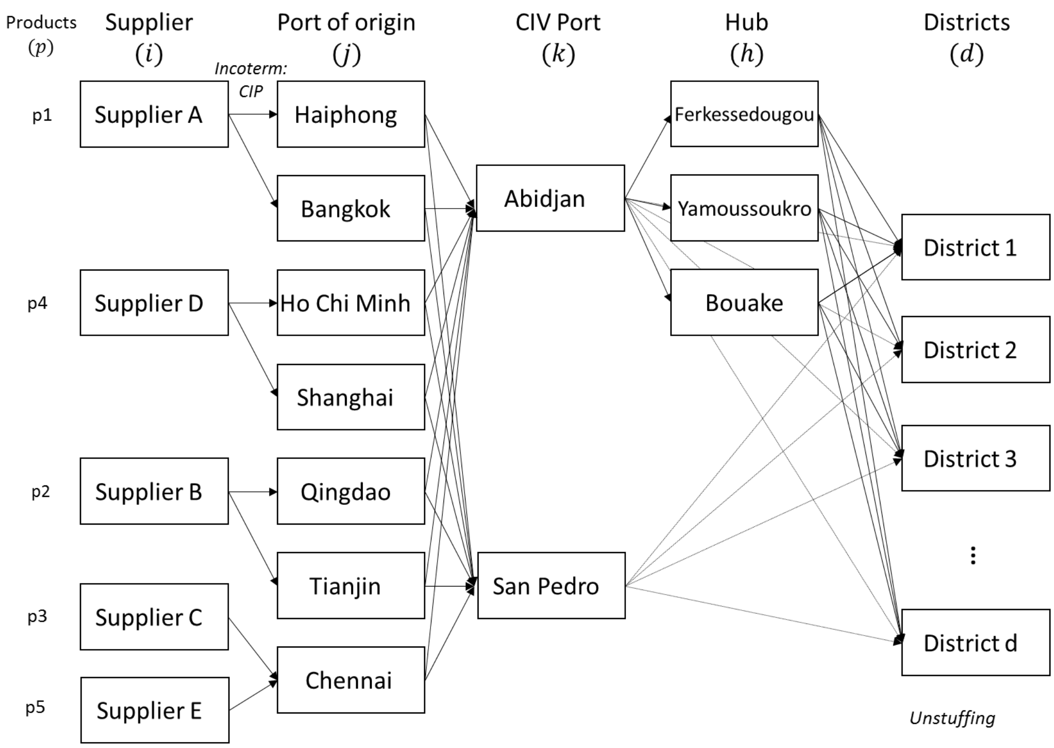

Figure 5: Supply chain structure (adapted from Brito et al., 2014)

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 Index Mundi (2017), Investing (2017a; 2017b) and the United States Energy Information Administration (USEIA, 2017) databases. Actual transportation and procurement costs are omitted due to confidentiality. It is worth noting that the China Containerized Freight Index (CCFI) would be a more adherent proxy since it is specific for container freight; however, unlike the dry Baltic index, it is not publicly available.

The budgetary planning phase is considered as 12 months prior to the 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 6 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 ($K = 12$), the oil price reaches its maximum in March 2012 and is 15% more expensive than its predicted value, and the 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 the forecasted value.

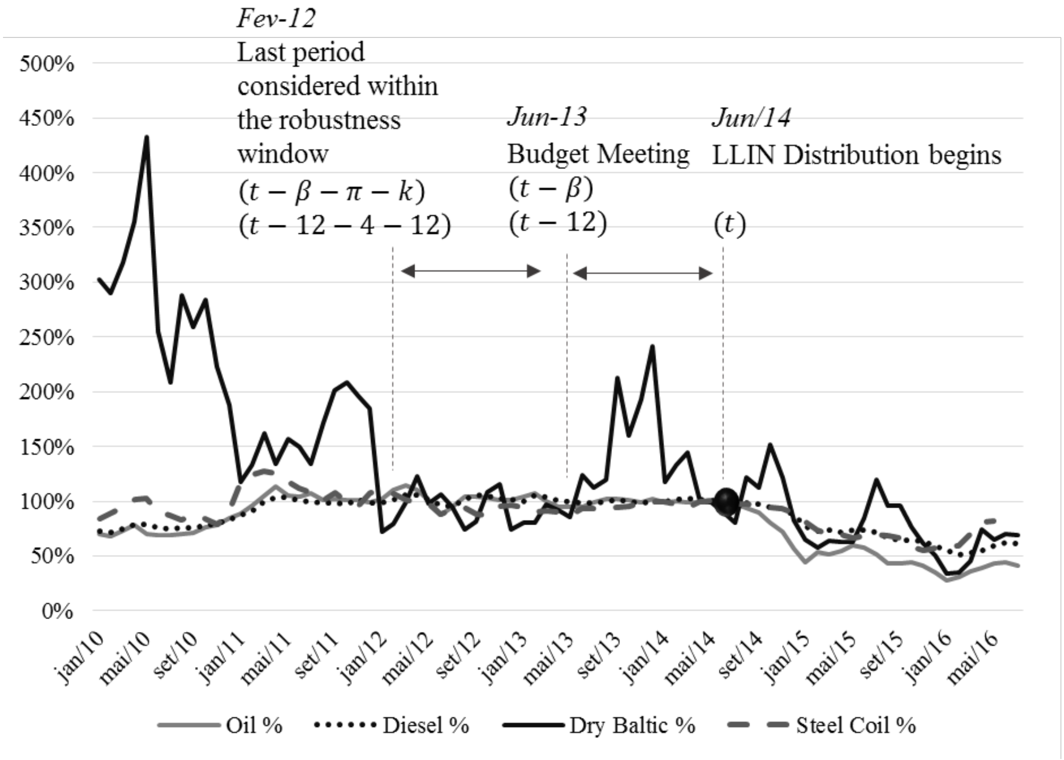

Figure 6: Data-driven robust optimization parameters and time series proxies.

The inventory costs of maintaining a safety stock within supplier facilities are considered to be 10% of LLIN procurement costs per LLIN unity stock. Demand and supply worst-case values are assumed to be a percentage of their nominal values in Brito et al. (2014), i.e., 105% and 75% for each health district and supplier, respectively.

Port of discharge capacities were obtained from Logistics Cluster (2017) Ivory Coast's port assessments and their monthly capacity significantly outweigh the project's container flow, so the model disregards the port of discharge robustness parameters. In addition, the 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.

6.1 Numerical results

The proposed robust optimization model and the described cases were implemented using 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 of 1% was set as the stopping criterion for the minimum cost model.

The impact of each type of uncertainty on the total costs and the overall effect on the supply chain design are assessed through the cases presented in Table 1.

First, the deterministic model (case 1) is used as a reference for the robust models. Next, cases 2.1 to 2.5 investigate financial cost uncertainties within the data-driven robust framework, in which the size of the robustness window ranges from one month to one year of consecutively 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 in each uncertain parameter robustness level.

Table 1: Minimum cost model investigated cases

#	**Uncertainty type**	**Modeling approach**	**Financial costs** (Robustness Window K)	**Demand** $(T_r^{demand} \forall r)$	**Supply** $(T_r^{supply} \forall r)$
1	N/A	Deterministic	0	0	0
2.1	Financial	Data-driven	1	0	0

2.2	costs	uncertainty sets	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

Because the deterministic approach is insensitive to variability in the uncertain parameters, the plans suggested by such models are very often rendered infeasible once 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 in a particular simulation, a solution is considered infeasible if it violates a constraint. Note that the violation probability proposed by Bertsimas and Sim (2004) assumes that random variables are independent, which is not true for the case under study; therefore, the proposed Monte Carlo simulation is required to assess the feasibility rates.

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

The minimum and maximum values inside a parameter uncertainty interval, e.g., $[sc_{rpi}\text{-}\widehat{sc}_{rpi},\ sc_{rpi}\text{+}\widehat{sc}_{rpi}]$, were used as input parameters for the uniform distribution. For the normal distribution, the nominal parameter's value was considered the average, e.g., sc_{rpi}, and the standard deviation was one third of the maximum deviation, $\frac{\widehat{sc}_{rpi}}{3}$. For the 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 an additional parameter, the mode, which was considered to be one standard deviation 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 to, instead of being subtracted from, the average value to achieve a more conservative distribution than the Gaussian distribution. In this context, Figure 7 illustrates the considered probability distributions for supplier B's production capacity (in thousands of LLINs) during the first implementation phase.

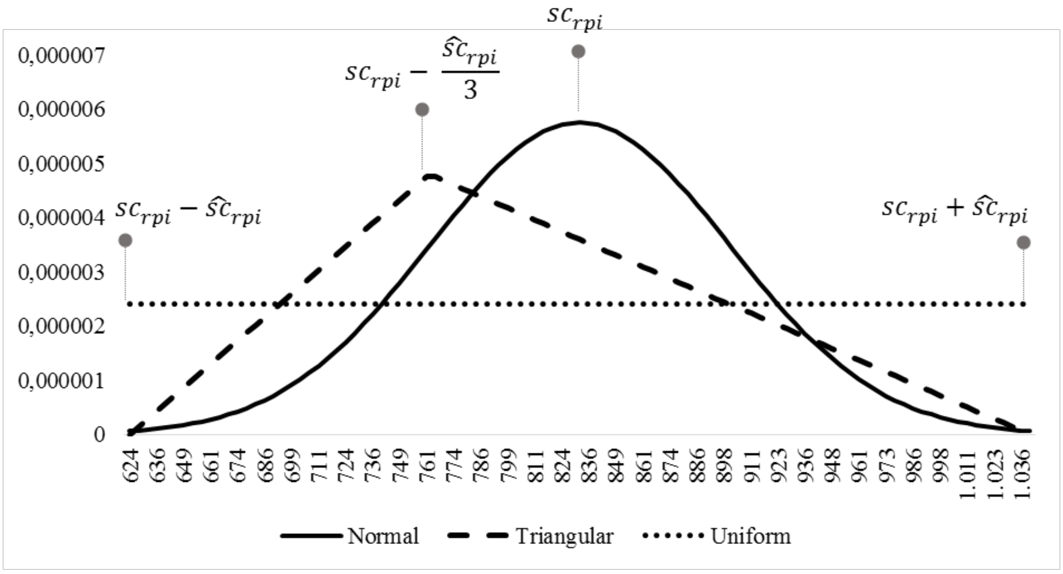

Figure 7: Estimated normal, triangular and uniform probability distributions for supplier B's production capacity (in thousands of LLINs)

6.1.1 Financial cost uncertainty

Financial cost uncertainties are evaluated through cases 2.1 to 2.5, in which Figure 8 presents the price of robustness for the data-driven robust model up to a one-year robustness window, as well as the results from the simulations that evaluated the robust solution feasibility rate.

To provide 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.

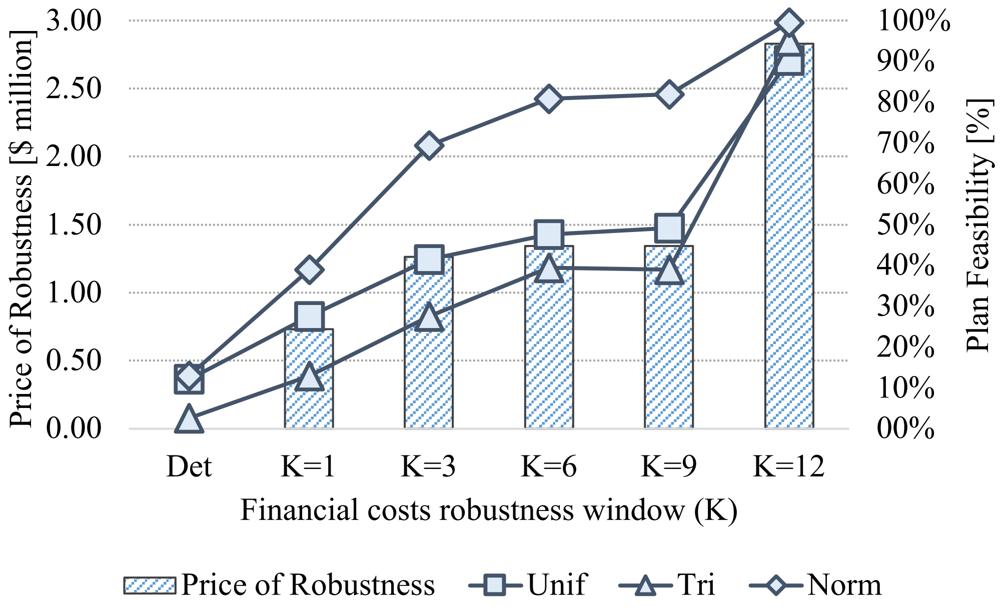

Figure 8: Price of robustness and robust plan feasibility for the robust model with financial cost uncertainty.

The total costs for the deterministic model are $22.31 million, and as the robustness window lag increases, it results in an average of a 2.4% increase over the prior robustness level. In the most conservative scenario, spanning a one-year robustness window, the cost increase reaches as much as 12.7% ($2.83 million) from its deterministic counterpart, comprising a total of $25.14 million. It also becomes clear that LLIN procurement costs represent by far the major cost share (average of 88.3%), followed by maritime transportation costs (7%), container procurement (3.4%) and inland transportation costs (1.3%). Total transportation costs from suppliers to port of origin are equal to zero because the dataset only allows for production distribution to ports in cities where suppliers are located. It is important to mention that cost profile differences among robust solutions are spurious. As the robust window increases, LLIN procurement also has the greatest average impact on total costs, at 7.1%. Further, the container and transportation plans in the robust models are, on average, 3.1% less expensive than in the deterministic case, indicating a solution that prioritizes an LLIN procurement plan to achieve the least expensive solution.

Regarding feasibility rates, when solutions are tested against the several realizations of uncertain financial cost parameters, the deterministic model has the highest likelihood of exceeding the optimal total costs (e.g., 97.4% under triangular distribution), thus violating constraints (28) or (29). In contrast, as the robustness window increases, so does the likelihood 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 a normal distribution and reaching up to 99.5% when $K = 12$ under the same distribution. As expected, in most cases, the results from the triangular distribution are more conservative than those from the uniform distribution, which in turn are more conservative than those from the normal distribution.

In general, the results show that supply chain design features, such as supplier utilization, container procurement and logistic infrastructure assessment, are little affected by increasing robustness windows. In this context, supplier A represents an average of 53.2% (6.6 million LLINs) of the total share, followed by supplier B with 25% (3.1 million), supplier C with 18% (2.2 million) and supplier D with 3.7% (0.4 million). In addition, suppliers A, B and C are almost fully utilized, while supplier D only uses 14.6% of its capacity. On average, 40 ft. HC containers represent 72.6% (354 units) of container procurement, followed by 40 ft. with 25.1% (124 units) and 20 ft. with 3.3% (16 units), which makes sense since 40 ft HC represents the best marginal value per capacity.

Concerning LLIN flow from ports of origin in Asia, on average, Haiphong port in Vietnam moves 536 twenty-foot equivalent unit containers (TEUs) (55.2%), followed by Qingdao port in China (208 TEUS, 21.4%), Chennai port in India (202 TEUs, 20.8%), and Shanghai port in China (24 TEUs, 2.5%). From ports and hubs in Ivory Coast directly to health districts, most containers are dispatched or unloaded in Abidjan port (average of 488 TEUS, 50.5%) since the Abidjan district alone accounts for almost 23% of the total LLIN demand. In contrast, 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 regions, which account for approximately 25% of the project's demand. Yamoussoukro hub, 236 km from Abidjan port, consolidates an average of 72 TEUs (6.4%), followed by Bouake (58 TEUs, 6%) and Ferkessedougou (7 TEUs, 0.6%).

In the light of the above, it is concluded that, despite the considerable impact on financial aspects, the data-driven robust approach imposed a 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.

6.1.2 Supply Uncertainty

Next, supply uncertainties are evaluated in cases 3.1 to 3.4. In this context, Table 2 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 manage 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 omitted from the robustness analysis because it is a standby supplier, representing a capacity buffer to avoid model infeasibility and the LLIN price of which is 42% greater than that of the cheapest supplier.

Table 2: 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

Regarding the procurement and transportation costs for the deterministic and robust models with supply uncertainties, on average, the gradual increase in supply robustness level, $\boldsymbol{T_{r}^{supply}}$, represents a 1.2% increase in total costs. The worst-case scenario, equivalent to Soyster's approach, in which all suppliers assume their lowest capacity values, reaches \$ 23.44 million, or \$ 1.13 million (5.1%) greater than with the deterministic model (Figure 9). Since LLIN procurement represents the highest share of the project's costs (88.1%), these findings confirm the expected significant impact of supply uncertainties on total expenses.

In addition, Figure 9 presents the solution's feasibility probability regarding constraint (31), which restricts procurement according to supplier's i uncertain production capacity. For the deterministic plan, the chances are virtually zero, and when

$T_r^{supply} = 1$, they remain limited (3.5% under normal distribution). Even when $T_r^{supply} = 3$, the plan has 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. This behavior might be explained by suppliers A, B and C having their production capacity nearly fully utilized in all cases. Note that the results from the triangular distribution are more conservative than those from the uniform distribution, which in turn are more conservative than those from the normal distribution.

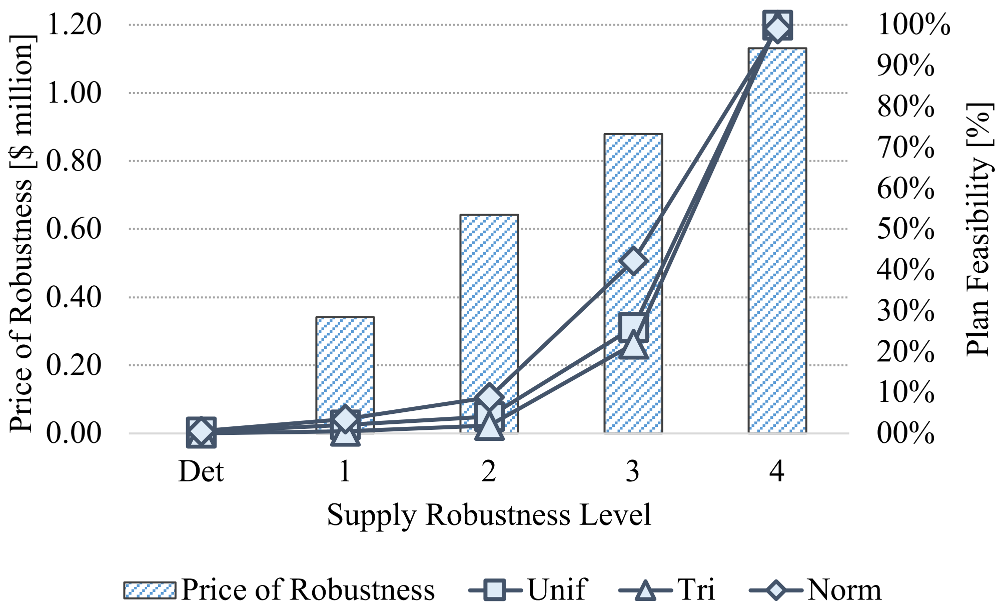

Figure 9: Price of robustness and plan feasibility for the robust model with supply uncertainty.

Figure 10 indicates LLIN procurement per supplier. Note that, as T_r^{supply} increases, suppliers that assume their minimum capacity value now represents a smaller share than with 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 the LLIN supply comes from three distinct suppliers (A, B and C). As supply robustness level increases, more suppliers are used, until the point at when three suppliers are allowed to assume their worst-case values, i.e., $T_r^{supply} = 3$, all five suppliers are used, including the standby supplier E, which in this case represents 4.6% of the supply share.

In this context, robustness can be translated into 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 additional costs by using more suppliers to ease the reallocation from the original procurement plan.

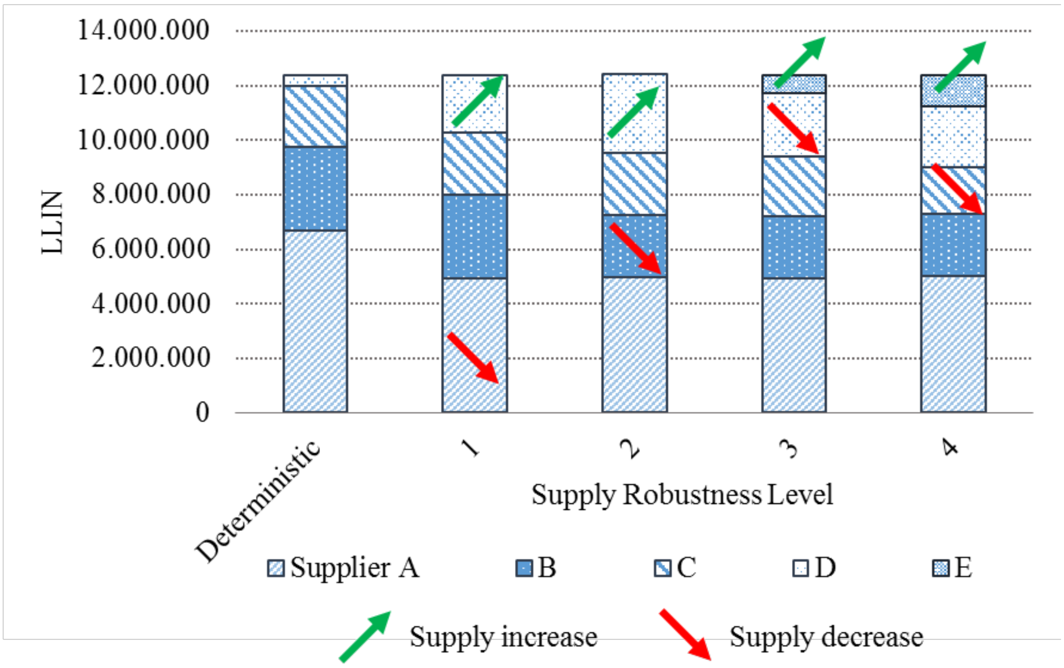

Figure 10: Impact of distinct supply robustness levels on the number of LLINs procured per supplier.

The overall effect of robust supply solutions on the remainder of the supply chain is a direct result of procurement plan changes. As UNICEF becomes more averse to supply shortage risk, Haiphong (Vietnam) and Qingdao (China) ports are used less since supplier A and B's shares decrease. In contrast, with suppliers D and E experiencing share growth, Shanghai (China) and Chennai (India) ports are preferred. However, no significant changes occur with the Ivory Coast port of discharge or the hub distribution plan.

6.1.3 Demand Uncertainty

Demand uncertainty is investigated in cases 4.1 to 4.5 and is addressed through the procurement of safety stocks that are stored at suppliers' facilities and that 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. Regarding 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 (1.85%) in overall costs (Figure 11).

In addition, Figure 11 presents the solutions' feasibility probability regarding constraint (33), which defines the minimum required safety stock for a given budget of uncertainty T_r^{demand}. The simulation shows that, when $T_r^{demand} = 20\%$, the robust plan performs well with a 36.9% chance of feasibility under a normal distribution, and from $T_r^{demand} = 40\%$ onward, the chance is already 100% for the same distribution. This sudden increase in the feasibility rates might be explained by 40% of the most demanding districts ($T_r^{demand} = 40\%$) representing a considerable 67% of total demand. In addition, constraint (33) simultaneously considers 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 likelihood of being violated. Note that, unlike previous results, instead of the triangular distribution, the uniform distribution produces the most conservative results.

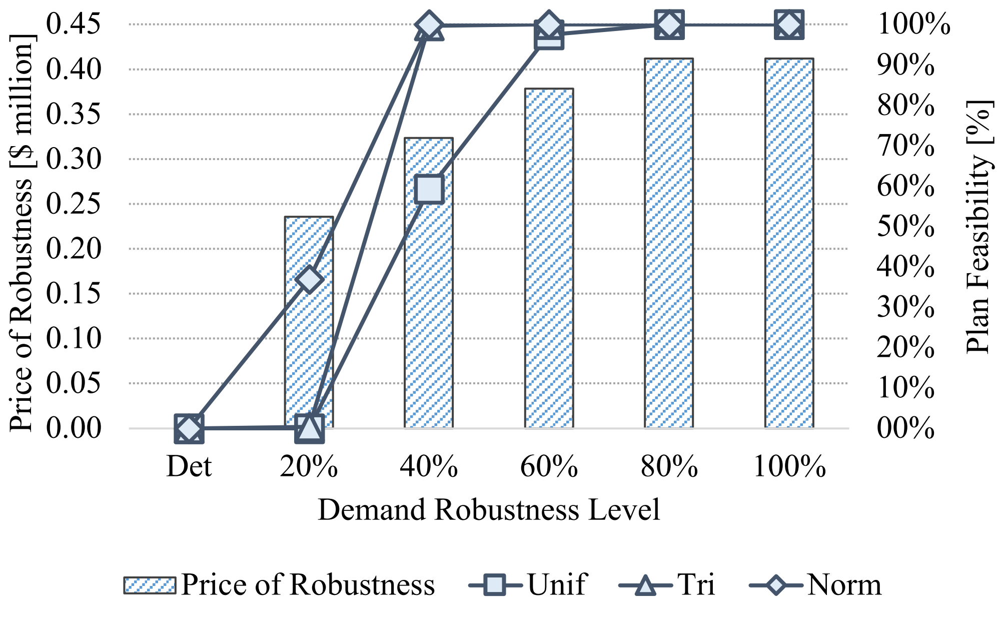

Figure 11: Price of robustness and plan feasibility for the robust model with demand uncertainty.

Note that, in Table 3, as robustness grows, the total number of LLINs procured rises 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 other suppliers almost remain constant, compared to the deterministic plan.

Table 3: Impact of distinct demand robustness levels on the number of LLINs procured per supplier.

Supplier proc. (millions of LLINs)	**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%	-	-

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 the supplier's original procurement plan to build the stock. In this context, the supplier's safety stock tends to be spread among suppliers A (average of 9.3%), B (21.2%) and C (68,5%), as seen in Figure 12.

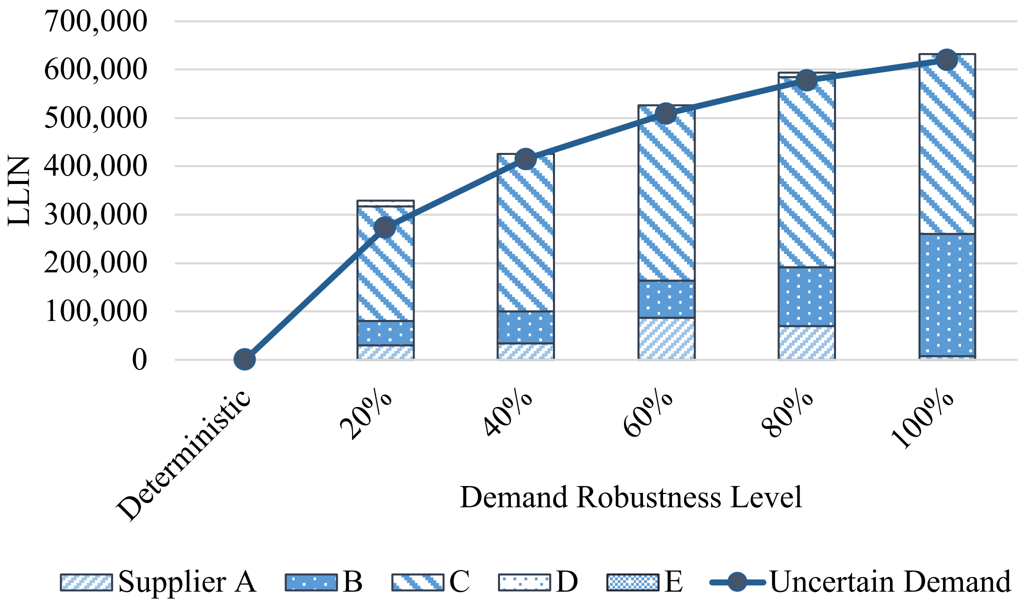

Figure 12: Impact of distinct demand robustness levels in safety stock levels per supplier.

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

Under demand uncertainty, robustness can also be understood as supply chain flexibility, since the prepositioning of safety stock in several suppliers before uncertainty is revealed, allowing for a timelier reaction with less of a financial burden than the release of a new tender.

6.1.4 Financial costs, supply and demand uncertainties

Next, financial costs and supply and demand uncertainties are simultaneously considered to investigate their combined effects (cases 5.1 to 5.5). When robustness is gradually increased in this model, each level accounts, on average, for 4% growth of the total costs, almost entirely due to LLIN procurement cost growth. In the worst-case scenario, total costs reach up to \$ 27.03 million, representing a substantial \$ 4.72 million (21.1%) surplus upon the deterministic model (Figure 17). Regarding the probability of the robust solution being feasible (i.e., not violating constraints (28), (29), (31) and (33)), only after case 5.4 does the robust plan perform reasonably well, with a 90.0% chance under normal distribution, but in contrast, under a more conservative distribution, the performance is still modest (e.g., 50.3% for a triangular distribution). This behavior is explained by the uncertain production capacity constraints, which produce similar 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 in order by the uniform and normal distributions.

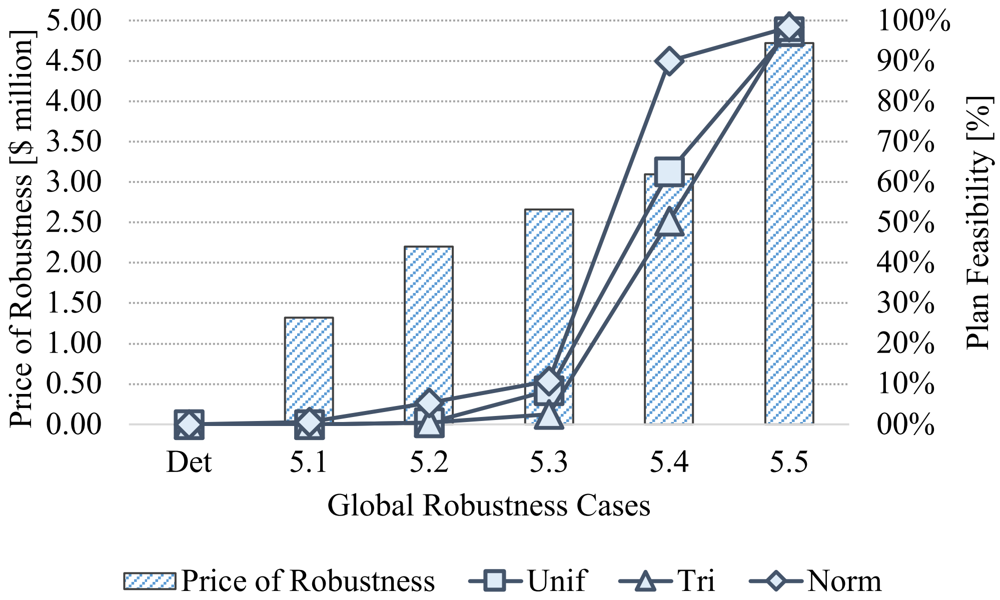

Figure 1: Price of robustness and plan feasibility for the robust model with financial cost, supply and demand uncertainty.

Source: Author

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

7. Conclusion

With increased efforts in prevention and control measures, several countries have significantly reduced the burden of malaria. Large-scale distribution campaigns of insecticide treated nets (ITNs) constitute one of the most effective ways to control and prevent malaria transmission. However, such distribution campaigns face significant challenges due to different types of constraints and uncertainties, and therefore they require careful financial and logistic planning.

This research proposed a robust optimization approach to minimize the total costs of a mass distribution campaign. Our proposed model adapts Bertsimas and Sim's (2004) framework to account for uncertainties in the constraints' independent terms, such as logistics and supply capacities. In addition, to consider financial cost uncertainties, our work adjusts to a static multi-period setting, the data-driven dynamic model with adaptive uncertainty sets of Fernandes et al. (2016).

To validate and illustrate features of the robust optimization model, we apply it to a UNICEF distribution campaign (Brito et al. 2014). The robust solution to the UNICEF campaign suggests procurement and logistics changes, according to the chosen level of conservatism toward uncertainties. In particular, robust solutions increase total costs (i.e., the price of robustness) from a marginal 1.1% (total of $ 22.55 million) up to a significant 21% ($ 27.03 million), compared to its deterministic counterpart ($ 22.31 million).

This cost increase can be interpreted as the required budget buffer to hedge against a pre-defined level of uncertainty. In return, the robust model provides a solution with improved supply chain flexibility by reallocating suppliers and logistic infrastructure utilization. In other words, the proposed (robust) model provides solutions that are robust in the sense that they mitigate the likelihood of needing to adjust procurement and transportation plans when the uncertainty is revealed (e.g., supply shortage risk), ultimately reducing time, effort, cost or performance penalties arising from the need for re-planning.

The robust solutions were assessed through Monte Carlo simulation against several realizations of uncertain parameter values, with solution feasibility increasing with the level of conservatism, as desired. At times (e.g., under supply uncertainty alone), the robust plan does not perform reasonably well until a high level of conservatism is set. Hence, considering uncertainties independently does not necessarily lead to much better performance, and it is important considering uncertainties simultaneously. In this context, it is critical to evaluate the trade-off between additional costs and improved reliability in the robust plan. Since the deterministic plan usually has a low likelihood of feasibility, it is important to question its optimality.

It is worth noting that it may be very challenging to set and approve an appropriate budget buffer to hedge against price volatility and other unforeseen expenses, especially in an environment where funds are scarce and humanitarian organizations compete fiercely for them. Furthermore, adopting an organizational culture that embraces risk aversion would likely require decisions that espouse unpopular and challenging trade-offs, such as changes in the current project portfolio (e.g., withdrawing a mass campaign project in a lower priority country to redistribute its budget and foster robust solutions in a higher priority one). Nevertheless, to ensure a viable strategic long-term vision, robust solutions are required to guarantee reliable campaigns and continuity of humanitarian aid.

There are several opportunities for further research related to this work. First, it would be worthwhile investigating the addition of hub location decisions within the robust model. While not frequently mentioned in the context of LLIN distribution campaign, it might yield interesting logistics insights. Second, the inclusion of a multi-product set to account for different LLIN sizes and other health commodities would capture other challenges associated with LLIN distribution campaigns. Third, the inclusion of the reverse supply chain of LLINs and other malaria commodities would also provide interesting research opportunity. Finally, driven by the simulation results, which indicated a high likelihood of constraint violations under lower levels of conservatism, 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 infeasible plan.

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APPENDIX

1. Model sets, parameters and variables

Table 1: 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 LLIN tracking purposes, P is defined as an auxiliary set that is equal to suppliers' set I.

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

	from port of discharge ***k*** to hub ***h*** within mode of transport ***m*** considered for period ***t***.	
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
Market Parameters		
dm_{rd}	Demand for LLINs in district ***d*** during implementation phase ***r***.	LLINs
$\widehat{dm}_{rd}$	Maximum allowed deviation from nominal value dm_{rd}.	LLINs
$T_r^{demmand}$	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 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 whether 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 whether 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 whether 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 whether 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 whether a route from hub ***h*** to district ***d*** is available for LLIN ***p*** during implementation phase ***r***.	-
Auxiliary Parameters		
$\mathcal{M}$	Large 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
S_{rpi}	Safety stock of LLINS ***p*** of supplier ***i*** during implementation phase ***r*** to account for uncertainties related to the 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	Containers

	implementation phase ***r***.	
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 in 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 equals 1 if a district ***d*** is supplied by an LLIN ***p*** and 0 otherwise. It is used to assure that a district is supplied by only one supplier.	-