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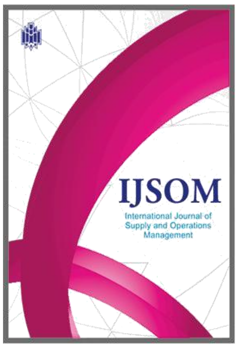

Risk Assessment in the Global Supplier Selection Considering Supply Disruption: A Simulation Optimization Approach

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Abstract

Increasing uncertainties in the supply chains have caused more attentions to the supply chain risk management approaches. Because of the inherent turbulences in the international transactions, these uncertainties in the global context are more important. On the other hand, due to competitive pressures, businesses has been prepared themselves to operate in a global context to take advantage of the international markets. In addition, supplier selection is a challenge for purchasing managers by having more uncertainties in supply from the foreign supplier (exchange rate risk, extended lead times, regional risks). On the other hand, lower price procurement and having more diversified suppliers are the benefits that a company could obtain from global supply chains. In this paper a scenario based supply chain model for global purchasing of substitutable products is introduced and as a solution method a simulation-optimization approach is proposed. The model is applied on the modified data adopted from a case study and sensitivity analyzes (on the risk attitude of retailers, product substitutability and exchange rate) are presented for different amounts of parameters.

Keywords: supply chain, risk analysis, simulation-optimization, substitutable product, global factors.

1. Introduction

Today, firms operate in ever evolving and complex environment. They increasingly depend on complex networks of partners to response to demands of customers in an accurate quantity at the right time and place (Munir et al., 2020). Supply chain is a complex system and usually is characterized by numerous activities across the organizations (Hou and Zhao, 2020). Effective management of the supply chain processes plays an important role in cost reduction of the network. For example an unexpected delay in transshipment of a part in automobile industry can cause a shutdown in the factory and can cost 20,000 dollar per minute and millions of dollars per day. Also in the cereal industry in US, decreasing only one cent per box, would result in 13 million dollars cost saving per year[1]. In addition to these industrial cost benefits, supply chain has been a popular research area. Besides the numerous researches in the field of supply chain management in the last two decades, recently, many researchers have been attracted to study the role of uncertainty in the supply chain models.
By extending a supply chain in the world context, new challenges will emerge (Munir et al., 2020). Most important differences between local and global supply chains are: Tariffs/duties, con-tariff trade barriers, currency exchange rate, corporate income tax, transportation time, inventory cost, worker skill/ availability (Meixell and Gargeya, 2005). A main motivation to maximizing the profits in a global environment stems from sourcing products from the lowest total

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procurement cost locations. In addition to the cost benefits of global souring, sometimes we have to supply from other zones (for example in the case of disaster or disruptions) to satisfy the customer demands. Figure 1 is a historical result from WTO which shows this growing tendency to international trade (the data is scaled base on year 2005, i.e. 2005=100).

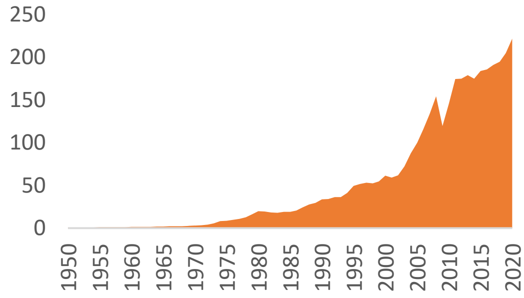

Figure 1. World merchandise exports between 1950-2020 (WTO; annual report, 2020)

The growing tendency to trade in the global context, has been caused different types of uncertainties threatening the procedure of international sourcing. These risks include supply disruption, supply delays, demand fluctuations, price fluctuations, and exchange-rate fluctuations. A global supply chain structured based on the production in low-cost countries, is vulnerable to the risk of supply disruption along with fluctuations in transportation prices and exchange rates (Chopra S. and Meindl, 2018).

A global supply chain risk management includes 5 processes: 1- risk identification, 2- risk assessment and evaluation, 3- selection of appropriate risk management strategy, 4- implementation of the mitigation strategy, 5- mitigation of supply chain risks (Manuj and Mentzer, 2008). This paper is focused on the second step of the risk management in the global supply chains: “risk assessment and evaluation”.

Simulation is a powerful and flexible technique which can be used in different areas of application. However, one of the most powerful tools in risk analysis is Monte Carlo simulation (Sari, 2017).

The remaining of the paper is organized as follows: In the next section, we will review the literature of risk simulation and risk assessment in the supply chain by concentrating to supply chain risk management, role of simulation in risk assessment and global aspects of supply chain management. Then a simulation-optimization approach is introduced and in the next section a case study is presented. The last section dedicated to some conclusions from the application of the proposed approach on the supply chain model.

2. Literature review

Related literature of the paper can be divided into three major categories: risk management in the supply chain, the role of the simulation optimization in the supply chain risk management, and global uncertainties.

2.1. Supply chain risk management

Different types of risks are classified by (Fan and Stevenson, 2018; Zhu et al, 2017). The process of risk management consists of four main approaches: risk identification, risk assessment, risk treatment and risk monitoring. Published papers in this field have could be categorized into quantitative or qualitative works. Only a small fraction of the papers on SCRM is based on quantitative methods (Tang and Musa, 2011). One of the most important challenges in the SCM is quantifying the risks. Most of the quantitative works focused on the risk assessment approaches. The effective management of risks in the supply chain requires a comprehensive, rapid and cost-efficient approach. Deleris and Erhun (2005) proposed a supply network risk assessment tool based on a simple flow model with Monte Carlo simulation to assess uncertainties in supply networks. Mangla et al (2014) developed a risk assessment framework based on Monte Carlo simulation in green supply chain to ensure ecological-economic gains and sustainability in the businesses. Miller and Engemann (2008) presented a model to simulate the effects of natural disaster risks in the supply chain. They also used Monte Carlo simulation approach for generating random trials. Olson and Wu (2011) by using DEA and Monte Carlo simulation developed a risk management model. They analyzed different scenarios of outsourcing in the supply chain by using their risk model. Silva et al. (2011) presented a risk assessment model considering the dependence between risks in the supply chain. They used Monte Carlo simulation to identify the probability of occurring risk events in the supply chain. Monte Carlo simulation has been widely used for quantifying the probabilistic uncertainties in the risk management models.

2.2. Simulation optimization in SRCM

In recent years, more researches have been focused on the supply chain simulation. For example there is a paper investigated the performance of supply chain collaboration using simulation (Ramanathan, 2014). Also Cigolini et al (2014) studied supply chain configuration based on the performance by using discrete event simulation.
Different types of simulation are: spreadsheet simulation, system dynamics, discrete-event simulation and business games (Kleijnen, 2005).
Integrating the simulation approach with optimization techniques is the other area of interest in the recent years. This hybrid approach could support the analysis of risk impacts and selecting the best strategies to mitigate the risk. Oliveira et al (2019) based on the extensive literature review, highlighted the role of simulation and optimization methods in the process of supply chain risk management. Hajian Heidary and Aghaie (2019) asserted that simulation techniques could be used efficiently in the risk assessment process. They used a hybrid agent based simulation and Monte Carlo method to analyze different risk attitudes of retailers. Ge et al (2016) also addressed the benefits of combining simulation techniques and optimization tools in the risk assessment process. They developed a hybrid S&O method to analyze the different strategies for mitigating risks of Canadian wheat supply chain.

2.3. Global supply chain management

There are some review papers about global supply chain management (Mari and Lee, 2015; Meixell and Gargeya, 2005; Pravin et al, 2007) that reviewed different aspects of globalization in the supply chain management. Main international issues in the literature are as follows (Vidal and Goetschalcks, 1997): Stochastic features (such as Exchange rate fluctuation), Taxes and duties, General factors (such as Selection of manufacturing technology), and Trade barriers (such as Quotas, Local content). Key decision variables in the literature are: Facility selection; production/shipment quantities; supplier selection. Based on their survey, globalization considerations in the literature are: Tariffs/ duties; Non-tariff trade barriers; Currency exchange rate; Corporate income tax; Transportation time; Inventory cost; Worker skill/ availability (Meixell and Gargeya, 2005). Designing an efficient approach to quantify the risk is a main problem in the global supply chains (Cohen and Lee, 2020).

Srivastava and Rogers (2021) discussed effects of the industry sector in managing global supply chain risk. They used profile deviation and ideal profile methodology to identify top performers in different sectors of the industries. Choi et al. (2019) used mean-variance approach to quantify the risk the global air logistics operations. Hajian Heidary and Aghaie (2015) also used Monte Carlo simulation method to measure the risk in the global supply chain. One of the risk strategies to cope with the disruption risks is substitutable products (Farahani et al., 2017).

Above mentioned literature consists the basic concepts which have used in this paper. These concepts are: Demand Uncertainty, Supplier Disruptions, Global factors, Risk assessment, Multi period modeling, Risk mitigation strategies. Table 1 shows the related works and difference of our model with them.

To the best of our knowledge, there is no research in the literature about the modeling global purchasing from uncertain suppliers and customers considering substitutability of products. In addition we proposed a novel simulation-optimization approach to solve the problem.

3. Problem definition

Consider a two echelon supply network consisting some suppliers (with different monetary units) and some retailers located in different zones. Retailers receive a local customer demand in each period and to response these demands, they have to place an order to satisfy the customer's demand (a retailer demands only a specific type of products). In this paper we assume that local supplier does not exist and thus the only way to supply the product is to ordering from global suppliers or transshipment from excess inventory of the local retailers. Because of the global issues, a first option for the retailers is the transshipment from the local retailers, but the stochastic demand of the customers may cause a shortage in retailer's inventory and thus they could not supply their total demand from local retailers. Thus, retailers have to order from global suppliers. Ordering from a global supplier takes more time and cost.
In addition, suppliers have a predetermined capacity and cannot supply more than their capacity in each period. On the other hand, some disruption events may be happen in each period for each suppliers. It takes some periods to recover from the disruption event. During a disruption event in a zone, disrupted suppliers cannot respond to the retailer's orders.

To illustrate the problem, we first explain the mechanism of the transactions in the global supply chain and then we introduce the mathematical model. Figure 2 shows a basic global supply chain with 3 substitutable products.

Table 1. The main related works

	Demand Uncertainty	Supplier Disruption	Global factors	Risk analysis	Multi-period	Risk mitigation strategies	Solution approach
Silva et al. (2020)	*	*		*		*	Simulation
Hajian Heidary and Aghaie (2019)	*	*		*	*	*	Simulation-Optimization
Ge et al. (2016)	*	*		*		*	Simulation-Optimization
Srivastava and Rogers (2021)	*	*	*	*			Mathematical modeling
Farahani et al. (2017)	*	*		*		*	Optimization
Hammami et al. (2014)	*		*				Optimization
Zhang et al. (2016)	*		*				Stochastic programming
Park and Kim (2016)	*		*	*			Simulation-optimization
Hammami and Frein (2014)	*		*				Optimization
Schmitt and Sing (2009)	*	*			*		Simulation
Aqlan and Lam (2015)		*	*	*			Fuzzy programming
Aqlan and Lam (2016)		*	*	*			Simulation & optimization
Our model	*	*	*	*	*	*	Simulation-Optimization

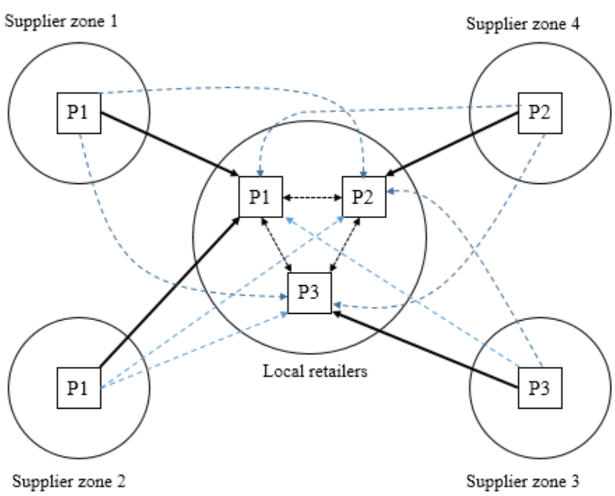

Figure 2. A schematic view of the problem (small scale problem)

As shown in the figure 2, we assume that all the retailers are located in a currency zone and each one is the representative of a specific product in the local zone (i.e. the market is monopole for each product in the local zone). Customers put their orders to the retailers. On the other hand, Original Equipment Manufacturer (suppliers) are located in the different currency zones. It is notable that in a currency zone may exist suppliers of different products. However, in this configuration we assume that disruption events will result in a loss (as a percentage) in the capacity of OEMs. To cope with the possible shortages, based on the risk attitude of retailers, they can decide to purchase from the primary OEM (for example if a retailer is representative of product 2, its primary OEM is an OEM which supply product 2) or secondary OEM (for example OEMs which supply product 1 or 3 are the secondary suppliers of the retailer). Additionally because of the capacity constraint, OEMs cannot supply whatever retailers order from them. In this case, if the retailers have excess inventory at the end of each period, they can order from each other. Obviously, ordering from the global market may incur some transportation costs and also may take more time from local ordering. We assume that there is no local supplier in the system. Thus, retailers have to order from the global primary OEMs and in the case of shortage they have to decide between ordering from secondary suppliers or retailers. As showed in figure 2, for a simple three product configuration (with 4 OEMs in 4 currency zones and 3 retailers), there are many possible decisions.

Assumptions considered in this paper are as follow:
- In a two echelon supply chain (suppliers and retailers), there are different zones with different currencies.
- All of the retailers are located in a specific zone. Suppliers are located in the other zones.
- Suppliers only provide one specific product.
- The market for a specific product in the local zone is monopole.
- Demands receiving by each retailer are for a specific product (primary product), in the case of shortage, retailers can present a secondary product to the customer.
- Secondary products can be supplied from the local market (from other retailers) or from a global market.
- Retailers can order from a secondary supplier if products are substitutable.

We assumed that the substitutable products are electrical and electronic components and we use the data from a case study surveyed by (Amin and Baki, 2017).

4. Mathematical Formulation

In this paper, due to the uncertainties in demands and disruptions, decision on the amount of ordering from primary supplier should be made before when the uncertainties are realized. Additionally, to deal with uncertainties some scenarios are generated using sampling for demands. Also Poisson process is used to conduct disruption events. Thus at the beginning of each period with using the revealed uncertainties, each retailer (based on the ordering policy) makes a decision on the ordering amount from primary suppliers and after realizing the uncertainties, scenario based variables are determined.

Before presenting the mathematical formulation, problem notation is introduced.

4.1. Notations

Sets:
I: set of retailers i ϵ {1, … , I}
J: set of suppliers j ϵ {1, … , J}
K: set of products k ϵ {1, …, K}
M: set of countries of suppliers m ϵ {1, …, M}
T: set of time periods t ϵ {1, …, T}
U: set of possible scenarios u ϵ {1, …, U}

Variables:

$x_{i,j,t}$: Order amount of retailer i from primary supplier j at time t, $\forall i \in I, j \in J, t \in T$

β_i : risk attitude of retailer i (smaller amount of β results in risk averse attitude and greater amounts results in risk taker attitude)

$x^u_{i,j,t}$: Order amount of retailer i from secondary supplier j at time t in scenario u, $\forall i \in I, j \in J, t \in T$

$y^u_{i,l,t}$: The amount transshipped from retailer i to retailer l at time t in scenario u, $\forall i \in I, l \in I, t \in T$

$e^u_{i,t}$: Shortage amount of retailer i at period t in scenario u.

$I^u_{i,t}$: Inventory level of retailer i at time t in scenario u

$d^u_{i,t}$: Amount of the customer demand satisfied by retailer i at time t in scenario u

Parameters:

p_{k_i} : selling price of product k_i

$c_{k_j jm}$: procurement cost of product k_j determined by supplier j in currency of country m

$f_{k_j jm}$: customs duty rate of product k_j from supplier j in currency of country m

$tg_{ijk_j m}$: transportation cost of product k_j per km between supplier j and retailer i in currency of country m

$dg_{i,j}$: distance (in km) between retailer i and supplier j

$D_{i,k_i,t}$: Random demand of product k_i at time t which should be satisfied by retailer i. (It is assumed that demand is distributed normally in each period)

τ_i : shortage cost of retailer i

h_i : holding cost of retailer i

l_{ij} : denoting leadtime between ordering from supplier j by retailer I (we assume that leadtime for local transshipment is equal to zero)

$\theta_{m,t}$: exchange rate of the currency of country m at time t

ς_j : the parameter of the exponential distribution shows the times between occurring disruptions in supplier j (Disruptions for supplier j are assumed to take place based on a poison process)

R_j : The time that supplier j requires to recover from the disruption (It is assumed that recovery time is distributed normally)

$\pi_{j,t}$: Intensity of the disruption occurred in supplier j at time t (percentage of the supplier j's capacity which will be out of service in the case of disruption; $0<\pi_{j,t}\leq 1$)

cap_j : Fixed capacity of supplier j

As discussed in the previous section, the products of the certain suppliers (each supplier supply only one product), possess a degree of substitutability, i.e., each product's price has an effect on its own demand and on the other product's demand. Based on the definition of (Hsie and Wu, 2009), if k_1 and k_2 are defined as two substitutable products, the substitutable demand is as follows:

$$D_{i,k_i,t}=\alpha_{i,k_i,t}-\gamma_{k_i}^{i\to j}p_{k_i}+\gamma_{k_j}^{i\to j}p_{k_j},(k_i,k_j\in K) \tag{1}$$

Where, $\alpha_{i,k_i,t}$ is a random normal variable. Also $\gamma_{k_i}^{i\to j}-\gamma_{k_j}^{i\to j}$ is defined as the degree of substitutability between products k_i and k_j ($\gamma_{k_i}^{i\to j}>\gamma_{k_j}^{i\to j}>0$). The smaller amount of difference between these parameters shows higher substitutability.

Indeed, k_i is the primary product of the retailer "i", and k_j is the only product which supplier "j" can present to the received orders. In other words, if $k_i=k_j;(i,j\in K)$ supplier j is the primary supplier of retailer "i" and if $k_i\neq k_j(k_i,k_j\in K)$ substitutability of product k_i and product k_j should be checked.

Indeed, two products are substitutable if $\Lambda_{k_i\to k_j}=1$ as follows (ε is a very small number and M is a big number):

$$\varepsilon\Lambda_{k_i\to k_j}\leq\gamma_{k_i}^{i\to j}\gamma_{k_j}^{i\to j}\leq M\Lambda_{k_i\to k_j} \tag{2}$$

Therefore retailer i can order from supplier j if $\Lambda_{k_i\to k_j}$ equals to one.

Maximizing the profit function is a usual objective in the inventory models. Based on the notations introduced above, the profit function in scenario "u" is:

$$z_u = \sum_t \sum_i p_{k_i} d_{i,t}^u + \sum_t \sum_{i,l \in I} p_{k_i} y_{\mathrm{i,l,t}}^u - \left(\begin{array}{l} \sum_t \sum_m \sum_i \sum_j \sum_k \theta_{m,t} ((1+f_{k_j jm}) c_{k_j jm} + tg_{ijk_j m} dg_{i,j})(x_{i,j,t} + x_{i,j,t}^u) \\ + \sum_t \sum_i \tau_i e_{i,t}^u + \sum_t \sum_i h_i I_{i,t}^u + \sum_t \sum_{i,l \in I} (p_{k_i} + v_{il}) y_{\mathrm{l,i,t}}^u \end{array} \right) \tag{3}$$

The constraints of the model are defined as follows.
Constraint (4) is an equilibrium equation for the retailer's inventory.

$$I_{i,t}^u = I_{i,t-1}^u + \sum_j x_{\mathrm{i,j,t-l}_{ij}} + \sum_j x_{\mathrm{i,j,t-l}_{ij}}^u + \sum_{l \neq i, \mathrm{l} \in I} y_{\mathrm{l,i,t}}^u - d_{i,t}^u - \sum_{l \neq i, \mathrm{l} \in I} y_{\mathrm{i,l,t}}^u \tag{4}$$

$$d_{i,t}^u + e_{i,t}^u = D_{i,t}^u \tag{5}$$

The following constraints show the limitations of supplier's capacity and transshipment of retailers.

Consider $\mathrm{z}_{j,t}$ a binary variable which equals to "1" if supplier "j" at time t is disrupted and equals to zero otherwise.

$$\sum_i (x_{\mathrm{i,j,t}} + x_{\mathrm{i,j,t}}^u) \leq cap_j (\mathrm{z}_{j,t}(1-\pi_{j,t}) + (1-\mathrm{z}_{j,t})), \forall i,t \tag{6}$$

$$\sum_{l \in I} y_{\mathrm{i,l,t}}^u \leq I_{i,t}^u \tag{7}$$

$$\varepsilon \Lambda_{k_j \to k_i} \leq x_{\mathrm{i,j,t}} \leq M \Lambda_{k_j \to k_i} \tag{8}$$

$$\varepsilon \Lambda_{k_j \to k_i} \leq x_{\mathrm{i,j,t}}^u \leq M \Lambda_{k_j \to k_i} \tag{9}$$

$$\varepsilon \Lambda_{k_l \to k_i} \leq y_{\mathrm{i,l,t}}^u \leq M \Lambda_{k_l \to k_i} \tag{10}$$

According to Mizgier et al. (2015), two important properties of a disruption event are: inter arrival time and recovery time. Also same as their work, in this paper disruption events are assumed to take place based on the Poisson process such as figure 3.

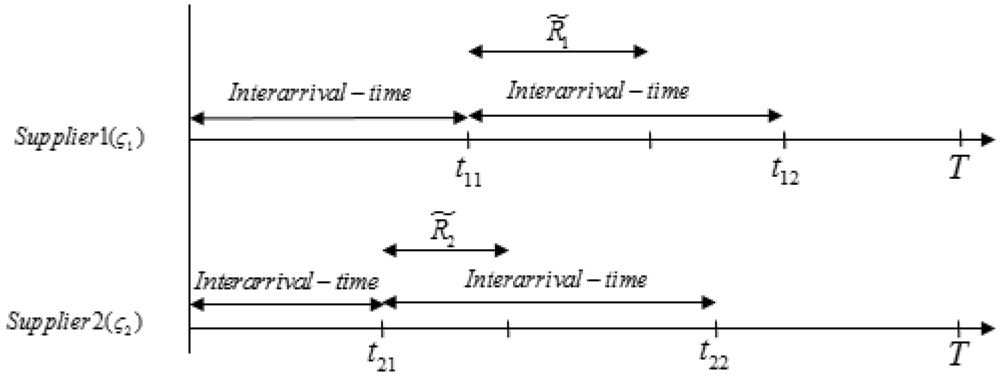

Figure 3. Disruption mechanism for two suppliers ($\varsigma_2 < \varsigma_1$) based on Poisson process

Supplier sharing condition depends on the risk attitude of the retailers. Based on the assumptions of Poisson process, following inequality, shows the extent of the decision on the risk attitude of retailer "i".

$\min\{\varsigma_1, \varsigma_2, ..., \varsigma_J\} \leq \beta_i \leq \max\{\varsigma_1, \varsigma_2, ..., \varsigma_J\}$; Smaller values for β_i, show more risk averse behavior of retailer "i". If mean disruption probability of supplier "j" is greater than risk attitude of retailer "i", and if supplier "j" is not a primary supplier of retailer "i", means that retailer "i" is not tending to buy from supplier "j".

Based on the value of β_i, retailer "i" decides on the shared buying with other suppliers. We define a binary variable ($\varphi_{i \to j}$) which equals to 1 if he decides to have a shared buying with supplier "j" and equals to zero O.W. (based on the risk attitude of retailer "i").

$$\varphi_{i \to j} \varsigma_j < \beta_i \leq M \varsigma_j \varphi_{i \to j} + \varsigma_j \tag{11}$$

$$x^{u}_{\mathrm{i,j,t}} \le M\varphi_{i\to j} \tag{12}$$

In the remaining parts of this section, we introduce the expected profit and the CVaR model.

EP- model: A basic expected profit objective function for the problem is as follows:

Max $W_1 = \sum_u P_u z^u$

Subject to

Constraints 2-12

$$x_{\mathrm{i,j,t}}, x^{u}_{\mathrm{i,j,t}}, y^{u}_{\mathrm{i,l,t}}, e^{u}_{i,t}, I^{u}_{i,t}, d^{u}_{i,t} \ge 0; \forall i,l \in I, \forall j \in J, \forall t \in T, \forall u \in U \tag{13}$$

$$\lambda^{u}_{i,j,t}, \omega^{u}_{\mathrm{i,l},t}, \Lambda_{k_i \to k_j}, \varphi_{i\to j} \in \{0,1\} \quad \forall i,l \in I, \forall j \in J, \forall t \in T, \forall \{k_i, k_j\} \in K, \forall u \in U \tag{14}$$

$$0 \le \beta_i \le 1, \ \forall i \in I \tag{15}$$

In order to quantifying the risk in the supply chain, we used conditional value at risk (CVaR). Basically, there are two popular risk assessment measure to quantifying the risk: VaR and CVaR; Figure 4 shows the difference between VaR and CVaR.

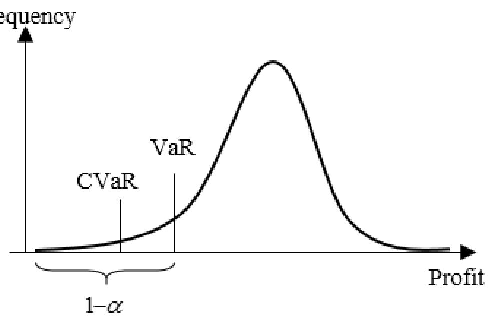

Figure 4. The comparison between VaR and CVaR in a profit function

In our problem, the amount of profit in α percent of time, which will not be less than a specific value, is called VaR_α (i.e. it measures $1-\alpha$ quantile of the profit). In order to considering values smaller than VaR, an alternative risk assessment tool is CVaR (Rockafellar and Uryasev, 2000). Indeed, CVaR is a more completed tool to analyze the risk and calculates the expected amount of profits which are smaller than VaR. According to Uryasev (2002) optimizing VaR in the scenario modeling approaches, is very difficult. He asserted that for discrete distributions (scenario based models), CVaR is equal to finding the maximum of the following formula:

$$F_\alpha(x,\Psi) = \Psi + \frac{1}{1-\alpha}\sum_u P_u[f(\mathrm{x},\vartheta_u) - \Psi]^+ \ , \ [\mathrm{x}]^+ = \max\{0,x\}$$

Based on Uryasev (2002), maximization of $F_\alpha(x,\Psi)$ is equal to maximization of $CVaR_\alpha$. Therefore the basic model can be attained as follows ($0 \le \alpha \le 1$ is a confidence level for CVaR):

CVaR-profit Model:

Max $W_2 = VaR - (1-\alpha)^{-1}\sum_{u=1}^{U} P_u \psi_u$

Subject to

Constraints 2-15

$$\psi_u \ge VaR - z_u$$

$$\psi_u \ge 0$$

Up to here, we introduced two scenario-based mathematical programming models of the global supply chain with substitutable products. It has been proved that a supply problem with one retailer and some unreliable suppliers is not computationally tractable in the large size problems (Ray and Jenamani, 2016). By increasing the number of suppliers, the number of sub-problems to be solved increase exponentially ($2^n - 1$). However, in our problem, there are “I” retailers which order from “J” unreliable suppliers. Thus the problem presented in this paper is more complex than (Ray and Jenamani, 2016). Hence, in the section 5 we will introduce a simulation-optimization approach for risk assessment and obtaining near-best solution.

5. Risk assessment approach

In this paper we propose a simulation optimization framework to solve a global purchasing problem with substitutable products. Figure 5 shows the overall process of simulation-optimization procedure.

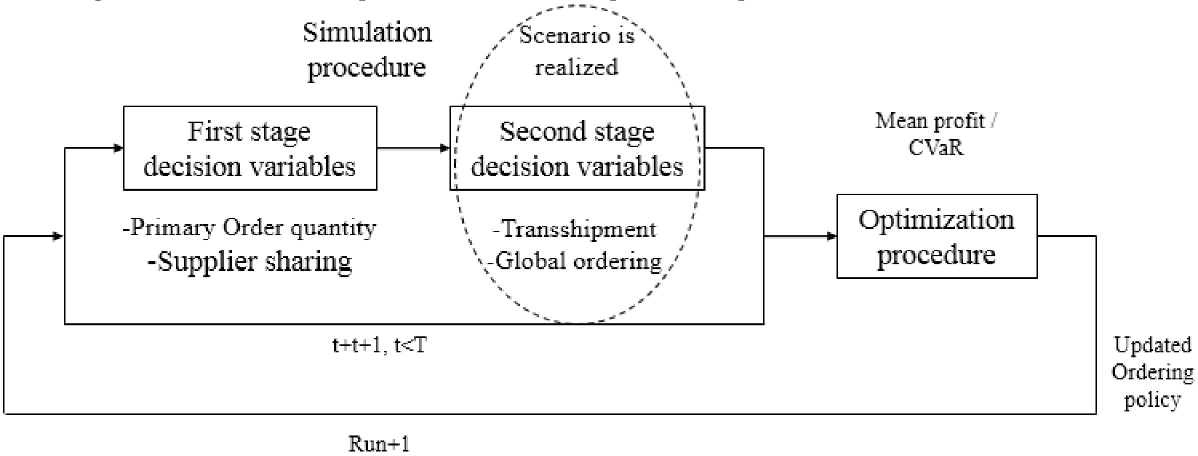

Figure 5. An overview of the simulation optimization approach

In the simulation-optimization approach, the Monte Carlo simulation used with a single run and "U" iterations. Indeed in each iteration, the algorithm executes a scenario with regarding to the parameters of demand and disruption randomly. At the end of the simulation run, outputs (decision variables, objective function, and performance criteria) of the simulation, enter into the optimization procedure and the best solution of the optimization will be inserted in the simulation and a new run with previous scenarios (iterations) will be executed. This procedure continues until the termination conditions are satisfied.

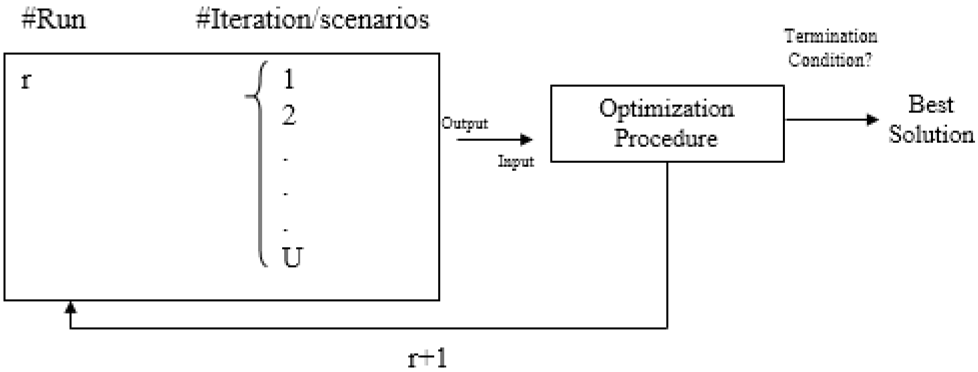

Figure 6. Relation between the inputs and outputs of the simulation and optimization

5.1. Simulation procedure

Simulation process consists of two stages (figure 7): determining first stage decision variables and based on the obtained results, in the second stage, algorithm looks for the second stage variables. To simulate the supply chain, Monte Carlo simulation is used. Figure 7 shows the two stage scenario based simulation of the decision variables related to retailer "i" at time "t". This procedure is performed for all other retailers and for whole the time horizon of the simulation.

Adopted ordering policy in this paper is based on the usual (s, Q) inventory policy. It means that in each period, based on the reorder point, retailers order a fixed amount of Q. But Q is an initial value which could be changed according to the supplier capacity.

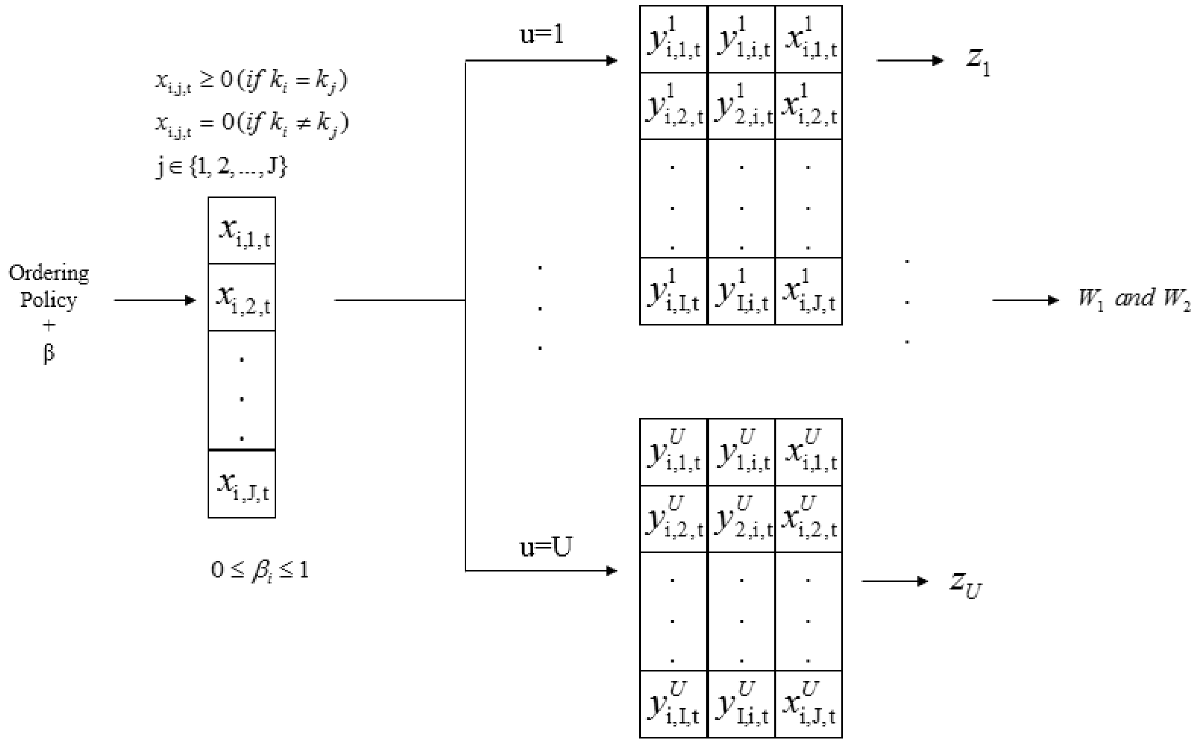

Figure 7. An overall view of the simulation procedure

Indeed the basic values which should be optimized in the heuristic optimization procedure are s_i and Q_i. Based on the disruption events (Poisson process), capacity of the suppliers can be determined and if the inventory position of the retailer "i" will be smaller than s_i a fixed order (Q_i) will be issued, otherwise the amount of order from primary supplier will be zero. Optimization procedure is described in section 5.2. The rules to determine $x_{i,j,t}$ (according to s_i and Q_i) at the beginning of period "t" and after realizing demand scenario are as follows:

$$-M\chi_i + s_i \le I^u_{i,t-1} + \sum_j x_{i,j,t-l_{ij}} + \sum_j x^u_{i,j,t-l_{ij}} < s_i + M(1-\chi_i) \quad \forall i,t$$

$$-\mathrm{M}\chi_{ij} + \left[cap_j(\mathrm{z}_{j,t}(1-\pi_{j,t}) + (1-\mathrm{z}_{j,t}))\right] \le Q_i < \left[cap_j(\mathrm{z}_{j,t}(1-\pi_{j,t}) + (1-\mathrm{z}_{j,t}))\right] + \mathrm{M}\chi_{ij} \quad \forall i,j,t$$

$$x_{i,j,t} = Q_i\chi_i\chi_{ij} + \left[cap_j(\mathrm{z}_{j,t}(1-\pi_{j,t}) + (1-\mathrm{z}_{j,t}))\right]\chi_i(1-\chi_{ij}), \quad \forall i,j,t$$

$$\chi_i, \chi_{ij} \in \{0,1\}, \quad \forall i,j$$

Therefore, simulation algorithm is as follow:

Run #r of the simulation algorithm	
Inputs:	Demand distributions and disruption probabilities
	$\beta_i,\ x_{i,j,t}(\mathrm{s}_i,\mathrm{Q}_i)(\forall i \in I, j \in J, t \in T)$ of all iterations
Outputs:	W_1 and W_2
1. Executing the simulation roles same as the Figure7.	
2. Calculating scenario-based decision variables $y^u_{i,l,t}, y^u_{l,i,t}, x^u_{i,j,t}(\forall i,l \in I, j \in J, t \in T, u \in U)$	
3. Objective functions are calculated based on the import decision variables (W_1 and W_2)	

The simulation procedure is shown in the figure 8:

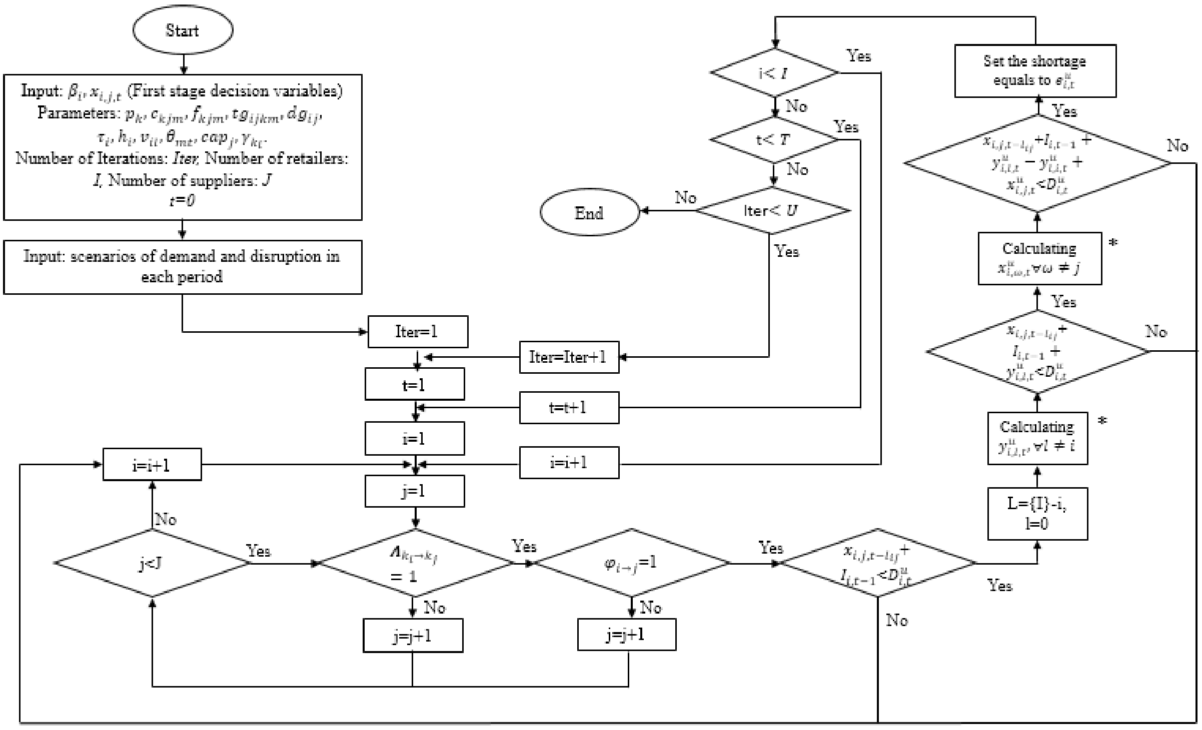

Figure 8. Overall rules per run #r in the simulation

In the figure 8, for calculating $y^u_{i,l,t}$, $y^u_{l,i,t}$ (have the same rule) and $x^u_{i,j,t}$ there are two sub-algorithms which are explained below.

a. transshipments between retailers

The best decision on the transshipment between retailers with qualified conditions (positive inventory) is ordering from a retailer with lowest product price and higher substitutability ratio. Therefore, in the following sub-algorithm, retailers are sorted based on these criteria.

Note that this algorithm will execute for all the retailers, thus $y^u_{i,l,t}$, $y^u_{l,i,t}$ are calculated simultaneously.

b. reordering from global suppliers

In the case that local retailers could not satisfy excess demands, reordering from global suppliers is the second way to cope with the uncertainties. Following sub-algorithm shows the mechanism of determining $x^u_{i,j,t}$. Ordering from global suppliers takes more time and cost, thus ordering from local retailers has more cost benefits. Hence in the previous part (a), retailers first try to replenish from local retailers and then they will try to reordering from global suppliers.

Sub-algorithm (calculating transshipments between retailers)
Input: $x_{i,j,t}$, $I^{u}_{i,t}$, p_{k_i} Output: $y^{u}_{i,l,t}$
$d^{u;1}_{i,t} = I^{u}_{i,t-1} - I^{u}_{i,t} + \sum_{j} x_{i,j,t-1_{ij}}$ if $d^{u;1}_{i,t} < D^{u}_{i,t}$ L={} $l = \{1:i-1\} \cup \{i+1:I\}$ for $l = 1:I$ $y^{u}_{i,l,t}$=0   if $I^{u}_{l,t} > 0$ if $\Lambda_{k_l \to k_i} = 1$; L=L∪{ l }; $p' = p_{k_l}$ end   end   end   [sorted {L}, $p_{k_l} \frac{\gamma^{l\to i}_{k_l}}{\gamma^{l\to i}_{k_i}}$]=sort($p_{k_l} \frac{\gamma^{l\to i}_{k_l}}{\gamma^{l\to i}_{k_i}} \forall l$)   for l =1:|L| if $I^{u}_{l,t} \ge (D^{u}_{i,t} - d^{u}_{i,t})$: $y^{u}_{i,l,t} = I^{u}_{l,t} - (D^{u}_{i,t} - d^{u}_{i,t})$, $I^{u,new}_{l,t} = I^{u}_{l,t} - (D^{u}_{i,t} - d^{u}_{i,t})$, $I^{u}_{l,t} = I^{u,new}_{l,t}$ else $y^{u}_{i,l,t} = I^{u}_{l,t}$, $I^{u}_{l,t} = 0$ end   end   else $y^{u}_{i,l,t} = 0$ end

Proposition1. Reordering from global suppliers depends on some conditions regarding the suppliers: substitutability of products, intensity of disruption and exchange rates; and some condition regarding retailers: share of the retailer in total revenue and total cost. In order to select the best values for the decision variable $x^{u}_{i,j,t}$ (considering constraints), we need to define a measure to sort the retailers ($K_i = \frac{p_{k_i}}{h_i + \tau_i}$) and then we need a measure to sort the suppliers ($m_{i,j,t}$):

$$m_{i,j,t} = \left(\left(c_{k_j jm}(1+\mathrm{f}_{k_j jm})\theta_{m,t}\right) + tg_{ijk_j m} dg_{ij}\right)\left(\pi_{j,t} pr_{j,t} + (1 - pr_{j,t})\right)\frac{\gamma^{l\to i}_{k_l}}{\gamma^{l\to i}_{k_i}}$$

Where $pr_{j,t}$ is the probability of occurring disruption in supplier “j” at time t; Sorting based on $m_{i,j,t}$ results in the lowest cost of purchasing.

Proof. p_{k_i} represents the ratio of revenue to the cost of retailer “i". Value of K_i shows the priority of the retailer “i" in ordering from the suppliers. $m_{i,j,t}$ represents the expected unit cost of the products purchased from supplier “j” by retailer “i". Therefore the optimal decision for $x^{u}_{i,j,t}$ is to select a retailer with the most impact on the revenue/cost ratio and then select a supplier with least expected cost. Thus, first of all, retailers must be sorted based on their K_i .For retailer “i" (if retailer “i" would be the first rank of the list) by sorting suppliers in increasing order of $m_{i,j,t}$ and assigning the excess demand of retailer “i" to them individually, the corresponding expected profit obtained by retailer “i" will be sorted in a decreasing order. First we select a retailer and then for that retailer we find a supplier.

Corollary 1: According to the supplier disruption probability, if the supplier with the lowest value for $m_{i,j,t}$ cannot satisfy the total order quantity of retailer i, the next suppliers in the increasing order of $m_{i,j,t}$ must be considered in the sequence. The sub-algorithm will repeat for all retailers in the increasing order of K_i to assign all excess demands to the suppliers. Finally, because of the disruption uncertainty, if any excess demand exists in the network, it will considered as a shortage.

Therefore, the sub-algorithm of reordering from global suppliers is as follow:

Sub-algorithm (calculating reordering from global suppliers)

Input: $x_{i,j,t}$, $y^u_{i,l,t}$, $y^u_{l,i,t}$, $I^u_{i,t}$, p_{k_i}

Output: $x^u_{i,j,t}$

$d^{u;2}_{i,t} = I^u_{i,t-1} - I^u_{i,t} + \sum_j x_{i,j,t-l_{ij}} + \sum_{l\neq i, l\in I} y^u_{l,i,t} - \sum_{l\neq i, l\in I} y^u_{i,l,t}$

Ξ ={}

$\Omega = \{\}$

for i=1:I

if $d^{u;2}_{i,t} < D^u_{i,t}$

$\Omega = \Omega \cup \{i\}$

[sorted {Ω }, $\frac{p_{k_i}}{h_i + \tau_i}$] = sort(K_i)

else $x^u_{i,j,t} = 0$

end

end

for j=1:J

$rcap_{j,t} = cap_j - \sum_i x_{i,j,t}$

if $rcap_{j,t} > 0$

$\Xi = \Xi \cup \{j\}$

[sorted {Ξ }, $p_{k_i} \frac{\gamma^{l\to i}_{k_i}}{\gamma^{l\to i}_{k_i}} \theta_{m,t}(\pi_{j,t} pr_{j,t} + (1 - pr_{j,t}))$] = sort($m_{i,j,t}$)

else $x^u_{i,j,t} = 0$

end

end

for i' = $\Omega_1 : \Omega_{|\Omega|}$

for j' = $\Xi_{[1]} : \Xi_{[|\Xi|]}$

if $rcap_{j',t} > D^u_{i',t} - d^{u;2}_{i',t}$

$x^u_{i',j',t} = D^u_{i',t} - d^{u;2}_{i',t}$

else $x^u_{i',j',t} = rcap_{j',t}$

end

end

end

5.2. Optimization procedure

As mentioned before, the optimization procedure that we used in this paper is genetic algorithm (GA). Genetic algorithm is an evolutionary optimization algorithm which have been built originally based on the bio sciences (genetic science) and is the most widely-investigated evolutionary algorithm. The idea behind this algorithm stems from the natural breeding of the animals and humans. There are a set of rules describing how living organisms are working in dairy life. These rules are summarized in the genes. A string of some genes are called a chromosome. The evolution mechanism of the chromosomes will be happened based on the mating of them results in a new (child) chromosome which has some properties of each parent chromosomes. In the genetic algorithm it will be done by the operators such as crossover or mutation. Then, the evolution procedure will continue with selecting the best child chromosomes and substituting them with the worst parent chromosomes. This set of chromosomes builds a population set. Usually initial population consists of random chromosomes or some historical data. This evolution procedure repeats until the termination conditions are attained.

Genetic algorithm has been developed and used in different areas, but in this paper will connect the outputs of the simulation algorithm with optimization algorithm simultaneously. The optimization algorithm (considering the output of the simulation as input of the algorithm) is as follows: (optimization process is done by linking the simulation process with GA toolbox of the Matlab software)

GA algorithm for Run #r

Inputs: $\beta_i, Q_i, s_i \ \forall i \in I$

Outputs: $\beta_i^*, Q_i^*, s_i^* \ \forall i \in I$

1. Set size of the pop_chrom equals to pop_chrom_size
2. Compare the members of the pop_chrom with the inputs (based on the objective function)
3. Select the best members of the inputs and substitute them with the worst pop_chrom members (the pop_chrom will change to new_pop_chrom)
4. With a crossover probability, perform crossover on the new_pop_chrom
There are some conditions to guarantee the feasibility of the solutions
5. With a mutation probability, perform mutation on the new_pop_chrom
Feasibility conditions to be considered same as crossover.
6. Compare the new childes from crossover and mutation with new_pop_size (based on the objective function)
7. Substitute the new childes from crossover and mutation (which have better objective function in relation to the new_pop_chrom members) with new_pop_chrom members
8. Set $\beta_i^*, Q_i^*, s_i^* \ \forall i \in I$ *equal to the decision variables of the best objective function in new_pop_chrom*

5.3. Simulation- optimization

In the previous sections, we have explained the process of simulation and optimization separately. In the simulation section, the rules of the simulation introduced and in the optimization section a meta-heuristic approach introduced to analyze and optimize the results of the simulation. The interaction between simulation and optimization is shown in the following pseudocode.

```
Start
Sample from distribution functions and generate scenarios
  for Run = 1: Max_Run
    Execute simulation procedure
    Execute optimization procedure
    Substitute the best solution of the optimization in the simulation
    Calculate W_1,W_2
  end
end
```

In the next section, a real case study description will be explained and the simulation-optimization algorithm will be applied on it.

6. Numerical example

In order to conduct numerical experiments and according to the complexity of the problem (which has discussed before), the mathematical program explained in section 4 will be solved by the simulation-optimization algorithm presented in section 5. The main goal of the experiments are:

- Evaluating and solving a global purchasing problem considering disruption probabilities.
- Driving some insights which would be interesting for the researchers and practitioners.

6.1. Case study description

In this section we first explain a case study from Amin and Baki (2017), and with adding some assumptions to that, we analyze the performance of the proposed simulation-optimization algorithm. They analyzed a supply network of electrical equipments in a closed loop multi-product global supply chain. In this paper we neglect the return process and on the other hand we assumed that the products are substitutable. In addition our supply chain consists of two echelon: global suppliers and local retailers. To form the numerical parameters, we assumed that local retailers are located in Canada and two global suppliers are located in USA and China. Figure 9 shows the transactions between retailers and primary and secondary suppliers. In addition we assumed that suppliers face different disruption probabilities.

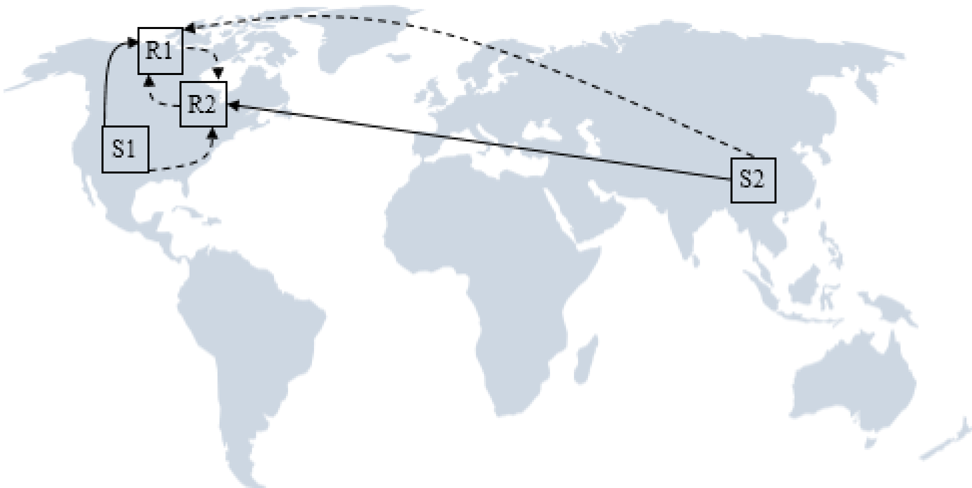

Figure 9. A basic illustrative and schematic global supply chain

Retailer 1 and 2 are two local retailers which order two substitutable products from supplier 1 and supplier 2. In this model we assumed that each supplier is located in a separate country and supply only one type (or brand) of the product, and each retailer only works with one of the suppliers. Because of the substitutability of the products, in the case of disruption, retailers can order from other supplier to satisfy the customer demand. On the other hand, we assumed that the customer demand is stochastic. Consequently, increasing demand may result in a shortage. In this case, retailers (after revealing the demand) can sell the product to each other (if they have positive on hand inventory). We assumed that transportation cost between retailers (as they are in the same region) are negligible. Obviously, local supplying takes smaller time than global one.

The currency of three countries are: CAD (Canadian Dollar) for the local retailers, USD (US Dollar) and CNY (Chinese Yuan) for two global suppliers. Followings, exchange rate of CAD/USD and CAD/CNY are shown between 2016 and 2020.

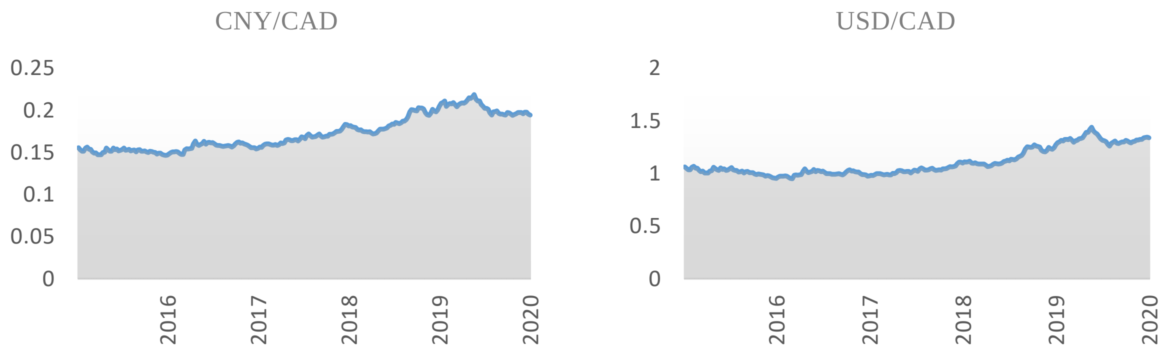

Figure 10. Foreign exchange rate of Canadian Dollar in relation to China Yuan (left) and US Dollar (Right) between 2016-2020 (www.federalreserve.gov/releases/hist)

Obviously the variation in CNY (between 4.5 and 6.8) is more than USD (between 0.69 and 1.05).
Based on the reports of International disaster database, during 2016 to 2020 disasters occurred in these two regions are as follows:

Table2. Number of technological disasters occurred in USA and China during 2016-2020

	USA	China
2016	2	28
2017	0	15
2018	3	11
2019	3	11
2020	4	18
Average	2.4	16.6

Therefore the mean parameters of Poisson process for disruption events are equal to 2.4 (disruption/year) for USA and 16.6 (disruption/year) for China (disruption probabilities are in a uniform distribution with min=2.4-0.5 and max=2.4+0.5 for the US supplier and likewise for Chinese supplier, thus the risk attitude parameter is selected from a uniform distribution between zero and one). A technological disaster is a type of malfunction in a technological structure caused by a human error. We adopted required values of the parameters considered by Amin and Baki (2017) with some modifications to considering disruption of suppliers and also the substitutability of products. Other parameters such as disruption and exchange rate adopted from the facts which had been occurred during 2016 and 2020. To reduce complexity of computations, size of the problem has been reduced to two tires with two suppliers, two retailers and two substitutable products.

Selling price of the products (p_{k_1}) is equal to 3000 for both two products. Transportation cost between retailer and suppliers for product 1 equals to 0.0035 and for product 2 is equal to 0.0040 per km in currency of local country, additionally the custom duty rate for this kind of product is equal to 0.13. We supposed that the average demand of retailer “j” for product “k” is 1% of the population of the retailer’s city. To the purpose of this paper, we assumed that the retailers are located in Waterloo and Brantford (these two cities are close together approximately and thus we neglected the transportation cost between them). Based on the statistics from the government and the municipalities, we can conclude that the average demand of waterloo is 5750, and average demand of Brantford is 960. We assumed that standard deviation of demands are equal to one tenth of the average. It is assumed that the retailer in Brantford work with the supplier located in China (Original supplier of product 1) and the retailer located in waterloo work with the supplier located in USA (original supplier of product 2). In addition, we assumed that the capacity of suppliers 1 and 2 are equal to 8000 and 1000 respectively. Distances between retailers and suppliers are calculated using Google Map. In addition we assumed that procurement cost of the products is 10 percent less than the selling price. Holding cost usually equals to the interest rate times the price of the product. Thus holding cost is equal to 22.5; we assumed that shortage cost per unit is equal to 100. Finally customs duty can be calculated based on the import and export cities. Regarding substitutability of the products, it is supposed that 30 percent of each product can be used to satisfy the excess demand of the customers. On the other hand, Chinese suppliers provide product with half price of the USA supplier. Also in the model there are lead-times to prepare retailer’s order. The lead-time to ordering primary product is 2 weeks for both suppliers but the lead-times of ordering for secondary product for USA is 3 weeks and for China is 4 weeks. Additionally, 50 percent of the product 1 could be substituted by product 2.

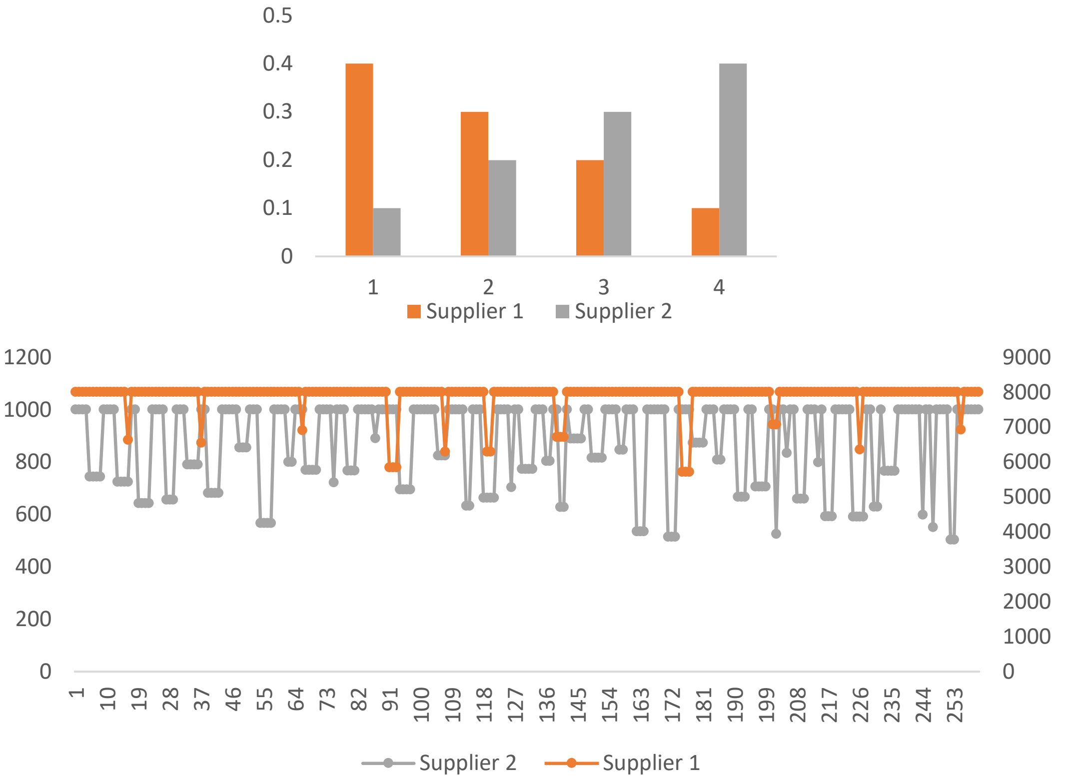

Figure 11. Discrete distribution of the length of disruption (weeks) in supplier 1 and 2 (up), Disruption events during the time horizon (down)

Followings, based on the above configuration, results of applying the simulation-optimization (we have considered 50 iterations or scenarios with 100 runs) algorithm are shown. Mutation and crossover probabilities are equal to 0.1 and 0.5 respectively.

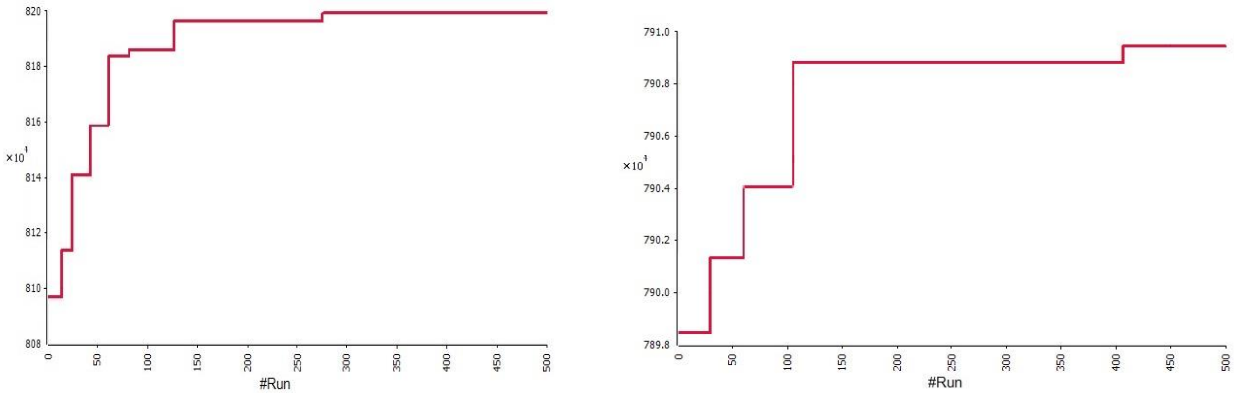

Figure 12. Results of the Simulation-optimization algorithm for CVaR (left) and mean-profit (right) objective functions

Detailed results of the executing simulation-optimization algorithm (500 runs) have been shown in the table 3.

Table3. Detailed results of the optimization algorithm for mean-profit objective function

#Run	s_1	s_2	Q_1	Q_2	β_1	β_2
1	18800	8300	8900	300	0.1	0.9
29	20000	8300	10000	300	0.2	1
60	18800	8300	10000	300	0.4	1
104	19600	8400	9900	300	0.2	1
406	19600	8500	9900	300	0.2	1

Amounts of the β_1 and β_2 show the best decision for retailer 1 is the smaller amount of β and for retailer 2 is the greater amount of β.

Results of the table 4 prove the conclusions obtained in table 3 regarding the risk behavior of retailers. Followings, sensitivity analyzes are discussed.

Impact of risk attitude of retailers

In this section the attitude of the retailer to the risk is considered as a parameter and a sensitivity analysis has been conducted for different values of the risk attitudes. Considering that retailer 1 is risk taker and retailer 2 is risk averse, table 5 shows the results of the simulation optimization algorithm regarding the percentage of change in the amounts of CVaR and mean-profit of retailers.

Table4. Detailed results of the optimization algorithm for CVaR objective function

#Run	s_1	s_2	Q_1	Q_2	β_1	β_2
1	800	1500	9000	300	0.1	0.4
13	19800	6700	8900	400	0.2	0.4
14	13800	1200	9000	400	0.1	0.5
24	19600	1100	9200	300	0.4	0.8
43	18400	1100	9100	300	0.4	0.8
60	18800	1100	9100	300	0.4	0.8
80	20000	1100	9100	300	0.3	0.8
124	20000	1200	9100	300	0.3	0.8
274	19200	1200	9100	300	0.3	0.8

Table5. Change percentage of the objective functions according to the risk attitude of retailers

	β_1														
	0.5			0.6			0.7			0.8			0.9		
	β_2			β_2			β_2			β_2			β_2		
	0.1	0.2	0.3	0.1	0.2	0.3	0.1	0.2	0.3	0.1	0.2	0.3	0.1	0.2	0.3
Z	48%	46%	41%	35%	34%	38%	27%	25%	24%	16%	9%	**0%**	11%	10%	8%
W	51%	50%	42%	45%	41%	39%	31%	25%	23%	19%	16%	14%	8%	**1%**	7%

As shown in the table 5, decreasing β_1 will result in a major change (negative impact) in Z and W.

Impact of product substitutability

In this paper, product substitutability considered as a parameter and a sensitivity analysis has been performed for different values of this parameters. Table 6 shows the sensitivity analysis on the different amounts of $\frac{\gamma_1^{1\to 2}}{\gamma_2^{1\to 2}}$ (ratio of product substitutability when retailer 1 sells its excess inventory to retailer 2) and $\frac{\gamma_2^{2\to 1}}{\gamma_1^{2\to 1}}$ (ratio of product substitutability when retailer 2 sells its excess inventory to retailer 1).

Table6. Risk attitude of the retailers according to the substitutability of the products

$\frac{\gamma_1^{1\to2}}{\gamma_2^{1\to2}}$	0.1					0.3					0.5					0.7					0.9				
$\frac{\gamma_2^{2\to1}}{\gamma_1^{2\to1}}$	0.1	0.3	0.5	0.7	0.9	0.1	0.3	0.5	0.7	0.9	0.1	0.3	0.5	0.7	0.9	0.1	0.3	0.5	0.7	0.9	0.1	0.3	0.5	0.7	0.9
β_1	0.1	0.1	0.1	0.1	0.15	0.1	0.1	0.15	0.15	0.15	0.1	0.2	0.3	0.35	0.35	0.15	0.3	0.35	0.4	0.55	0.2	0.2	0.25	0.45	0.6
β_2	0.1	0.2	0.25	0.3	0.35	0.2	0.35	0.4	0.45	0.6	0.5	0.6	0.8	0.85	0.85	0.5	0.5	0.6	0.7	0.75	0.7	0.8	0.9	1	1

Based on the table 6, small values of product substitutability results in the more risk taking behavior of the retailers. Also we can conclude again that retailer 2 is more risk averse rather than retailer 1.

Impact of exchange rate uncertainty

In this section the impact of considering constant exchange rate and fluctuating exchange rate is discussed. Same as Hammami et al. (2014), to analyzing the impact of considering constant exchange rate we first solve the problem with the historical exchange rates (between 2016 and 2020) and constant exchange rate (mean of the historical data as a constant value).

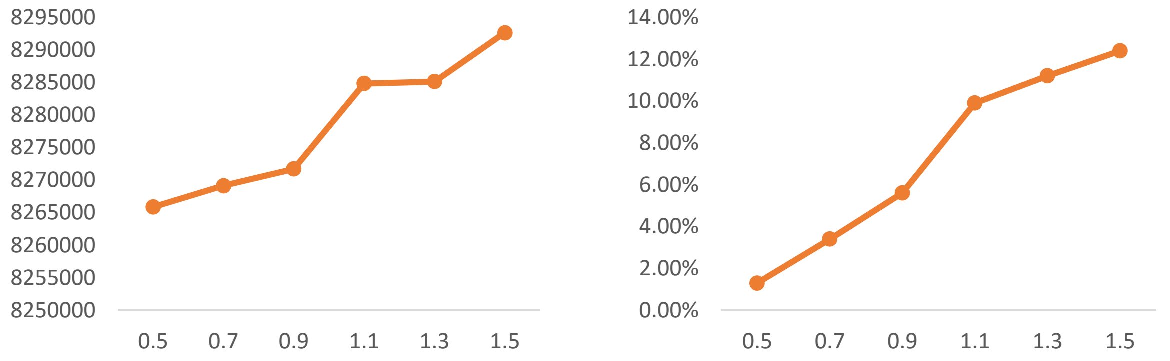

Figure 13. Effect of constant USD/CAD on the mean profit (left); percentage of increasing in order from US (Right)

As shown in the figure 13, neglecting exchange rate uncertainty results in increasing mean profit. In addition, by increasing the exchange rate of USD/CAD, ordering amount from US supplier will increase.

7. Conclusions

Dealing with uncertainties in the supply chain researches has attracted many researchers in the recent years. Considering different uncertainties will result in a more realistic problem but simultaneously increase the complexity of the problem and solution approach. Global supply chains inherently have uncertain factors such as exchange rate, disruptions, etc. Hence, in this paper a global purchasing problem considering demand uncertainties (and substitutability of the products) and disruption events was modeled as a scenario based multi-stage stochastic problem. In addition, a simulation-optimization approach was developed based on the characteristics of the problem. The mathematical characteristics of the model was matched by the nature of simulation. In other words, in the simulation process sampling from distributions was assumed as the scenarios. Finally a set of modified data was adopted from a real case study and some analyzes was performed on the data and some managerial insights extracted from those sensitivity analyzes. For the future research, applying the proposed simulation optimization on the larger problems, developing proactive and preventive risk strategies to decrease uncertainties could be two important opportunities for interested researchers. Additionally, surveying the economic aspects of the product substitutability in the supply chains with uncertain demand and supply would be another suggestion for the future study.

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