# Design of Robust Global Sourcing Networks


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**Abstract**

A global sourcing network consists of a set of suppliers located globally to satisfy the demands of an international factory network. The design of a global sourcing network consists of two interrelated decisions: *supplier selection* and *order allocation*. The supplier selection is a strategic decision that involves an one time capital investment in developing the selected suppliers. The order allocation is of tactical nature, in which the decisions regarding the allocation of suppliers to the factories are made. For optimal design, both the above decisions are contingent on each other and hence made in tandem at the beginning of the planning horizon. Uncertainties in the form of deviations and disruptions may be realized before the implementation of order allocation, which can render the original design inefficient and sometimes infeasible. The supplier selection decision is irreversible and hence cannot be altered based on realized uncertainties, but the order allocation can be changed. This operational flexibility is assumed for a global firm to be resilient, so that it can shift production among factories and switch orders from suppliers seamlessly. In this work, we develop a robust optimization based methodology to design a robust global sourcing network, which functions at acceptable levels under a wide range of pre-identified uncertain scenarios.


## 1 Introduction

Advent of global markets enhanced the emergence of global firms which have factories in different countries. Manufacturers typically set up foreign factories to benefit from tariff and trade concessions, low cost direct labor, capital subsidies, and reduced logistics costs in foreign markets [3]. The classical way of managing a multinational is to operate each firm as a domestic firm in its respective country. In the last two decades, global firms started adopting integrated management strategies, which blurs the national borders and treat the set of factories from different countries as a part of the same supply chain network. Global sourcing is one such integrated strategy, where suppliers located worldwide are selected to meet the demands of the factories, which are also located internationally [6, 16].

Global sourcing is used as a competitive strategy by firms to face the international competition. The main reasons are lower costs, improved quality, operational flexibility, and access to new technology [6]. One of the primary objectives of firms operating globally is *risk management* [5] and global sourcing is no exception. The risk might manifest in the form of *deviations*, *disruptions*, or *disasters* [4]. The deviations refer to the change in the certain parameters of the sourcing network like the demand, supply, procurement cost, and transportation cost. The deviations may occur due to macroeconomic factors and the default sourcing strategies may become inefficient and expensive under deviations. Disruptions change the structure of the supply network due to the non-availability of certain production, warehousing and distribution facilities or transportation options due to unexpected events caused by human or natural factors. For example, Taiwan earthquake resulted in disruption of IC chip production and the foot-and-mouth disease in England disrupted the meat supply. Under such structural changes, the normal functioning of supply chain will be momentarily disrupted and can result in huge losses. The third kind of risk is a disaster, which is a temporary irrecoverable shut-down of the supply chain network due to unforeseen catastrophic system-wide disruptions. The entire US economy was temporarily shutdown due to the downturn in consumer spending, closure of international borders and shut-down of production facilities in the aftermath of the 9/11 terrorist attacks. In general, it is possible to design supply chains that are robust enough to profitably continue operations in the face of expected deviations and disruptions. However, it is impossible to design a supply chain network that is robust enough to react to disasters. This arises from the constraints of any system design, which is limited by its operational specification.

The global supply chains are characterized by leanness and JIT principles for maximum efficiency. With the advent of Internet, IT, and trade liberalization, the firms evolved to be *truly* global by adopting integrated management strategies, whereby a set of factories in different countries are treated as a part of the same supply chain. This makes the supply chain highly vulnerable to exogenous random events that create deviations, disruptions, and disasters. Much writings in the recent past as white papers, thought leadership papers, and case studies on supply chain risk management have emphasized that *redundancy* and *flexibility* are preemptive strategies that can mitigate loses under random events. But this is against the leanness principles of global supply chains and increase the cost. It is required to tradeoff between the *leanness* under normal environment and *robustness* under uncertain environments. The tradeoff should be quantitatively determined for any problem instance by a mathematical model, so that the recommendations of the model could be deployed in practice. It is in this context, this work provides significant contribution. In particular, a mathematical programming model based on robust optimization is developed to design a robust global sourcing network that can function at acceptable levels of cost, when faced with wide range of pre-identified risks.

To handle unforeseen events in sourcing network or in general, supply chain network, there are two obvious approaches: (1) to design networks with built in risk-tolerance and (2) to contain the damage once the undesirable event has occurred. Both of these approaches require a clear understanding of undesirable events that may take place in the network and also the associated consequences and impacts from these events. The robust global sourcing network proposed in this paper can continue operations under the wide range of pre-identified deviations and disruptions. This is a preemptive strategy that can be used by the firms to build risk-tolerant networks. The model is prescriptive and provides alternate sourcing strategies once the expected uncertainty is resolved. We consider both deviations and disruptions via a *scenario* based approach and use robust optimization based methodology to design the robust global sourcing network.

The rest of the paper is organized as follows. Section 2 defines mathematically a global sourcing network and discusses the deviations and disruptions that occur in global sourcing. Approaches for design under uncertainty are briefly described in Section 3. The robust optimization based methodology for design of robust global sourcing networks is proposed in Section 4. The computational experiments to study the proposed methodology and the results are given in Section 5. Section 6 concludes the paper with a note of further research.

# 2 Deviations and Disruptions in Global Sourcing

In this section, we first define a global sourcing network and then discuss the deviations and disruptions that occur in global sourcing.

## 2.1 Global Sourcing Networks

Global sourcing network (GSN) is a set of suppliers in various countries to support the demands of the firm's international factory network. There are two kinds of decisions that are made in the design of GSN:

- *Supplier selection*: The subset of suppliers to be included in the sourcing network. This is a strategic investment decision that is made at the beginning of planning horizon, which incurs the one-time supplier development costs to the firm.
- *Order allocation*: The allocation of orders from the selected suppliers to the factories to meet the demand at the factories. This is a tactical decision, influenced by the procurement costs.

The first decision is implemented before the planning horizon and the second is implemented during it. This is a single-period problem as there is only one order allocation. The supplier selection decision is assumed fixed and irreversible during the planning horizon *i.e.* no new suppliers can be added once the decision is made. Each supplier has a fixed development cost, which is the cost of including the supplier in the network. The objective is to minimize the total procurement cost that includes both the supplier development costs and the order allocation costs. Hence, both the decisions are contingent on each other and are made in tandem. In addition to the suppliers, we consider two other sources of supply: *redundant inventory* and *spot purchase*. Redundant inventory is a part of strategic decision, which once invested incurs a fixed cost irrespective of whether it is used or not. Thus it has a fixed cost and a maximum capacity associated with it. Spot purchase is another option that has no strategic component. If all other sources are unavailable, the organization can always go for this sure but costlier option. We assume that the capacity is infinite. The cost incurred due to lost in sales or unmet demand can also be modeled using this option. It essentially has the same characteristics: No fixed cost; no upper limit; sure but costlier option. All the above can be summarized as follows.

**Parameters**

- *International factory network*: The set of factories $\mathcal{I}$ denoted by index $i$. Total number of factories is $M = |\mathcal{I}|$ and their locations are assumed fixed.

- *Potential suppliers*: The potential set of global suppliers $\mathcal{J}$ denoted by index $j$. Total number of suppliers is $N = |\mathcal{J}|$ and their locations are fixed.

- *Demand*: The demand for the component to be sourced at each factory $i \in \mathcal{I}$ is $d_i$.

- *Supply*: The available supply quantity from each supplier $j \in \mathcal{J}$ is given as range $[\underline{a}_j, \overline{a}_j]$, which denote the minimum and maximum quantity that can be procured from the supplier.

- *Supplier development costs*: The fixed cost of developing supplier $j$ is $Fc_j$ if he is accepted in the sourcing network.

- *Procurement costs*: Unit cost of procurement from supplier $j$ for factory $i$ is $c_{ij}$.

- *Redundant inventory*: A possible investment in redundant inventory for each factory $i$ with capacity $r_i$ and total cost $Ic_i$. It is more realistic to assume different levels of investments with varying capacity and cost $\{(r_i^l, Ic_i^l)\}$. For the sake of brevity, we assume only one level of investment for each factory. However, all our models can be easily extended to include various levels.

- *Spot purchase*: For each factory $i$, there is a sure source of supply with unit cost $Sc_i$ and infinite capacity. Penalty incurred due to lost sales of unmet demand can also be modeled similarly. We have just restricted to one option of this kind per factory for the sake of brevity.

The design of GSN involves identifying an optimal set of suppliers, order allocation from the winning suppliers, investments in the redundant inventories, and the quantity to be spot purchased for the factory network, such that the total cost of procurement is minimized.

## 2.2 Deviations and Disruptions

Once the GSN is designed and the suppliers are developed accordingly, deviations and disruptions can occur in the network, making the original design inefficient or even infeasible.

- A strike at two GM parts plants in 1998 led to the shutdowns of 26 assembly plants, which ultimately resulted in a production loss of over 500,000 vehicles and an $809 million quarterly loss for the company.

- An eight-minute fire at a Philips semiconductor plant in 2001 brought its customer Ericsson to a virtual standstill.

- Hurricanes Katrina and Rita in 2005 on the U.S. Gulf Coast forced the rerouting of bananas and other fresh produce.

- In December 2001, UPF-Thompson, the sole supplier of chasis frames for Land Rover's Discovery vehicles became bankrupt and suddenly stooped supplying the product.

Thus several risk sources, may it be political or natural or intentional or economical, can result in deviations like exchange rate fluctuations, demand uncertainties, supply uncertainties and disruptions like supplier failures, transportation link failure, and factory shutdowns. Literature on handling risks in global sourcing is sparse. The deviation in cost due to exchange rates were considered in [6] and the deviations in both demand and exchange rates were considered in [16]. In the following section, we discuss the various approaches to design and optimization under uncertainty.

# 3 Approaches for Design under Uncertainty

The decision-making environments can be divided into three categories [13]: certainty, risk, and uncertainty. In *certainty* situations, all parameters are deterministic and known, whereas risk and uncertainty situations involve randomness. In *risk* environments, there are random parameters whose values are governed by probability distributions that are known to the decision maker. In *uncertainty* environments, there are random parameters but their probability distributions are unknown to the decision maker. The random parameters can be either continuous or discrete scenarios. Optimization problems for risk environments are usually handled using *stochastic optimization* and that for uncertain environments are solved using *robust optimization*. The goal of both the stochastic optimization and robust optimization is to find a solution that has *acceptable* level of performance under any possible realization of the random parameters. The *acceptable level* is dependent on the application and the performance measure, which is part of the modeling process.

Stochastic optimization (SO) problems [1, 8, 12] generally optimizes the *expectation* of the objective function like minimizing cost or maximizing profit. As probability distributions are known and expectation is used as the performance measure, the solution provided is *ex-ante* and the decision maker is *risk neutral*. SO has been successfully applied to facility location problems [11], which is similar in structure to the global sourcing network design problem. In this work, we use robust optimization based methodology for modeling the global sourcing network problem.

Robust optimization (RO) [10] is used for environments in which the probability information about the random events are unknown. The performance measure is hence not expectation and various *robustness* measures have been proposed. The two commonly used measures are *minimax cost* and *minimax regret*. The minimax cost solution is the solution that minimizes the maximum cost across all scenarios, where a scenario is a particular realization of the random parameters. The minimax regret solution minimizes the maximum regret across all scenarios. The regret of a solution is the difference (absolute or percentage) between the cost of that solution in a given scenario and the cost of the optimal solution for that scenario. Regret is sometimes described as opportunity loss: the difference between the quality of a given strategy and the quality of the strategy that would have been chosen had one known what the future held. Minimax cost problems can often be transformed into equivalent minimax regret problems, and vice versa, since the cost and regret of a given scenario differ only by a constant. Solution approaches for one criterion are often also applicable to the other one.

Our approach is based on RO, which is the use of worst case analysis and developing responses for various contingent scenarios. In other words, the decision-making environment is *uncertainty* (no probability information) and the random parameters are *discrete* (scenario based approach). The RO models capture the *risk-averseness* of the decision makers and are more suitable for the global sourcing decisions than SO [6]. A set of risk assessment and mitigation principles for managing supply chain risks is presented in [9]. Following is the subset of principles that are relevant to the global sourcing and our design methodology.

1. Preemption is better than mitigation of loses after the uncertainty is resolved;

2. Establishing back-up systems, contingency plans, and maintaining reasonable slack, can increase the level of readiness in managing risks;

3. Risk assessment and quantification ex ante is of fundamental importance in understanding the consequences of the the disruptions and for evaluating and undertaking prudent mitigation;

4. Flexibility and mobility of the resources are mandatory to reduce risks and increase the speed of response to contingencies;

We will discuss the relevance of the above principles with respect to our problem formulation and solution methodology in detail in the following. Firstly, the design approach of building risk-tolerant sourcing network is a *preemptive* strategy of handling uncertainties. The second principle emphasizes on use of back-up systems and contingency plans. Literature and best practices in global supply chains have always focused on *leanness* of the supply chain operations. However, in order to minimize risk, and ultimately loss from supply chain disruptions, attention must be given to the tradeoff between *robustness* (to handle deviations and disruptions) and *leanness* (efficiency under normal operations).

The third principle is about assessment and quantification of possible deviations and disruptions. The scenario based approach is one such quantification technique. It has the advantage of allowing uncertain parameters to be statistically dependent. Dependence is often necessary to model reality, as a supplier disruption in one country will increase the cost of procurement of a supplier in another country (as every firm will try to procure from this alternate supplier). The fourth principle on *flexibility* is pivotal to the problem definition and design methodology adopted here. Flexibility has been emphasized for risk management in global supply chain design [7, 14]. Flexibility allows operational hedging whereby a firm can shift its operations seamlessly based on the observed cost or demand fluctuations. We assume that the firm for which the GSN is designed is flexible so that the order allocation for a particular contingent scenario can be implemented. The formulation using the scenarios is explained in detail in the following section.

# 4 Design of Robust Global Sourcing Networks

The sourcing network is subject to the following kinds of changes:

- *Cost deviation*: Deviations in procurement cost.
- *Demand deviation/disruption*: Change in demands at the factories or factory shutdown.
- *Supply deviation/disruption*: Change in the supply or supplier disruption.
- Any combination of the above.

Such a change in the network is called as a *scenario*. The *robust* design takes in to account the different possible scenarios and identifies a sourcing network that will function at acceptable levels if any of the scenario is realized. Let $S$ be the set of discrete scenarios, where a scenario $s$ is defined by parameter values $\{\{c_{ij}^s\}, \{d_i^s\}, \{[\underline{a}_j^s, \overline{a}_j^s]\}\}$. It follows from the definition that for any two different scenarios, value of at least one of the parameters is different. Let $s = 0$ denote *default* or *regular* scenario that has the original unperturbed values. Note that the parameters $\{Fc_j\}$, $\{Ic_i\}$, $\{r_i\}$, and $\{Sc_i\}$ are not scenario dependent. $\{Fc_j\}$, $\{Ic_i\}$, and $\{r_i\}$ are strategic components and hence are utilized before the uncertainty is realized. Though the $\{Sc_i\}$ influences directly the order allocation, it is assumed to be certain. The above categorization is intended to show the base model and for modeling any real world scenario, the model can be easily extended to include categories derived from the above. In the following, we develop mixed integer linear programming formulations to determine various costs associated with the design of robust GSN.

## 4.1 GSN under scenario $s$

Design of GSN under scenario $s$ is equivalent to that of under certainty. As noted in the previous report, this is equivalent to the capacitated version of the well studied *facility location problem* [2] with the suppliers as the facilities and the factories as the markets with the demand. The rationale behind designing the network for a specific scenario $s$ in isolation is to study its impact on the network. Following are the decision variables in the formulation.

### Decision variables

- $x_j$: The binary decision variable $x_j = 1$ denotes the inclusion of supplier $j$ in the sourcing network and $x_j = 0$ denotes the rejection.
- $y_{ij}^s$: The linear variable that denotes the quantity supplied to factory $i$ from supplier $j$.
- $u_i$: The binary decision variable that decides whether to invest or not in the safety stock redundant inventory with cost $Ic_i$ and capacity $r_i$.
- $v_i^s$: The linear variable that denotes the quantity utilized from the inventory to meet the demand at factory $i$.
- $w_i^s$: The linear variable that denotes the quantity procured using the spot purchase option.

### MILP formulation

$$(\text{GSN}^s): \qquad \min \sum_j Fc_j x_j + \sum_i \sum_j c_{ij}^s y_{ij}^s + \sum_i Ic_i u_i + \sum_i Sc_i w_i^s \tag{1}$$

subject to

$$\textstyle\sum_j y_{ij}^s + v_i^s + w_i^s = d_i^s \quad \forall i \in \mathcal{I} \tag{2}$$

$$\underline{a}_j^s x_j \leq \textstyle\sum_i y_{ij}^s \leq \overline{a}_j^s x_j \quad \forall j \in \mathcal{J} \tag{3}$$

$$v_i^s \leq r_i u_i \quad \forall i \in \mathcal{I} \tag{4}$$

$$x_j \in \{0, 1\} \quad \forall j \in \mathcal{J} \tag{5}$$

$$y_{ij}^s \geq 0 \quad \forall i \in \mathcal{I},\ \forall j \in \mathcal{J} \tag{6}$$

$$u_i \in \{0,1\} \qquad \forall j \in \mathcal{J} \tag{7}$$
$$v_i^s \geq 0,\ w_i^s \geq 0 \qquad \forall i \in \mathcal{I} \tag{8}$$

The optimal solution to the above provides the least cost sourcing network for the given scenario $s$, with the set of global suppliers. Let $(X^s)$ denote the optimal sourcing network for the scenario $s$ and let $L^s = Z^s(X^s)$ denote its optimal cost. Hence, $L^s$ will be the least cost incurred if it is known a priori that scenario $s$ will be realized. If $(X)$ denotes any sourcing network, then $L^s \leq Z^s(X)$. The relative regret of solution $(X)$ for scenario $s$ is:

$$r^s(X) = \frac{Z^s(X) - L^s}{L^s} \tag{9}$$

For the regular scenario, $L^0 = Z^0(X^0)$ is the optimal cost and $(X^0)$ is the optimal network. If scenario $s \neq 0$ is realized during the planning horizon, then the cost of the network $(X^0)$ is $Z^s(X^0)$. We denote this as the *deviation cost* $D^s = Z^s(X^0)$ of scenario $s$. It is the cost incurred if $s$ is encountered when the regular scenario was expected. Let $U^s$ denote the worst case cost, when scenario $s$ is encountered.

$$U^s = \max_X Z^s(X) \tag{10}$$

The $U^s$ will help in identifying the *graveness* of scenario $s$. If $U^s - L^s$ is negligible, then the scenario is not sensitive to the solution. On the other hand if $U^s >> L^s$, the scenario $s$ has to be judiciously handled, even if it is a low probable event, as it might end up with huge increase in the cost. In the following, we develop MILP formulations to determine $D^s$ and $U^s$.

### 4.2 MILP formulation to determine the deviation cost $D^s$

The deviation cost is the cost incurred in scenario $s$ if the sourcing network of the regular scenario is used. Let $(\{\overline{x}\}, \{\overline{u}\})$ represent the solution vectors of sourcing network $(X^0)$. Note that these are the strategic decisions of supplier selection and investments in the redundant inventories. The tactical order allocation for scenario $s$ using the above solution provides the deviation cost. This is obtained by solving the following linear programming problem.

$$\min \sum_j Fc_j \overline{x}_j + \sum_i \sum_j c_{ij}^s y_{ij}^s + \sum_i Ic_i \overline{u}_i + \sum_i Sc_i w_i^s \tag{11}$$

subject to

$$\textstyle\sum_j y_{ij}^s + v_i^s + w_i^s = d_i^s \qquad \forall i \in \mathcal{I} \tag{12}$$
$$\underline{a}_j^s \overline{x}_j \leq \textstyle\sum_i y_{ij}^s \leq \overline{a}_j^s \overline{x}_j \qquad \forall j \in \mathcal{J} \tag{13}$$
$$v_i^s \leq r_i \overline{u}_i \qquad \forall i \in \mathcal{I} \tag{14}$$
$$y_{ij}^s \geq 0 \qquad \forall i \in \mathcal{I},\ \forall j \in \mathcal{J} \tag{15}$$
$$v_i^s \geq 0,\ w_i^s \geq 0 \qquad \forall i \in \mathcal{I} \tag{16}$$

### 4.3 MILP formulation to determine the maximum cost $U^s$

The maximum cost $U^s$ for scenario $s$ cannot be determined directly by maximizing the objective function of GSN$^s$. The objective function includes the redundant inventories and spot purchase costs whose cost will be significantly larger than the procurement costs $\{c_{ij}\}$. Further the capacity of spot purchase is infinite and hence the $U^s$ will be $\sum_i Sc_i d_i^s$ for all scenarios. The intention is not determine this cost, but the *worst* cost realizable with a sourcing network that consists of suppliers. Note that the spot purchase is the last option when no suppliers are available to meet the demand. So to determine $U^s$, the objective function of GSN$^s$ should be suitable modified as follows.

$$\max \sum_j Fc_j x_j + \sum_i \sum_j c_{ij}^s y_{ij}^s \tag{17}$$

subject to

$$(2) - (8)$$

Let $(\{\overline{x}\}, \{\overline{y}\}, \{\overline{u}\}, \{\overline{v}\}, \{\overline{w}\})$ be the opimal solution to the above problem. Then the worst case cost is given by

$$U^s = \sum_j Fc_j \overline{x}_j + \sum_i \sum_j c_{ij}^s \overline{y}_{ij}^s + \sum_i Ic_i \overline{u}_i + \sum_i Sc_i \overline{w}_i^s \tag{18}$$

## 4.4 MILP formulation for the design of robust GSN

Robust optimization (RO) [10] is used for environments in which the probability information about the random events are unknown. The performance measure is hence not expectation and various *robustness* measures have been proposed. The two commonly used measures are *minimax cost* and *minimax regret*. The minimax cost solution is the solution that minimizes the maximum cost across all scenarios, where a scenario is a particular realization of the random parameters. The minimax regret solution minimizes the maximum regret across all scenarios. The minimax regret objective is given by

$$\min_X \max_s r^s(X) \tag{19}$$

In general, the minimax versions are overly conservative as the emphasis is on the worst possible scenario, which may occur very rarely in practice. Hence, a solution that is good with respect to the worst-case scenario may perform poorly on the other commonly realizable scenarios. Another measure of robustness is to constrain the regret within a pre-specified value $p^s$: $r^s(X) \leq p^s$ [15]. Small values of $p^s$ make the solution $(X)$ to perform *close* to that of the optimal solution $(X^s)$ for scenario $s$. Thus, by judiciously selecting $p^s$, the decision maker can characterize the importance of scenario $s$. To implement the above, the following constraints are included in the formulation for robust design.

$$\sum_j Fc_j x_j + \sum_i \sum_j c_{ij}^s y_{ij}^s + \sum_i Ic_i u_i + \sum_i Sc_i w_i^s \leq (1 + p^s) L^s \ \forall s \in \mathcal{S} \tag{20}$$

Note that $L^s = Z^s(X^s)$ is the optimal cost for the scenario $s$. Hence, for each scenario $s$, the GSN$^s$ has to be solved. For any sourcing network $X$,

$$L^s \leq Z^s(X) \leq U^s$$

As $Z^s(X) \leq (1 + p^s) L^s$, the maximum value of $p^s$ is given by

$$p^s \leq \tilde{p}^s = \frac{U^s}{L^s} - 1$$

The $\{p^s\}$ are the input parameters provided by the decision maker to define the acceptable levels of operation for different scenarios. Determining $U^s$ will aide the decision maker in choosing an appropriate value for $p^s$.

Let $(X^R)$ be a robust solution that satisfies the constraints (20). Then,

$$r^s(X^R) \leq p^s \; \forall s \in \mathcal{S} \tag{21}$$

Given the set of robust solutions $\{(X^R)\}$, the objective is choose the *best* one. We use the following measure: $\min_{(X^R)} \sum_s r^s(X^R)$. This is a $l_1$ norm and one can consider any $l_p$ norm, including the $l_\infty$ norm, which is the minimax regret objective. The formulation for the design of robust global sourcing network is as follows:

$$(\text{GSN}^R): \qquad \min \sum_s \frac{\sum_j Fc_j \overline{x}_j + \sum_i \sum_j c_{ij}^s y_{ij}^s + \sum_i Ic_i \overline{u}_i + \sum_i Sc_i w_i^s - L^s)}{L^s} \tag{22}$$

subject to

$$\sum_j Fc_j x_j + \sum_i \sum_j c_{ij}^s y_{ij}^s + \sum_i Ic_i u_i + \sum_i Sc_i w_i^s \leq (1+p^s)L^s \quad \forall s \in \mathcal{S} \tag{23}$$

$$\sum_j y_{ij}^s + v_i^s + w_i^s = d_i^s \quad \forall i \in \mathcal{I},\ \forall s \in \mathcal{S} \tag{24}$$

$$\underline{a}_j^s x_j \leq \sum_i y_{ij}^s \leq \overline{a}_j^s x_j \quad \forall j \in \mathcal{J},\ \forall s \in \mathcal{S} \tag{25}$$

$$v_i^s \leq r_i u_i \quad \forall i \in \mathcal{I},\ \forall s \in \mathcal{S} \tag{26}$$

$$x_j \in \{0,1\} \quad \forall j \in \mathcal{J} \tag{27}$$

$$y_{ij}^s \geq 0 \quad \forall i \in \mathcal{I},\ \forall j \in \mathcal{J},\ \forall s \in \mathcal{S} \tag{28}$$

$$u_i \in \{0,1\} \quad \forall j \in \mathcal{J} \tag{29}$$

$$v_i^s \geq 0,\ w_i^s \geq 0 \quad \forall i \in \mathcal{I},\ \forall s \in \mathcal{S} \tag{30}$$

The objective function is linear due to the $l_1$ norm and the above is a large deterministic MILP formulation which can be solved using commercial optimization packages like CPLEX.

# 5 Computational Experiments

The main objective of this work is to conduct numerical experiments with simulated data to study the proposed formulations. We developed a test suite that generates different instances of problems. To make the randomly generated instances meaningful, certain fundamental parameters are created, out of which a random problem instance is generated.

## 5.1 Factories and suppliers network

The number of factories $M$ and the number of suppliers $N$ belong to the fundamental parameters. In addition, number of regions $R$ is given. The $N$ suppliers are alloted randomly to one of the $R$ regions. Let $\beta_r$ be the set of suppliers belonging to region $r$. In the numerical experiment for this work, the parameters were assigned the following values: $M = 5$, $N = 50$, and $R = 7$. The base cost $\alpha_{ir}$ is the mean cost of procurement for factory $i$ from a supplier in region $r$. Table 1 shows the mean cost of procurement for factories from different regions. The other parameters for the problem instance are chosen as follows:

| | | (Region) | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| | 1 | 70 | 105 | 120 | 120 | 100 | 110 | 100 |
| | 2 | 95 | 80 | 145 | 120 | 115 | 135 | 100 |
| **(Factory)** | 3 | 80 | 115 | 110 | 130 | 105 | 115 | 110 |
| | 4 | 75 | 110 | 110 | 125 | 105 | 105 | 105 |
| | 5 | 85 | 95 | 135 | 105 | 100 | 125 | 85 |

Table 1: Mean unit cost of procurement

- Procurement costs $\{c_{ij}\}$:

$$c_{ij} = (1 + X \sim U(\{-0.25, -0.20, \dots, 0.25\}))\alpha_{ir},\ r : j \in \beta_r$$

- Demand $\{d_i\}$:

$$d_i = X \sim U(\{10000, 15000, \dots, 30000\})$$

- Supply range $\{[\underline{a}_j, \overline{a}_j]\}$:

$$\underline{a}_j = X \sim U(\{250, 500, \dots, 1000\})$$

$$\overline{a}_j = X \sim U(\{3000, 3500, \dots, 6000\})$$

- Fixed cost $\{Fc_j\}$:

$$Fc_j = X_r$$

  where $r$ is the region to which $j$ belongs and the $X_r$ is the random variable whose distribution for different regions is shown in Table 2.

- Inventory capacity $\{r_i\}$:

$$r_i = (X \sim U(\{0.15, 0.2, \dots, 0.3\}))\, d_i$$

- Inventory cost $\{Ic_i\}$:

$$Ic_i = (X \sim U(\{2, 2.2, \dots, 3\}) \times \max_j\{c_{ij}\} \times r_i$$

- Spot purchase $\{Sc_i\}$:

$$Sc_i = (X \sim U(\{3, 3.2, \dots, 4\}) \times \max_j\{c_{ij}\}$$

| **Region** $r$ | $X_r$ |
|---|---|
| 1 | $U(\{15000, 16000, \ldots, 20000\})$ |
| 2 | $U(\{15000, 16000, \ldots, 20000\})$ |
| 3 | $U(\{8000, 8500, \ldots, 10000\})$ |
| 4 | $U(\{10000, 10500, \ldots, 13000\})$ |
| 5 | $U(\{20000, 21000, \ldots, 25000\})$ |
| 6 | $U(\{10000, 11000, \ldots, 15000\})$ |
| 7 | $U(\{18000, 19000, \ldots, 22000\})$ |

Table 2: Random variable $X_r$ for generating $Fc_j$

## 5.2 Scenario generation

The above parameters are for the regular or default scenario. As discussed earlier, a scenario $s$ is characterized by $\{\{c^s_{ij}\}, \{d^s_i\}, \{[\underline{a}^s_j, \overline{a}^s_j]\}\}$. Any change in any of the above parameters from that of the regular values represents a scenario. First, the GSN$^s$ is solved for the regular scenario. Using its optimal solution, other possible scenarios are generated. The solution for the regular scenario is used to generate scenarios that are meaningful. For example, consider the generation of scenario related to the disruption of a supplier. If that supplier is not a winning supplier, then the disruption will not affect the network. Table 3 lists 15 different scenarios that were considered in the numerical experiment. First 10 of them are isolated events and the rest five are combinations of single events.

## 5.3 Numerical experiments

Two types of experiments were conducted. First one involved only the solving of GSN$^s$ in isolation for all scenarios. The second experiment considered the design of robust GSN. The objective of experimenting with the scenarios in isolation is to study the costs $L^s$, $D^s$, and $U^s$ individually for each scenario.

## 5.4 Scenario analysis

Using the experimental setup discussed in the previous section, 100 instances of factory-supplier network was created. Each of them were solved for the regular scenario and for each individual scenario. Let $Z^*$ be the optimal cost of the regular scenario. The $L^s$, $D^s$, and $U^s$ form each scenario were then expressed in terms of $Z^*$ as follows:

- $\tilde{L} = \frac{L^s - Z^*}{Z^*} \times 100$
- $\tilde{D} = \frac{D^s - Z^*}{Z^*} \times 100$
- $\tilde{U} = \frac{U^s - Z^*}{Z^*} \times 100$
- $\tilde{p} = \frac{U^s}{L^s} - 1$

The average of the above for 100 instances are shown in Table 4. Some of the notable observations are:

| Type | Deviation/ Disruption | Reason | Description |
|---|---|---|---|
| 1 | Cost deviation | Exchange rate fluctuation | For each region, deviate the procurement cost randomly by a maximum of 10%. |
| 2 | Cost deviation | Exchange rate fluctuation | For each region, deviate the procurement cost randomly by a maximum of 30%. |
| 3 | Cost deviation | Macro-economic change | Choose a region $r$ randomly that has a winning supplier and deviate the procurement cost from $j \in \beta_r$ randomly by a maximum of 40%. |
| 4 | Supply deviation | Capacity failure | Choose a winning supplier $j$ randomly and decrease $\overline{a}_j$ randomly by a maximum of 40%. |
| 5 | Supply deviation | Upstream capacity failure | Choose a region $r$ randomly with that has a winning supplier and decrease the $\overline{a}_j$ for all $j \in \beta_r$ randomly by a maximum of 40%. |
| 6 | Supply disruption | Bankruptcy | Choose a winning supplier $j$ randomly and assign $\underline{a}_j = \overline{a}_j = 0$. |
| 7 | Supply disruption | Link failure | Choose a region $r$ randomly with that has a winning supplier and assign $\underline{a}_j = \overline{a}_j = 0$ for all $j \in \beta_r$. |
| 8 | Demand deviation | Market uncertainty | Change the demand of factories randomly by a maximum of 10%. |
| 9 | Demand deviation | Market uncertainty | Change the demand of factories randomly by a maximum of 30%. |
| 10 | Demand disruption | Factory shutdown | Choose a factory $i$ randomly and make $d_i = 0$. |
| 11 | | | Scenarios 2 + 5 + 9 |
| 12 | | | Scenarios 3 + 5 + 6 + 8 |
| 13 | | | Scenarios 2 + 5 + 7 + 8 |
| 14 | | | Scenarios 2 + 5 + 8 + 10 |
| 15 | | | Scenarios 3 + 5 + 7 + 9 + 10 |

Table 3: Scenarios

| **Type** | $\tilde{L}$ | $\tilde{D}$ | $\tilde{U}$ | $\tilde{p}$ |
|---|---|---|---|---|
| 1 | -0.71 | 0.01 | 82.88 | 0.84 |
| 2 | -6.78 | -1.10 | 89.29 | 1.03 |
| 3 | -1.77 | 0.12 | 83.00 | 0.86 |
| 4 | 0.14 | 2.16 | 81.11 | 0.80 |
| 5 | 0.59 | 14.22 | 80.77 | 0.79 |
| 6 | 0.61 | 20.36 | 81.10 | 0.79 |
| 7 | 3.50 | 112.72 | 79.14 | 0.73 |
| 8 | 0.52 | 6.60 | 81.75 | 0.80 |
| 9 | -0.47 | 14.21 | 79.96 | 0.81 |
| 10 | -21.12 | -20.02 | 46.42 | 0.86 |
| 11 | -21.66 | -17.45 | 62.33 | 1.08 |
| 12 | -6.01 | 7.26 | 73.79 | 0.85 |
| 13 | -6.82 | 90.47 | 77.27 | 0.91 |
| 14 | -30.20 | -25.95 | 47.42 | 1.12 |
| 15 | -33.54 | -21.46 | 26.36 | 0.91 |

Table 4: Scenario analysis

- Uncertain events do not necessarily result in the increase in cost from the regular scenario. As seen from the results, many scenarios resulted in decrease in costs (negative entries). However, this does not imply that uncertainty is favorable and hence one need not consider preemptive strategies. Rather it implies if such scenarios are taken into account a priori, one can construct networks that are robust and provide better performance.
- For scenarios 7 and 13, the $\tilde{D} > \tilde{U}$. It implies that $D^s > U^s$, which seems incorrect. The $D^s$ is determined using the optimal solution of regular scenario and hence results in very high cost when the optimal network is disrupted. This again reiterates the claim of taking into account the scenario in designing robust networks.

## 5.5 Robust design

For solving the robust optimization problem GSN$^R$, we considered all the 15 scenarios, with different $\{p^s\}$ values. The following indicators were used to study the performance:

- $FEA$: Number of feasible instances.
- $INF$: Number of infeasible instances ($\{p^s\}$ values were too close to find a feasible solution).
- $\overline{N}$: Average number of winning suppliers for the regular scenario.
- $\tilde{N}$: Average number of winning suppliers for the robust solution.
- $\tilde{Z}$: Average increase in the strategic investment for robust solution from the regular solution (in %).

| **S. No** | $\{p^s\}$ | $FEA$ | $INF$ | $\overline{N}$ | $\tilde{N}$ | $\tilde{Z}$ |
|---|---|---|---|---|---|---|
| 1 | $p^s = 0.05$, $\forall s$ | 58 | 42 | 25.20 | 30.05 | 14.51 |
| 2 | $p^s = 0.05$, $\forall s$, except for $s = 2, 11, 13, 14, 15$ | 93 | 7 | 23.64 | 28.47 | 15.46 |
| 3 | $p^s = 0.1$, $\forall s$ | 100 | 0 | 23.56 | 28.05 | 15.20 |

Table 5: Experiments for the design of robust GSN

Three experiments were conducted, each with 100 instances and the results are shown in Table 5. The increase in the strategic cost was on average around 15%, but assures of containing costs within 10% for uncertain events, which otherwise would have resulted in more 100% increase in cost.

# 6 Conclusions

Global sourcing networks are subject to *deviations* (exchange rate fluctuations, supply uncertainties, demand uncertainties) and *disruptions* (supplier failure, transportation link failure, factory shutdown) due to economic, political, natural, industry, and intentional risk sources. Deviations and disruptions can render the original sourcing network inefficient and costly, and even sometimes inoperable and inefficient. If the deviations and disruptions are pre-identified by the decision maker, then it is possible to design built-in risk tolerant sourcing networks. In this report, we demonstrated the above using numerical experiments. For the particular case considered in the work, it was shown that by a 15% increase in the strategic investment, it is possible to contain the hike in cost of uncertain events within 10%, which otherwise would have resulted in more than 100% increase in cost.

The methodology used was robust optimization and was solved using CPLEX solver. There are several issues that has to be addressed with respect to solution technique.

- The decision make would often require $K$ best solutions rather than a single optimal solution.
- The problem becomes infeasible due to the values of $\{p^s\}$ that are provided by the decision maker. However, there is no mechanism to identify which of the values are responsible for the infeasibility so that it can be altered.
- The problem size of 5 factories, 50 suppliers, and 15 scenarios were solved within few minutes on a desktop computer. More testing are required to test the scalability of the algorithms for larger problems.

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