DITS (02/2021).
Working Paper del Departament d'Organització d'Empreses de la Universitat Politècnica de Catalunya.

A Simulation Model to Test the Robustness of Supply Chains

Murat Orhon[1], Albert Sunyer[2], Roberto Pinto[3]

[1] Universitat Politècnica de Catalunya. ESEIAAT. C. Colom, 11. 08222 Terrassa. murat.morhon@gmail.com
[2] Departament d'Organització d'Empreses, Universitat Politècnica de Catalunya. ESEIAAT. C. Colom, 11. 08222 Terrassa. albert.sunyer.torrents@upc.edu
[3] Department of Management, Information and Production Engineering, Università degli Studi di Bergamo. Viale Marconi, 5 –Dalmine (BG)–I-24044. roberto.pinto@unibg.it

Abstract

Significant decrease in supply chain robustness can be observed in case of major supply chain disruptions. Recently, many companies experienced it with the Covid-19 pandemic, and it created big losses in companies' revenues. One of the major reasons was these companies could not be supplied by some of their suppliers across countries. In this study, some solutions are investigated to keep high robustness in case of major disruptions by considering the supplier selection problem. The case of a food product supply across countries is simulated under uncertainty by developing a mathematical model. This model includes three steps which are i) plausible scenario creation, ii) candidate supply chain design and iii) supply chain robustness and costs evaluation. Supply chain designs are simulated by using plausible hazard scenarios and Covid-19 scenario. According to results of robustness and cost evaluations, the best supply chain design is selected. Two different supply chain designs show the best performance for the plausible hazard scenarios and for Covid-19 scenario, respectively. Results show that increasing warehouse capacity shows good performance for plausible hazard scenarios, but having multiple suppliers shows better performance for the Covid-19 scenario. Lastly, the combination of these two cases is simulated and possible strategies are discussed.

Keywords: Supply chain robustness, Supply chain design, Supply chain performance, Supply chain management, Uncertainty, Simulation

1. Introduction

Supply chain designs play a critical role for company competitiveness. However, supply chains are vulnerable to man-made or natural disasters. The uncertainty of these disasters makes supply chain designs complicated, and in fact, uncertainty is increasing further in today's world. According to data from the Centre for Research on the Epidemiology of Disasters (www.cred.be), the world experiences disasters more frequently than before. Climate change, war or terrorist attacks can be shown as an example of natural and man-made disasters respectively. For example, Ericsson lost 400 million euros when its supplier suffered from disaster in 2000, Dole's revenue decreased after a banana plantation in Central America was hit by a hurricane, and Ford had to close five plants due to lack of suppliers after the September 11 terrorist attack in 2001(Tang, 2006).

Recently, many supply chains were affected by Covid-19 pandemic. Due to the Covid-19 pandemic, many countries declared lockdown in 2020, and this caused long lead times.

According to ISM (2020), lead times increased for China, Europe and North America. Many companies suffered from lack of supplies because many suppliers could not provide material. This created delays and problems in supply chains. Additionally, demand for some specific goods such as foods increased significantly. Some companies could not meet demand due to increasing demand and decreasing supplies. Therefore, they experienced big losses in their revenues. Addressing these problems, Covid-19 pandemic can be shown as an example for supply chains' vulnerability to disasters. According to Ivanov and Dolgui (2020), supply chains are tested in terms of their robustness, which can be considered as capability of meeting demand, flexibility, and recovery.

As it can be understood from these examples, suppliers play critical roles for supply chain performance. Therefore, selecting correct suppliers may increase the robustness of supply chain. Reliable suppliers may be selected to have high robustness value. However, choosing these suppliers may result in high cost for supply chain. Because of randomness, supplier selection problem becomes very complicated. Therefore, the main aim of this study is assessing the robustness of supply chain considering Covid-19 lockdown and exploring the supplier selection decision techniques in order to improve supply chain robustness.

2. Literature review

2.1. Literature review on supply chain robustness

Brandon-Jones et al. (2014) describe supply chain robustness as the capability of a supply chain to cope with disruption and maintaining its functions. Moreover, Behzadi et al. (2018) defines robustness as the capability of a supply chain to cope with disruption with acceptable decrease in performance, while resilience is the capability of recovery. If a supply chain is resilient, it is also certainly robust, however, a robust supply chain is not necessarily resilient because robust processes are not adaptable (Christopher and Rutherford, 2004).

Supply chain can be classified as robust if it has the capability of maintaining its functions under uncertain circumstances such as demand and lead time of supplies (Peng et al., 2011). In order to create a robust supply chain, strategic decisions are required (Klibi, Martel and Guitouni, 2010). Commonly, redundancy is a strategy to increase robustness of supply chains and decrease their vulnerability to change (Azadegan et al., 2013). According to Wieland and Wallenburg (2013), robustness has a positive effect for the customers of a supply chain, and integration, communication and cooperation have positive effect on robustness.

Robustness has to be accomplished on both inter-organizational and intra-organizational levels in order to create a robust supply chain (Durach et al., 2015). Durach et al. (2015) presents four antecedents for both intra- and inter- organizational robustness. These antecedents of intra-organization robustness are leadership commitment, human capital, relationship magnitude and risk management orientation. The antecedents of inter-organizational robustness are node criticality, bargaining power, visibility and network complexity.

Tang (2006) presents nine robust supply chain strategies which are postponement, strategic stock, flexible supply base, make-and-buy, economic supply incentives, flexible transportation, revenue management, dynamic assortment planning and silent product rollover. Each strategy increases the capability to manage either supply or demand. Postponement, strategic stock,

flexible supply base and make-and-buy strategies can be implemented into a simulation due to their definitions. They can be modelled quantitatively, and their effects can be calculated.

Postponement strategy allows companies to customize the order size. Companies first can determine order size according to total demand and then they can customize order size. This strategy provides flexibility to ordering decisions because in case of disruption a company can change its order size. However, this flexibility can be limited by agreement conditions of ordering policy. The reason is that this flexibility causes demand uncertainty for suppliers. Suppliers may face stockout problems when there is an immediate big increase in demand. Therefore, agreements that allow postponement strategy increase robustness of the supply chain network, but it is limited by agreement conditions.

Stock strategy means having safety stock. This strategy can be very useful when suppliers cannot provide enough raw material after an unexpected disruption. This safety stock allows the supply chain to continue its functions for a period of time. However, having more safety stock also means having higher costs for holding inventory. Therefore, stock strategy can increase the robustness of supply chain greatly, but it also increases the cost of holding inventory.

Flexible supply base strategy indicates having supply base in different locations. For example, working with less suppliers may reduce cost of supply management and unit price. However, in case of disruption of one supplier can affect the amount of received raw material greatly. Therefore, having more suppliers means affecting less in case of unexpected disruptions. If these suppliers are in different countries, it can increase robustness even more. The reason is that when there is a major disruption in one country, a company may still work with the supplier in other countries.

These are the three examples of strategies that can be followed in order to increase robustness of the supply chain. Although all of them can increase robustness, they all have some limitations as well.

2.2. Literature review on risk in supply chain design

Different approaches are generated to make better decisions for design of the supply chain by considering different conditions. Rosenhead et al. (1972) divides decision situations into three categories, which are certainty, risk and uncertainty. According to them, certainty indicates the situation where there is no change of altering decisions and outcomes. Risk indicates the situation where the relationship between outcomes and decision is probabilistic. Uncertainty indicates the situation where relationship between outcomes and decision cannot be defined by probabilities. However, Klibi, Martel and Guitouni (2010) propose two categories which are certainty and uncertainty for the decision making process based on availability of data.

According to Klibi, Martel and Guitouni (2010), a major part of supply chain network failures is due to a spectrum of catastrophic events. Therefore, consideration of catastrophic events while designing supply chain networks is increasing (Chopra and Sodhi, 2004). Christopher and Peck (2004) suggest that risks can be simply divided into three categories that are internal to the firm, external to the firm but internal to the supply chain network and external to the network. Chopra and Sodhi (2004) extends these risk categories into nine categories which are disruption, delays, systems, forecast, intellectual property, procurement, receivables, inventory and capacity. Disruption category includes natural disasters, labour dispute, supplier

bankruptcy, war and terrorism. Forecasting and controlling risk make supply chains extremely competitive and prevent loses. This concept is called risk management (Hohenstein et al., 2015; Christopher and Peck, 2004).

Another popular concept in production management is yield uncertainty. Yield uncertainty occurs when the final produced product quantity is not always the same as ordered raw material quantity. Yield uncertainty can be observed frequently in the agricultural sector, mechanical manufactories, chemical and electronics (Gurnani et al., 2000; Jones et al., 2001). Yield uncertainty may occur due to several reasons such as production process risk, quality of input material or weather conditions (Inderfurth and Vogelgesang, 2013). For example, production yield is generally less than 50% in LCD (Liquid Crystal Display) manufactures (Gurnani et al., 2000).

Yano and Lee (1995) made a literature review about yield uncertainty and they proposed seven different ways to model yield uncertainty. For example, the first model, which they define as the simplest model, assumes that unit production is a Bernoulli process. The model has two parameters: Q, which is a batch size, and p, which is the probability of generating acceptable output. The output quantity has binomial distribution. In addition, the model assumes that generation of all units are independent from each other. They also indicate the advantages and disadvantages of this model. One advantage of this model is that the model only needs input parameter p. On the other hand, this model does not permit to specify different forms of variance of good units. They proposed that this model can be used for systems that are for long durations.

3. Methods

3.1. Supply chain design models

As indicated before, many parameters of a supply chain may include uncertainties. Therefore, uncertainty models for supply chain network design become more popular because these models can better simulate real supply chain conditions (Klibi, Martel and Guitouni, 2010). The objective of an uncertainty model is finding the design that has the capability of performing well under any possible scenarios (Govidan et al., 2017).

Demand, price, production efficiency can be modelled as random variables with known probability distributions. This situation can be considered as randomness. In production and inventory systems considering average production cost is a common technique for evaluating the cost effectiveness, however, in some scenarios such solutions may be infeasible (Sen and Higle, 1999). In order to simulate the entire input distribution, Monte Carlo approach can be used for uncertainty analysis (Saltelli et al., 2006). Stochastic programming approach can be used to consider random variables into optimization design problems. Shapiro (2007) proposed that Monte Carlo sampling techniques can be used to solve stochastic programming problems. As an example of stochastic models, Goh et al. (2007) proposes a stochastic model that includes many uncertainties such as demand, exchange rate for the global supply chain. Aryanezhad et al. (2010) propose a global supply chain design model where distribution centres have probability of disruptions under uncertain customer demand. Moreover, Hasani and Khosrojerdi (2016) proposed a global supply chain model, which considers six different flexible and resilience strategies in the design of supply chain networks under uncertainties.

If there is no information about probability distribution of random variables, fuzzy models and robust optimization models can be used. A robust optimization model is presented by Mulvey et al. (1995). The purpose is optimizing the worst case performance, and uncertain parameters can be continuous or specified by discrete scenarios in robust optimization problems (Govidan et al., 2017).

3.2. Randomness event modelling

Random events indicate the events that have probability of occurrence. This probability can be estimated. Three methods can be used to estimate the probability distributions for random events: exploiting historical data, classical forecasting and statistical analysis (Klibi and Martel, 2011). For example, supply, demand and cost failure rates information can be used as historical data.

Many researchers assume probability of disruption as pre-specified probability. Azad et al. (2014) assumed probability as a pre-specified parameter and they controlled the risk of the model by applying a value-at-risk (CVaR) approach. Moreover, Azad, Saharidis, Davoudpour, Malekly, and Yektamaram (2013) consider total and partial failure and they use Benders decomposition (BD) approach for solving this problem.

Klibi and Martel (2012a) develop a model to design resilient supply networks for location-transportation problems. They consider uncertainty parameters as a random variable that has cumulative distribution function, and they use plausible future scenario samples for simulation. In order to use a plausible future scenario approach, they use the Monte-Carlo simulation method. The risk modelling approach which is used by them is based on the suggestion of Klibi and Martel (2011). They can obtain a good distribution for disruption events by using Monte Carlo procedure, and they can compare the design approaches.

Santoso et al. (2005) propose a two-stage stochastic model in which random events are simulated by plausible future scenarios with specified probabilities. Due to the reason that the number of plausible scenarios is infinite, they use Sample Average Approximation (SAA).

4. Development of the simulation model

4.1. Supply chain network design

Supply chain networks must be designed for several years. Optimizing today's conditions only may result in failure. Therefore, they need to be made by considering the design should be robust enough to deal with all future uncertainties such as costs, demand or hazards. One way of considering uncertainties is creating plausible future scenarios. In plausible future scenario approach, each scenario simulates one possible future path by estimating the future events. However, the possibility of future events being the same as one scenario is very low. In addition, one scenario may not consider some uncertainties because the occurrence of any event depends on possibility functions. Therefore, one can make a good design based on one scenario, but this design may fail in the following years. In order to consider all future events, several plausible scenarios must be created. Klibi and Martel (2012b) used Monte-Carlo procedure to create a sample of plausible scenarios. Then, designs are made by considering different sets of scenario samples.

After selecting one set of scenario samples, one supply chain network design is created by considering the main purpose. This purpose may be maximizing the profit. The network design is tested for every scenario in the scenario set, and the profit is calculated for every scenario. Then, the average profit is found for a specific network design.

In order to select the best supply chain network design, one may consider only the profit values. For this purpose, designs need to be created by maximizing the profit. However, this idea would not be sufficient to create robust supply chain network designs. As described in the literature review section, there are some more parameters that need to be considered to assess a supply chain robustness. Also, these parameters may change from company to company according to their risk attitude and future aims.

In this study, Klibi and Martel (2012b) model is adopted. This model consists of three main steps. The same logic is used by creating these steps, but the model is further modified to solve the supplier selection problem. The first step is creating plausible future scenarios, the second step is creating candidate designs and the last step is evaluating candidate designs outcomes.

Plausible future scenarios are created in the first step. In order to estimate future events, historical data of specific locations are used defining three approaches. These approaches are pessimistic, as-is and optimistic approaches. By considering these approaches, the slope of the historical disaster frequency per year is adjusted. For example, if the number of disasters per year is increasing one each year in historical data, one can expect that the number of disasters in next year will be equal to the number of disasters in this year plus one. This situation represents the as-is approach. In as-is approach the slope is not changed. On the other hand, in a pessimistic approach, the slope is increased above average. Reversely, in an optimistic approach, the slope is increased below average. These approaches are named as future paths $k \in K$.

After creating a set of future scenarios, randomly selected a small set of scenarios is considered in the second step for creating candidate designs. Then, created candidate designs are sent to the evaluation and selection step. These designs are tested with a large set of scenario samples and performance parameters are calculated. After calculating performance parameters, the best design is selected. The details of these steps will be explained in the following sections. The main framework of the model is shown in Figure 1.

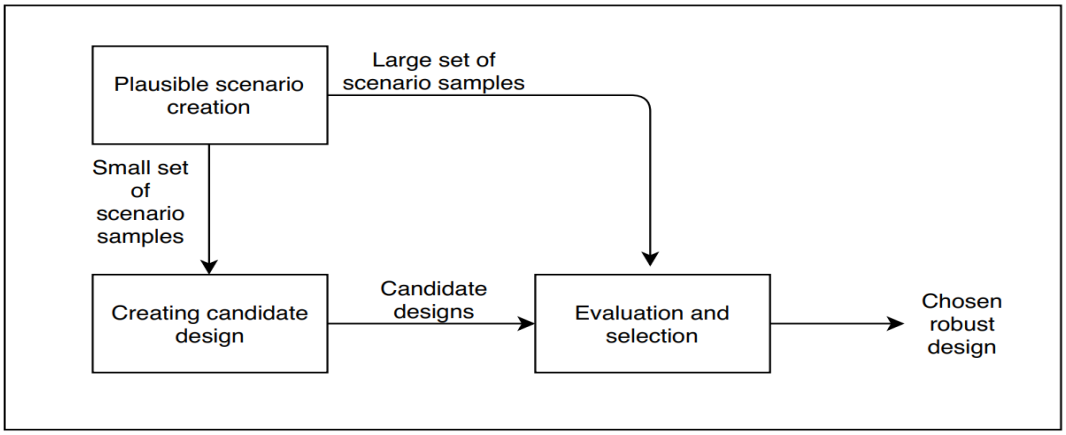

Figure 1. Main framework of the model

4.2. Supplier selection problem

As indicated above, the main purpose of this study is creating a robust supply chain network which includes solving the supplier selection problem. Robustness is considered as capability of meeting demand. To solve this problem, we will assume that suppliers are located in different countries and have different probabilities of having a hazardous event. Therefore, each supplier would have different characteristics. These characteristics are competitive for each other. For example, if the supplier is located in a very risky area in terms of hazardous events, the wholesale price is low, however, it may not provide the required raw material quantity during hazardous events. When a company makes a plan for all year, the advantage of low price may be higher than disadvantage of lack of supplies. Losses in supply capacity depends on hazard type. For example, during Covid-19, some suppliers' capacity decreased dramatically, and their recovery period was slow, however, in other hazardous events that have low impact, suppliers can recover very quickly with less capacity lost. Due to this reason, hazardous events are classified in five categories. These categories are called hazard types. Hazard type 1 has minimum effects and hazard type 5 has maximum effect to capacity loss. All suppliers have advantages and disadvantages according to their locations. In the case of no hazardous events, the supplier selection problem would become very easy to solve, however, uncertainty in hazardous events makes this problem very complicated.

It is assumed that a company has one demand zone in one country. Demand is also affected by hazardous events in this country. This effect may increase or decrease the demand with different proportions. For example, during the Covid-19, the demand for food products increased, although demand for many other products decreased. In addition, during an economic crisis, while demand for the luxury products decreased, the demand for the food products may increase. In both cases, demand for the food products increased but in different ratios. Same as suppliers' capacity, demand also has specific recovery functions. After the hazardous event, demand may increase or decrease gradually.

The main framework of the supply chain network is presented in Figure 2 and the details of every parameter will be discussed in the following sections.

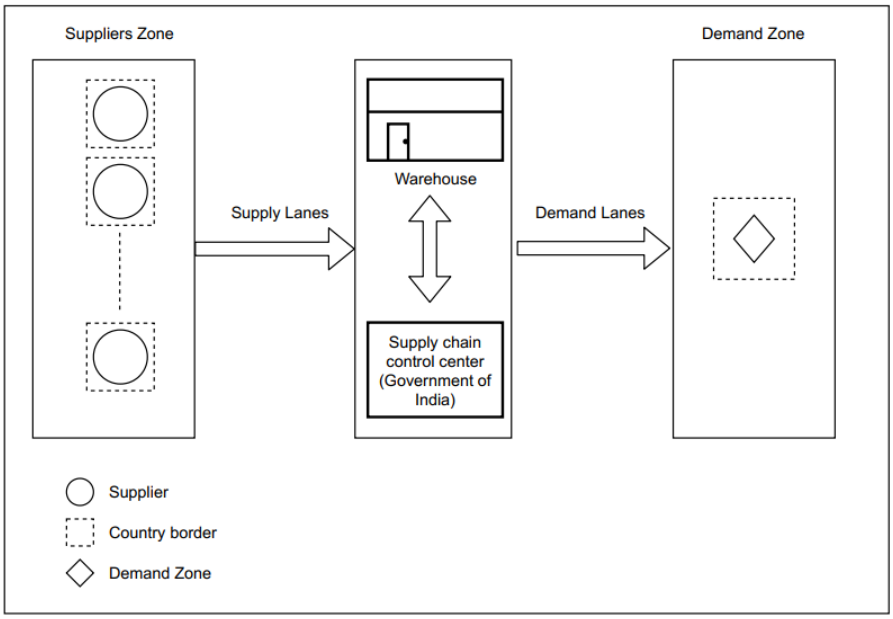

Figure 2. Supply chain network

Regarding simulated periods, there are two periods to be included in the model. One is planning periods $t \in T$, and the other is working periods $\tau \in T^u$. Planning periods represent the period for the strategic decisions. These decisions involve "Having agreements with which suppliers in which years and the warehouse capacity".

It is assumed that each planning period represents 1 year, and all strategic decisions can only be implemented at the beginning of each planning period. For example, a company changes the status of one supplier from agreed to non-agreed after having agreement for 1 year. The same situation is valid for the reverse case. On the other hand, working periods simulate the business life. In this study, working periods are assumed as 1 month. Therefore, one planning period is equal to twelve working periods. During this period, the company buys material from its agreed suppliers or from the free market to meet the demand.

Hazardous events may occur in some working periods. According to hazard type and recovery functions, the agreed maximum capacity of suppliers and demand can change at the beginning of each working period due to these events. Then, the company can react to these changes by changing the order quantities for each supplier. These reactions are given by a response algorithm. These decisions are given at the beginning of each working period, and profits and decision variables are calculated for each working period. The details of the response algorithm, profit function and decision variables will be given in the candidate design section. Then, for strategic decisions, profits and values of decision variables are aggregated to yearly periods. The working periods and planning periods are summarized in below Figure 3.

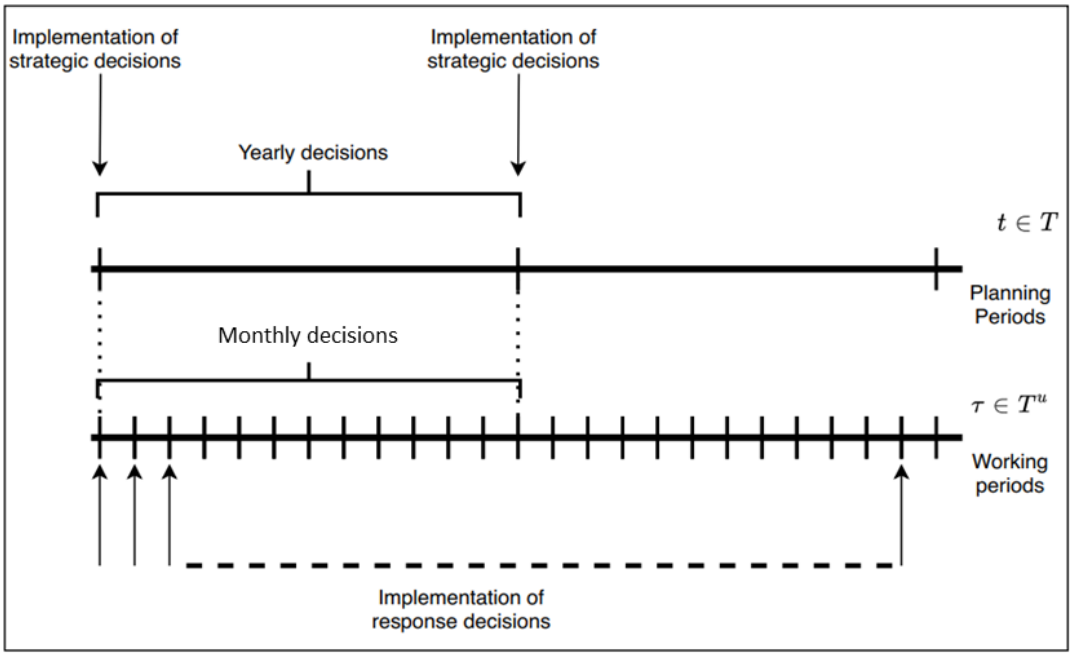

Figure 3. Planning and working periods

4.3. Scenario creation for demand and suppliers' zones

All supply chain networks include risks that originate from natural, accidental hazards. These can be divided into three categories for modelling purposes that are randomness, hazard and deep uncertainty. Except deep uncertainty, these categories can be characterized by random variables with probabilities. The required data to obtain probabilities can be taken from historical records. In this study, in order to determine probabilities, historical records of events in specific zones are obtained from the Centre for Research on the Epidemiology of Disasters (www.cred.be). Five zones are selected as candidate supplier zones. These zones are India, USA, Pakistan, Thailand, and Brazil. In addition, the demand zone is determined as India. Supplier in a country represents all suppliers in this country. For example, the capacity of suppliers in the USA represents the total export capacity of all suppliers in the USA, and demand represents all demand in India. Therefore, every hazard in a country affects the capacity of the supplier in other words total export capacity.

Figure 4. Supplier and Demand zones

One scenario represents one future period of the world. This period can be five years or ten years. If the scenario period is assumed as five years, the events in one scenario, simulates one possible five years' period of the world. Each supplier zone and demand zone may be affected by any kind of hazard and may experience production capacity losses. Another scenario simulates another possible five years. In order to create plausible future scenarios Monte-Carlo procedure is used. Scenarios represented by ω and all set of scenarios are represented by Ω. This procedure is summarized in Figure 5.

```
1)  For all ω ∈ Ω do
2)  Select an evolutionary path k randomly , k ∈ K
3) For all z ∈ Z, do
        η = 0
        while η ≤ T, do
        Compute next multihazard occurance day η = η + F^s_zk(u)
        Determine the hazard type h = f_z(u)
        Collect data into matrix T_z
        end while
   end for
4) Create initial capacity matrix for each supplier c_s(τ) = c_s
5) Create initial demand matrix d(τ) = d
6) For all z ∈ Z do
        For all τ ∈ T^u do
                Compute β^h_z = F_hz^(β^-1) and θ^h_z = f(β^h_z)^θ
                If τ ∈ T_z
                    Find the duration of hazard ζ = f(β^h_z)^ζ
                    Update capacity matrix c_s(τ) = f_τ(β^h_z, θ^h_z)^c · c_s(τ), τ = τ, .... , τ + ζ
                    Update demand matrix d(τ) = f_τ(β^h_z, θ^h_z)^d · d(τ), τ = τ, .... , τ + ζ
                end If
        end for
end for
7) Aggregate values over planning periods
8) Collect all scenario data
9) end for ω
```

Figure 5. Monte-Carlo procedure for scenario creation

The steps of the procedure will be explained in detail. As a summary, this procedure first chooses an evolutionary path randomly which is shown in Figure 6. Evolutionary path indicates the future assumption about disaster frequency. Disaster frequency can increase, decrease or remain the same. Second, it determines the next multi-hazard, which is the classification of hazards into small number of meta-events (Scawthorn et al., 2006), arrival time for each supplier and demand zones with the hazard type. In this study, arrival time of multi-hazard is measured in months. Third, it creates initial demand data and capacity data for each supplier. Fourth, if a disaster occurs, it updates the demand or capacity data by using the capacity loss function, the demand increase function and their recovery functions. Lastly, it aggregates all data to the planning horizon and collects all information into that specific scenario.

Firstly, procedure starts with choosing an evolutionary path k randomly. Evolutionary path is related to expectations for the future. Three approaches are considered for the evolutionary path. These are pessimistic, as-is and optimistic. Pessimistic approach indicates that there will be more disasters than average in the future. On the other hand, an optimistic approach indicates that there will be fewer disasters than average in the future. The assumptions of these approaches are summarized in Figure 6.

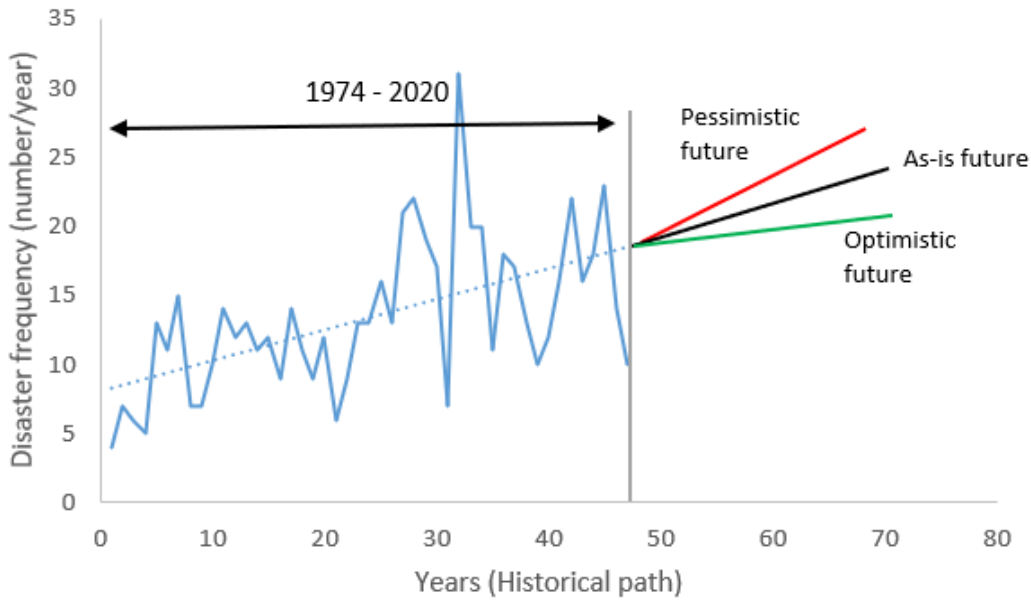

Figure 6. Evolutionary paths for a general region

In the Figure 6, a chart of disaster frequency according to years is presented. The historical data is taken from the Centre for Research on the Epidemiology of Disasters (www.cred.be). First recorded data belongs to year 1974 and last data belongs to year 2020. For the future year's estimation, the best-fitted line is created. Although the slope of historical data is known, this slope may be changed for the future data according to assumption of evolutionary path. As it can be seen in the figure 6, when the evolutionary path is assumed as pessimistic future, the slope of best-fitted line for future is higher than slope of best-fitted line for historical data. This means that there will be more disasters per year in the future. In the approach of as-is future, the slope remains the same. On the other hand, in optimistic future scenarios, the slope is decreased, and it is expected that there will be a smaller number of disasters.

Secondly, the procedure finds the next multi-hazard arrival month and the hazard type. In this procedure, η indicates the month number, and T is the working period. Month number η starts from zero and goes to the end of the month. For example, in second year η takes the value of twenty-four. In order to calculate next multi-hazard arrival time, specific functions based on historical data of each zone are used.

In order to present the behaviours of the created functions, a scenario example is prepared. The timeline of the scenario is 3 years (36 months). The graphs show which hazard type occurred in which month.

In order to test the simulation model, rice has been chosen as a product type in this study and a sample of the main international rice exporters in the period 2018/2019 from different areas have been considered, namely India, Thailand, Pakistan, USA and Brazil. For this study purpose, India has been selected as production and demand area, given this is the wold's major rice trader in the international market (https://www.statista.com). A scenario example of the studied nations hazard types is presented in Figure 7.

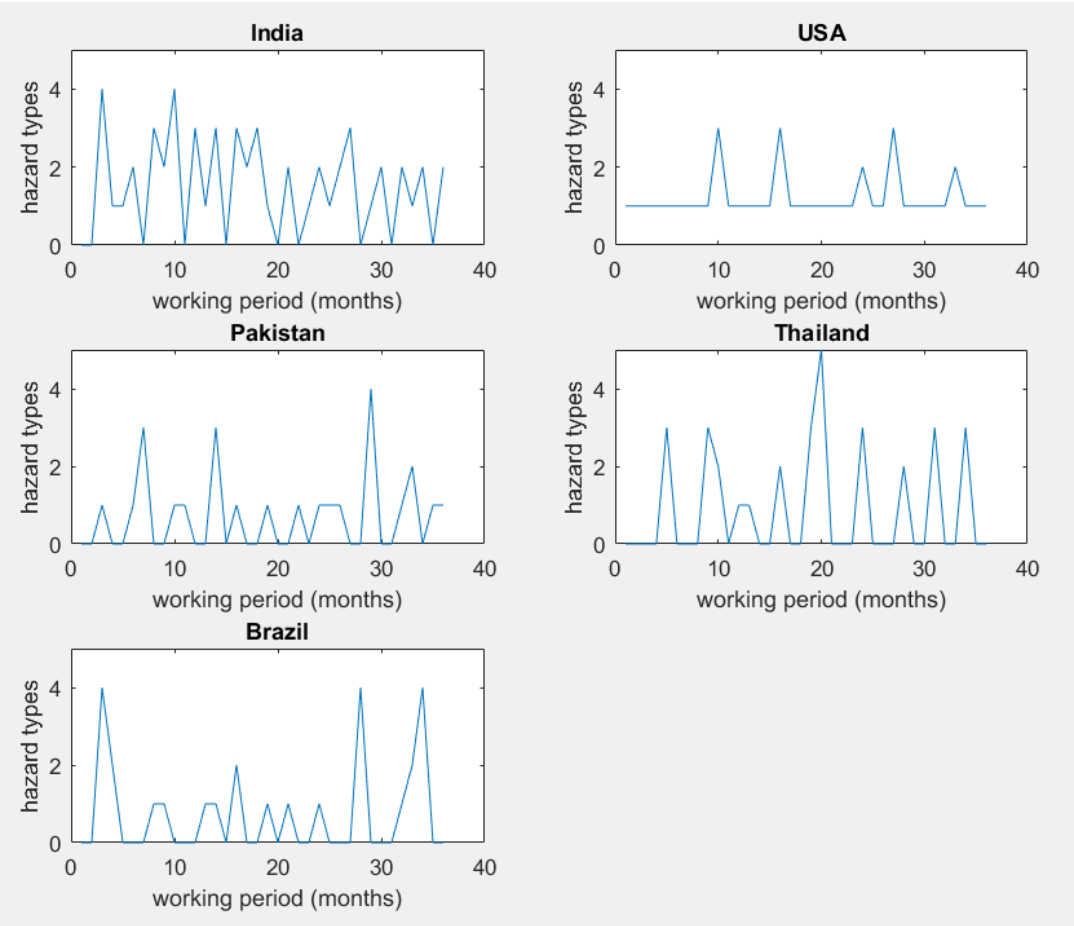

Figure 7. Scenario example

Figure 7 scenario shows one possible future in the next three years' period with disasters in the studied regions. Hazard type 0 means there is no disaster occurred in the specific month. Another scenario shows different outputs of future disasters. However, the general assumptions will be same for each scenario. For example, USA has the highest disaster frequency. Every month has type one or higher disasters in the scenario shown in Figure 7. On the other hand, Thailand has the lowest expected disaster frequency. In addition, USA has the highest probability for the occurrence of hazard type 1 in historical data. This can also be seen in the graphs. In comparison to other areas, hazard type one occurred mostly in the USA. However, hazards type 4 and 5 do not occur in the USA in this three years' scenario. In these three years, only Thailand would hazard type 5. The reason is that Thailand has the highest likelihood for hazard type 5.

After creating one scenario, change in demand, capacity losses of suppliers and recoveries are calculated. As discussed before, change in demand depends on the type of product. It may increase or decrease according to disaster type. Considering that the studied product (rice) is a commodity food product, it is assumed that the demand will increase in case of any disaster in India (by recalling that the demand zone is India). In addition, disasters at any other zone will not affect the demand in India, but they will affect the capacity of suppliers in that zone. Then, increase in demand, capacity loss and recovery functions are calculated according to hazard types. The rates are determined by considering the size of zones. For example, a disaster type 1 may occur anywhere in India or Thailand. Due to the size of both countries, Thailand, which is a country smaller than India, will be more impacted as a whole region. Therefore, the capacity

loss rate for Thailand must be greater than capacity loss rate for India for the same hazard type. Below assumptions are made in order to determine the increase in demand, capacity loss and recovery rates.

Impact severity for India:

- Production capacity reduction in India 2%xHazard type
- Demand increase in India 1%xHazard type
- Recovery rate of production +2%/month
- Recovery rate of demand -1%/month

Impact severity for other zones (considering the country size):

- Production capacity reduction in Brazil and USA 2%xHazard type
- Production capacity reduction in Pakistan and Thailand 5%xHazard type
- Recovery rate of production in Brazil and USA +2%/month
- Recovery rate of production in Pakistan and Thailand +5%/month

These steps are replicated for each scenario until reaching the target scenario number. Due to the randomness, each scenario is unique. Each scenario is a one possible future. Therefore, the total number of occurred hazards may change. However, if all scenarios are considered, a normal distribution curve may be obtained by number of occurred hazards. In order to present this, an example is shown in Figure 8. The timeline of this example is 3 years. Therefore, every scenario is simulated for three years. Two thousands scenarios are created and results are collected. By using these scenarios, Figure 8 is created for India.

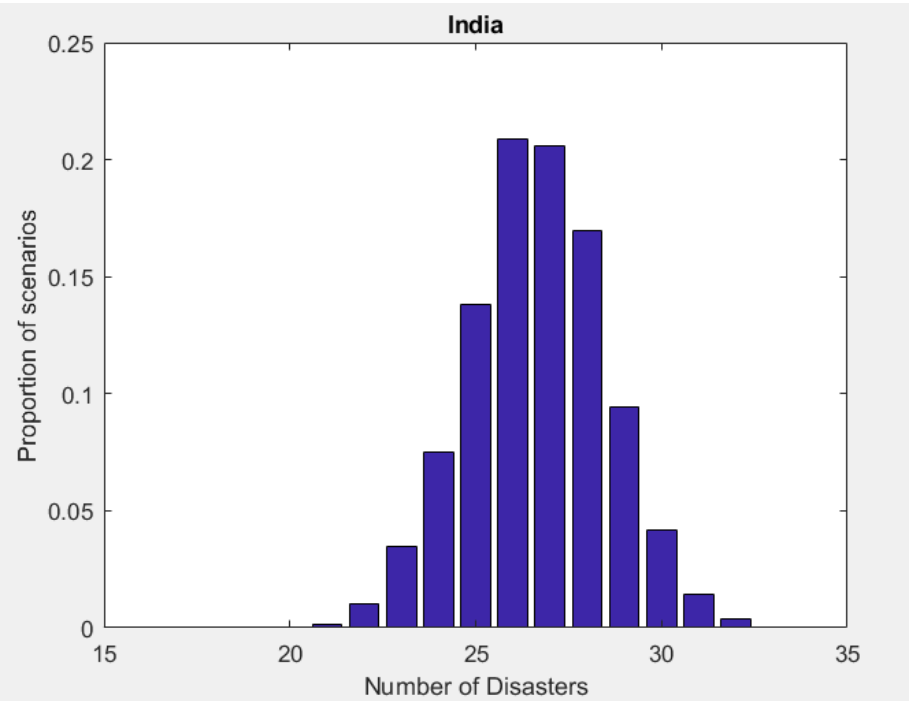

Figure 8. India scenarios by number of hits over 2000 scenarios created

Figure 8 shows the proportion of scenarios versus the number of hits. For example, there are total of 25 disasters in 15% of 2000 scenarios. According to Figure 8, there are not more than

32 disasters and not less than 21 disasters in all 2000 scenarios created for three years in India. The scenarios that have 32 disasters may be accepted as the worst-case scenarios for India.

While calculating the total number of disasters, paths are playing a critical role by the increasing timeline. The reason that, the procedure expects more or less disasters according to paths. For example, for 10 years' timeline, if the path is determined as pessimistic, the total disaster number in 10th year will be much greater than total disaster number at the beginning. Reversely, if the path is optimistic, the procedure may expect even less total disaster number. In order to show the difference, one 10 years' scenario example is presented in Figure 9.

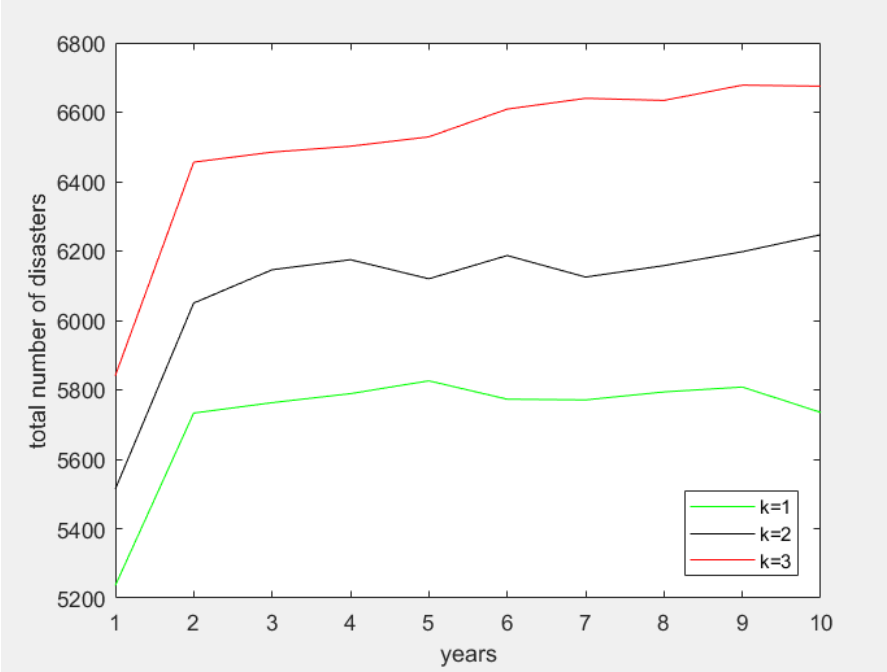

Figure 9. Total number of disasters according to paths "k"

As it can be seen in the Figure 9, the slope of each path is different. The slope of historical paths indicates that even if nothing changed, the number of total disasters in the future will be greater. This situation is represented by the path k=2. Due to the deviation, there may be fewer disasters than previous years in some simulated years, but the number tends to increase in the long term. On the other hand, if the k value is equal to one, this means that scenario is the optimistic path. When k is equal to one, the number of disasters does not increase as shown on Figure 9. It remains almost the same. Therefore, there is a positive effect to the as-is path. When k is equal to three, which is a pessimistic path, the increase in total number of disasters can be seen clearly.

4.4. Candidate design creation

In the scenario creation step, a large set of scenarios are created. Then, a small set of scenarios are considered to create candidate designs. In this study, total 2000 scenarios are created in scenario creation step and candidate designs are made according to 50 randomly chosen scenarios. As indicated before, in this study the chosen product is rice and the demand zone is India. The reason for choosing these is India has very high demand for rice, and in case of any disaster affecting rice production or demand, may result in hunger for thousands of people. Therefore, the aim of the simulated problem is fulfilling demand in India by minimizing the overall costs.

In order to fulfil its rice demand, India can use its own production capacity, use available rice on hand in its warehouses or can purchase rice from other producing nations. If India has an agreement with a supplier nation, it can buy rice with an agreed price, which is lower than the free market price, but India needs to buy at least 50% of the agreed maximum order capacity. On the other hand, if the India does not have an agreement with that supplier nation, it cannot buy rice from this nation. Furthermore, it is assumed that the free market has unlimited capacity but at higher cost than any supplier nation with trade agreement.

It is assumed that demand indicates the whole demand in India. In addition, suppliers in the studied countries represent all rice export in that country. For example, the capacity of suppliers in Brazil is equal to the whole export value of Brazil. India can buy rice from suppliers only if India has a trade agreement with this country. India can make new agreements or cancel them only at the beginning of every year. In addition, signing a new agreement or cancelling an existing agreement has a cost, however, renewing an agreement is assumed as free. The capacity of suppliers depends on disasters. If a disaster occurs in one supplier zone, the capacity of this supplier will decrease. In addition, for limitation purposes, it is assumed that if India has an agreement with the supplier nation, India needs to buy 50% of the nation net export's capacity. For example, if a disaster occurs in one supplier nation and capacity of this nation decreases according to the disaster type, the decreased capacity is the net capacity of the supplier. Demand quantity also depends on disaster occurrence. If a disaster occurs in India, rice demand will increase according to the disaster type. On the other hand, warehouse capacity represents the storage capacity of whole India. There is a maximum limit for warehouse capacity due to limited infrastructure. India can determine the warehouse capacity, and this capacity will be the same for whole scenario period. Therefore, the designs must show yearly-agreed supplier nations and warehouse capacity.

If the sum of total net capacity of agreed supplier nations and inventory on hand is less than total demand quantity, India can buy rice from the free market to meet the missing demand. However, the free market price is more expensive than the wholesale price of agreed suppliers. In this study, the robustness is accepted as a capability of meeting demand. Therefore, it can be claimed that buying from the free market indicates the decrease in robustness of the regular supply chain, and it is a negative indicator for the performance measures and evaluation parameters.

Designs are created by considering these assumptions. The best design for randomly selected small sets of scenarios is found by minimizing the overall costs. In order to minimize the overall costs, an optimization algorithm called "Differential Evolution" is used. One iteration of the algorithm is presented in Figure 10.

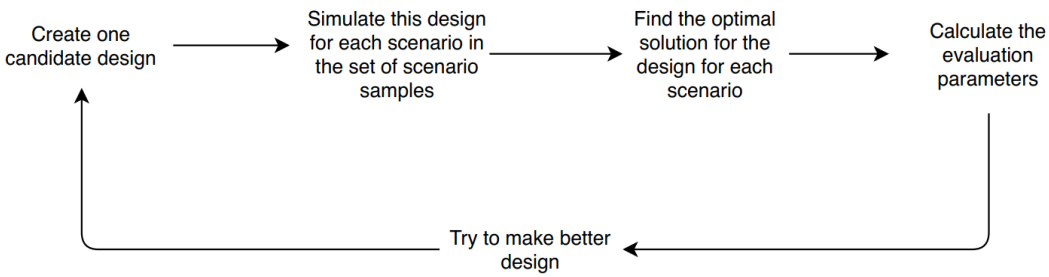

Figure 10. One iteration of the optimization algorithm

As it can be seen in Figure 10, the optimization algorithm also uses the set of scenario samples. This set of scenario samples are chosen before the algorithm starts running. For example, in this study 50 scenario sample are chosen randomly among the 2000 created scenarios. Then, the optimization algorithm builds designs for these selected 50 scenarios. First, algorithm creates a random design. Then, this design is assessed by the objective function. In the objective function assessment, the design is simulated for the selected 50 scenarios, and optimal solutions are found. According to these solutions, evaluation parameters are calculated for each scenario, and average values are found for these 50 scenarios. Then, all data is sent to optimization algorithm in an attempt to create better designs in each iteration. As a result, the optimization algorithm finds the best design for 50 scenarios. This design may not be optimal design for one specific scenario, but it is the design that gives minimum average cost for the 50 scenarios analysed. In the following sections, determination of all simulations parameters is explained.

Capacity of suppliers

For the capacity of suppliers, except India, the rice export values of countries are considered. These values are obtained from www.statista.com in the period 2018/2019 and presented below.

- USA $3*10^9$ kg/year
- Pakistan $4.5*10^9$ kg/year
- Thailand $7.5*10^9$ kg/year
- Brazil $1*10^9$ kg/year

The capacity for India is considered as total rice production of India. This value is obtained from www.atlasbig.com in the same period 2018/2019.

- India $159*10^9$ kg/year

Demand

Rice demand in India is considered as net internal amount. In order to calculate this value, data was obtained from www.statista.com and www.atlasbig.com

$$net\ internal\ amount(demand) = total\ production - export\ value$$

$$net\ internal\ amount(demand) = 159 * 10^9 - 10 * 10^9 = 149 * 10^9\ kg/year$$

Demand and capacity values are given in yearly period. Because the simulation period is monthly, yearly values are divided to 12 to obtain monthly values.

The cost parameters are listed as follows:

- Wholesale price of rice
- Warehouse holding cost
- Signing new agreement cost
- Cancelling agreement cost

Wholesale price of rice

The prices are obtained from www.numbeo.com. According to this database, the rice prices for the studied suppliers are presented below:

- India 0.71$/kg
- USA 4.01$/kg
- Pakistan 0.97$/kg
- Thailand 1.22$/kg
- Brazil 0.79$/kg
- Free market 5$/kg + signing new agreement cost

Warehouse holding cost

The required data to calculate this value is obtained from www.financialexpress.com. By considering this data, below assumptions are made.

- The maximum warehouse capacity of India is $70*10^9$ kg
- Warehouse holding cost 35$/ton per month

Signing new agreement and cancelling agreement costs

The cost of signing a new agreement and cancelling an existing agreement is assumed as the same and the value is 1 million US dollars. If India buys rice from the free market, India needs to make an agreement with the free market at same cost that is 1 million US dollars, and this agreement is valid for only 1 month. In addition, India does not have signing or cancelling agreement cost for local suppliers in India.

5. Simulation results

5.1. Simulation results for scenario 1

By considering previously presented parameters and parameters for capacity loss, recovery function and increase in demand quantity, charts are plotted for scenario one in Figure 11.

As stated before, capacity losses and increase in demand quantity depend on hazard type. In addition, these values are monthly values. As it can be seen in Figure 11, capacity and demand in India are in reverse relationship. In case of a hazard in India, demand tends to increase while capacity decreases. In addition, as expected, there are many fluctuations in the capacity and demand charts for India. On the other hand, USA shows the most stable performance although disasters occur in USA every month.

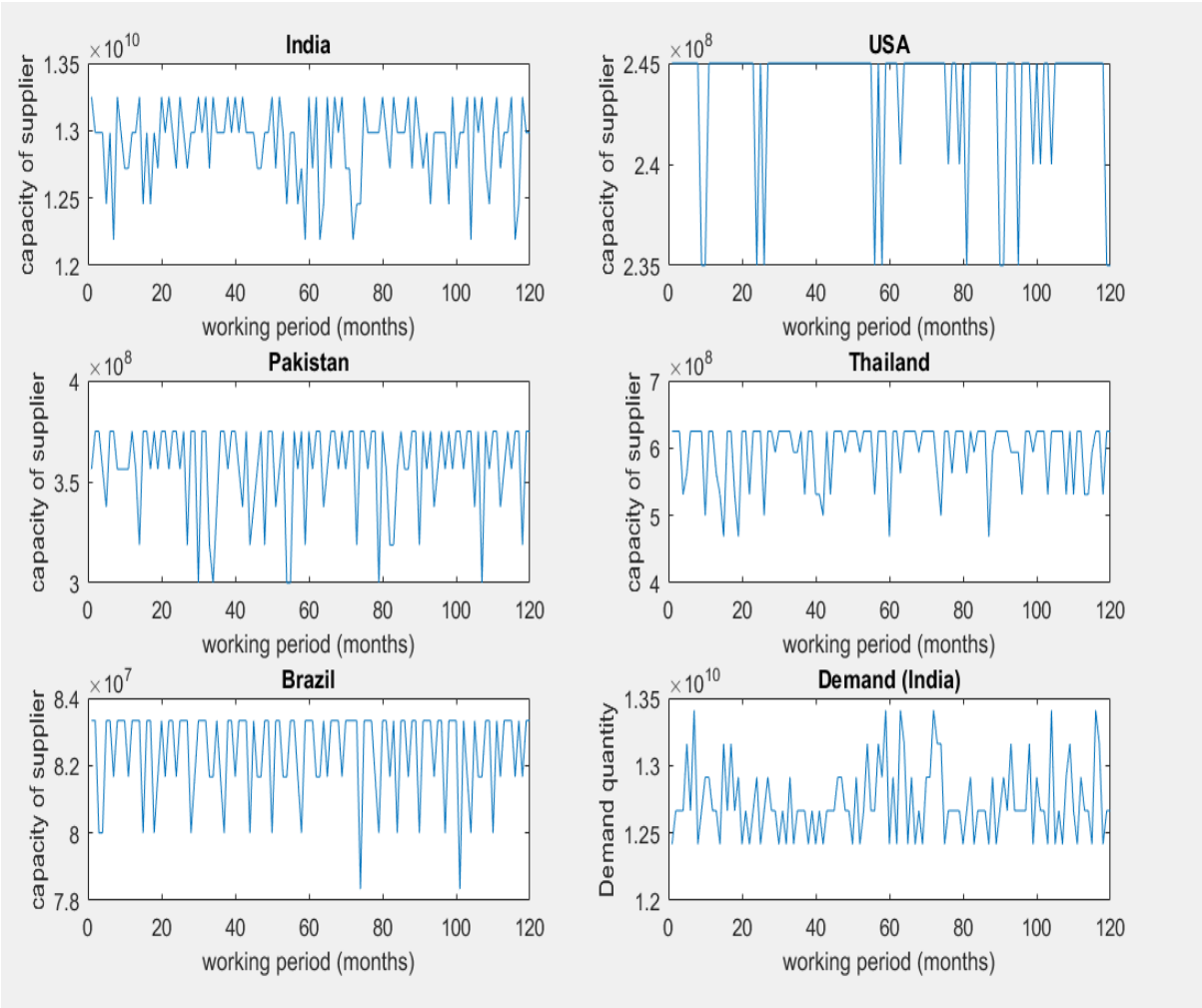

Figure 11. Change in capacities and demand for scenario one

Figure 11 shows a scenario example but, as said before, 50 scenarios are chosen among 2000 scenarios for a candidate design. Then, the optimization algorithm creates a design randomly for the first step. For example, it can choose first, second and third suppliers for the first year and first and fourth suppliers for second year. After creating the first iteration design, the objective function is assessed for a given period and finds the optimal values. These optimal values are order quantity from suppliers for each month. Finding optimal values are critical. The reason is that capacities and demand can be changed every month, and order quantities from suppliers and from market determine the total cost which is very important parameter for the evaluating the design. In order to find the optimal values, user responds procedure is used. This procedure is summarized in Figure 12.

```
User Respond

For all months do

    If required capacity to meet demand <= total capacity of agreed suppliers

        Buy all required raw material from agreed suppliers

         If current warehouse capacity < determined warehouse capacity

             Try to fill the warehouse

          end

      end

     else required capacity to meet demand > total capacity of agreed suppliers

        If required capacity to meet demand < (total capacity of agreed suppliers + current warehouse capacity)

            Use material in warehouse and update warehouse capacity

        else

            Use all material in warehouse and buy the rest amount from market

            Current warehouse capacity = 0
        end

    end

end
```

Figure 12. User response procedure

This user response procedure is created to find the minimum order quantities with minimum costs. As it can be seen in Figure 12, this procedure considers three conditions:

- First condition is capacity of agreed suppliers in specific month are greater than demand quantity in specific month. In this case, India tends to buy all demand quantity from agreed suppliers. Recalling that India must buy at least 50% of net capacity of suppliers. Therefore, India may buy more than demand in some cases. If there is no space in the warehouse, this extra amount will be wasted but the cost will be calculated. This assumption works as limitation for the number of agreed suppliers. Otherwise, algorithm can choose all suppliers as agreed supplier and buy only the required amount of rice. After buying 50% of all capacity, India decides the rest amount by considering wholesale prices. For example, India firstly tends to buy all required amount from agreed supplier that offers the cheapest price among agreed suppliers. If the capacity of this supplier is not enough to meet demand, India starts to buy from an agreed supplier that offers the second cheapest wholesale price among the agreed suppliers. In addition, inventory on hand may be less than warehouse capacity. If it is less, India tries to fill it as soon as possible by ordering more than the demand quantity.

- Second condition is capacity of agreed suppliers plus inventory on hand in a specific month is greater than demand quantity in that specific month. In this case, India buys all rice from agreed suppliers and takes the rest from warehouse. Then, if the next month first condition occurs, India tries to fill the warehouse again.

- Lastly, third condition is capacity of agreed suppliers plus inventory on hand in a specific month is less than demand quantity in that specific month. In this case, India buys all capacity of agreed suppliers, takes all inventory on hand from the warehouse, and buys the missing demand from the free market. If the India orders from the free market, it must sign a new trade agreement, but this agreement is only valid for 1 month. Therefore, for a following month, if India needed to buy rice again from the free market, it must sign a new trade agreement. The costs of these contracts also play a penalty role in the cost function, so that it forces to limit order quantities from the free market. Conceptually, supplying from the free market shows a regular supply chain disruption and is an indicator of supply chain robustness decrease. The aim of this design is preventing this condition by minimizing the cost.

According to initial parameters of demand and capacity in India, India can provide the required amount of rice to meet its domestic demand. However, in case of hazards, India may not be able to meet the domestic rice demand because its domestic demand increases, and its local capacity decreases as a consequence of hazards. In order to analyse the Indian rice demand and availability for scenario one, Figure 13 is created.

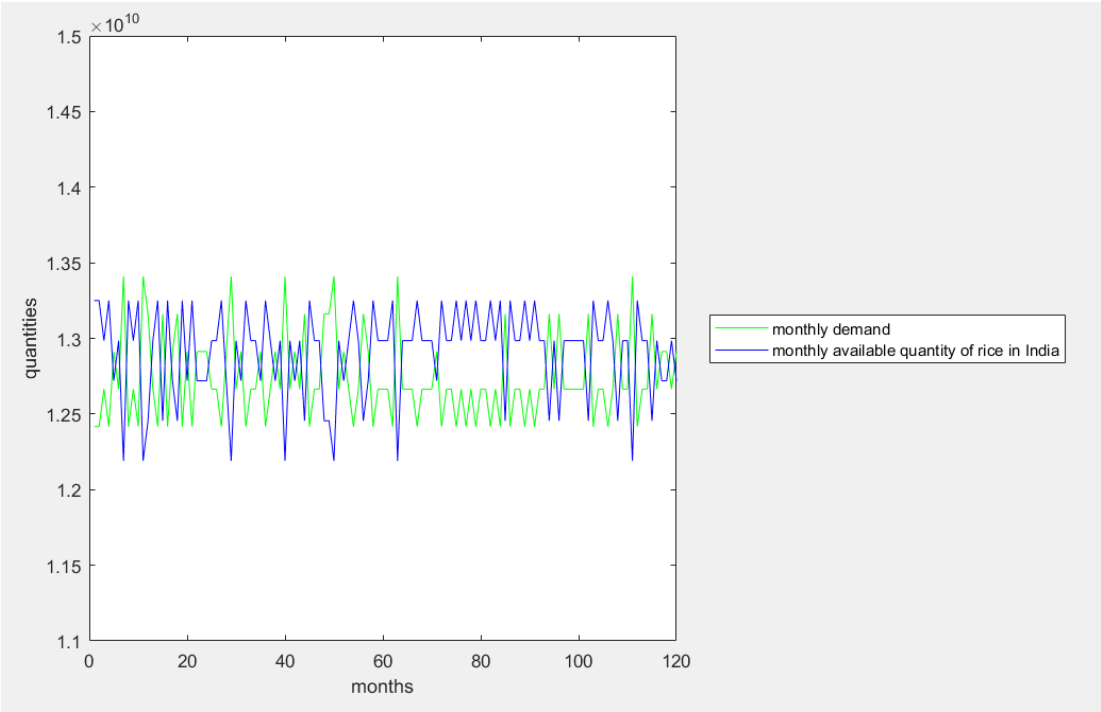

Figure 13. Available quantity of rice in India vs demand for one scenario

In the Figure 13, blue line indicates the monthly available quantity of rice in India, and green line indicates the monthly demand quantity. Therefore, if the blue line is above the green line, India can meet its domestic demand without external supplies. As it can be seen in Figure 13, India can meet demand at the first month. However, for some months, the available quantity of rice is not enough to meet the demand. This situation can last several months or a single month because it depends on hazard occurrence. Therefore, at least one foreign supplier is required to meet demand at these months.

In order to present behaviour of user respond procedure, two examples are prepared. These are examples of the same design in two different scenarios. In this design, India has a trade agreement with Brazil. Five parameters are used to plot these charts. These are inventory on hand, monthly demand, monthly total order quantity from agreed suppliers (including domestic production and free market), monthly total capacity of agreed suppliers, and market order quantity (only). Monthly order quantity from agreed suppliers (including domestic production and free market) represents the total order quantity that India make. The simulation results of first scenario sample are shown in Figure 14.

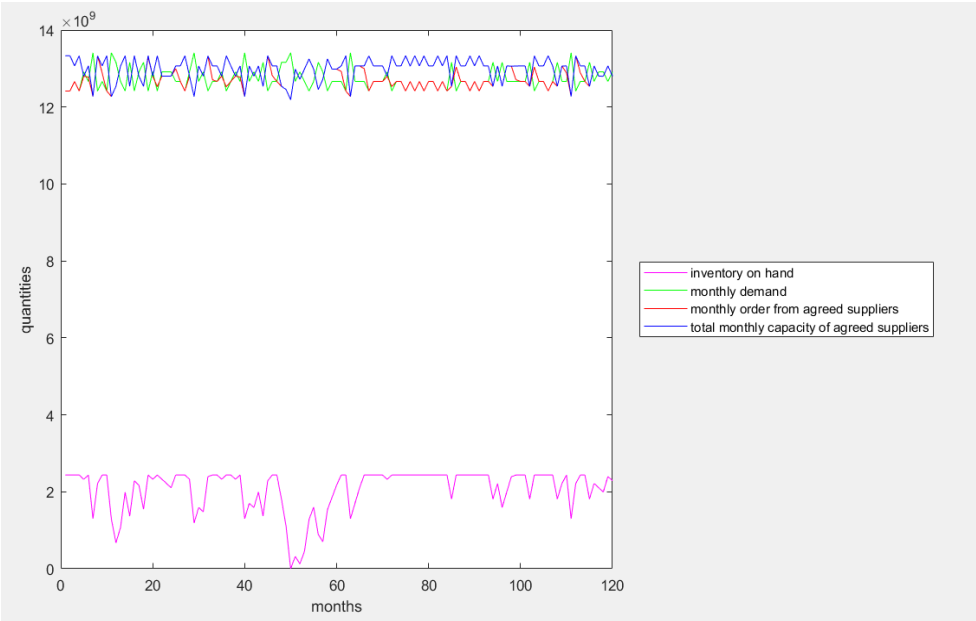

Figure 14. Simulation results of first scenario

As it can be seen in Figure 14, the 10 years' simulation of one specific design is presented. It is important to recall here that monthly demand, monthly production and monthly order quantity depend on disasters. Therefore, variation can be seen in every month. The monthly demand is shown with green line, and monthly capacity of agreed suppliers is shown with blue line. As it can be observed, monthly order quantity (red line) is less than monthly demand (green line) in some months and more than monthly demand (green line) in other months. The order quantity is determined according to conditions of the user response procedure. For example, for month number 80, the first condition is applied: The production capacity is higher than the demand, so the order quantity is equal to demand and inventory on hand in the warehouse is equal to warehouse capacity (inventory on hand is at maximum level and does not change). On the other hand, in some months, demand is higher than production capacity of agreed suppliers and the monthly order quantity is less than monthly demand. In these months (e.g. months 10-15, 30-35), India uses the inventory on hand to buffer the lack of capacity. Then, India tries to fill the warehouse by ordering more rice than demand in the following months, when possible. In order to investigate the third condition, market order quantity must be observed. Market order quantities for every month are plot in Figure 15.

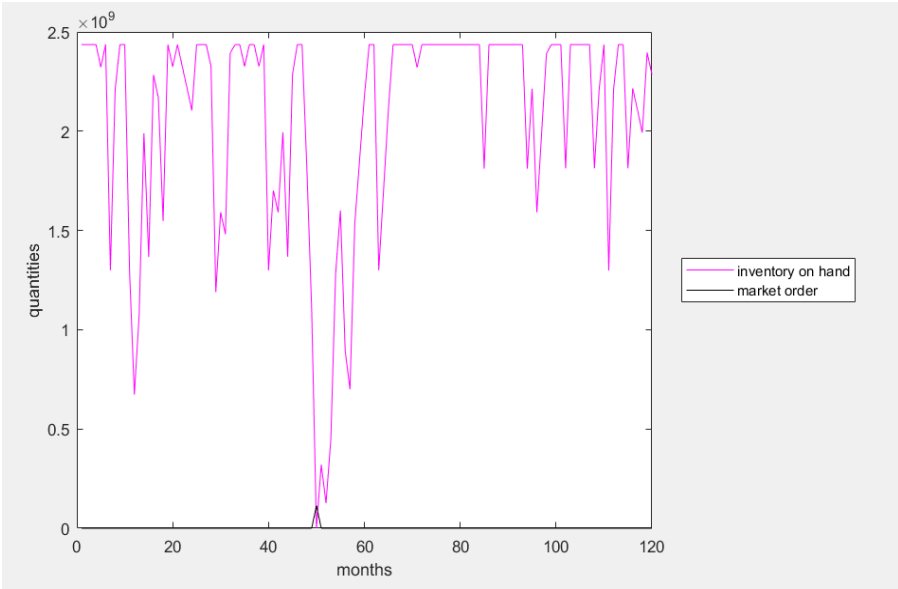

Figure 15. Market order quantity for the first scenario

As it can be seen in Figure 15, the market order quantity is equal to zero for all months, except month 50. This confirms that the robustness of supply chain design for this scenario is close to one. Therefore, this supply chain design may be the best design for this scenario. However, it must be considered that capacities and demand depend on several scenarios, and this design can be not optimal for another scenario.

5.2. Simulation results for scenario 2

The same supply chain design is also tested for a second scenario, and results are presented in Figure 16.

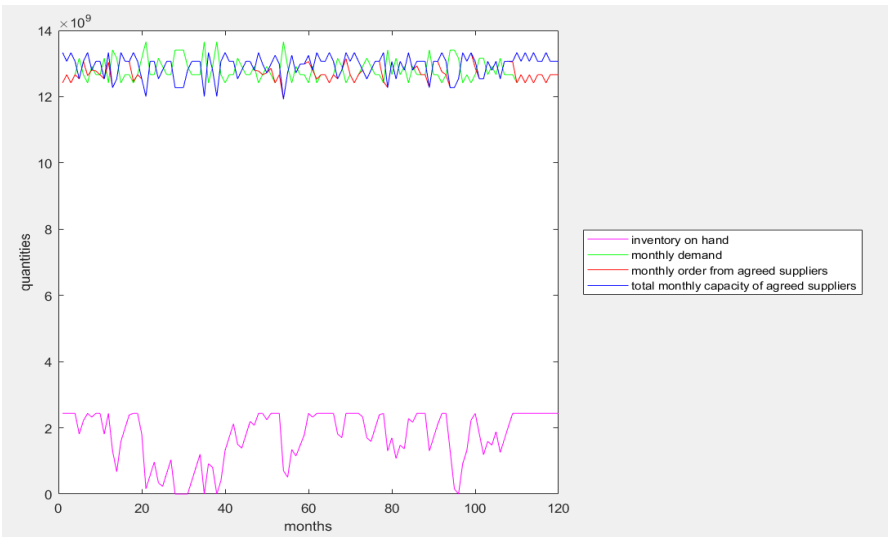

Figure 16. Simulation results of second scenario

Although the design is the same than for scenario 1, the capacity and demand values are different from the previous scenario. According to results for scenario 2, the inventory on hand drops the zero for some months (e.g. months 30, 35, 38, 95). This means that the robustness

value of the design for this scenario is lower than the previous scenario example. The free market order quantity chart for scenario 2 is shown in Figure 17.

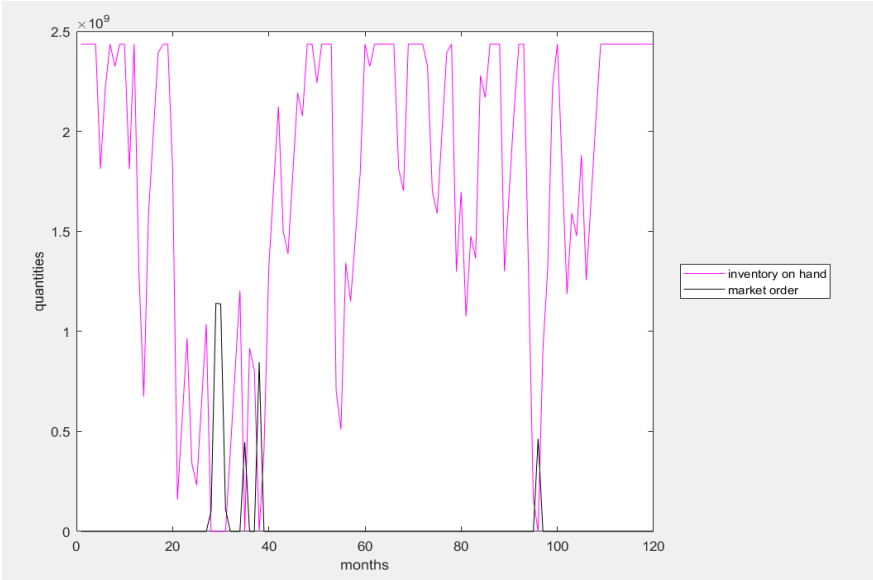

Figure 17. Market order quantity for the second scenario

According to Figure 17, India makes orders from the free market in case of inventory on hand is equal to zero. These orders mean the design cannot meet the demand for some specific times. There can be two reasons: Firstly, the capacity of suppliers decreases dramatically due to disaster in certain supplier zones. Secondly, a big impact hazard occurs in the demand zone and the demand quantity increases dramatically. For example, for in month 30, the increase in demand and decrease in agreed suppliers' capacity can be observed. It is possible to make supply chain design to face these possibilities and increase the supply chain robustness. However, this kind of design might become too costly. Therefore, alternative supply chain designs must be created by considering these two parameters (robustness and cost).

5.3. Cost calculation

The calculation of cost begins after the simulation has finished. In the simulation, order quantities to suppliers, order quantities to free market and inventory on hand are being calculated monthly. Then, suppliers purchase costs, market purchase costs and warehouse holding costs can be calculated.

Supplier purchase cost

The supplier purchase cost can be calculated with following equations:

$$wc_\tau = o_{s\tau} * wp_s \qquad \tau \in T^u, s \in S$$

$$wc_t = \Sigma wc_\tau \quad t \in T$$

where wc is purchase cost, o is order quantity, s supplier, S set of suppliers, wp are the supplier prices of all suppliers, τ is the working period and t is the planning period. Monthly purchase costs are aggregated to find annual purchase cost.

Free market purchase cost

The market purchase cost can be calculated with following equations:

$$mc_\tau = mo_\tau * mp + an_\tau * (mo_\tau > 0) \quad \tau \in T^u$$

$$mc_t = \Sigma mc_\tau \quad t \in T$$

where mc is market purchase cost, mo is market order quantity, mp is market price, an is the cost of signing a new agreement, τ is the working period and t is the planning period. Signing new agreement cost is only applied if there is a market order that month. Monthly market costs are aggregated to find annual market cost.

Warehouse holding cost

The warehouse holding cost can be calculated with the following equations:

$$whc_\tau = whq_\tau * hc \quad \tau \in T^u$$

$$whc_t = \Sigma whc_\tau \quad t \in T$$

where whc is warehouse holding cost, whq is inventory level, hc is holding cost, τ is the working period and t is the planning period. Monthly warehouse holding costs are aggregated to find annual warehouse holding cost.

Cost for signing a new agreement or cancelling an agreement with suppliers

The cost for signing a new agreement and cancelling an agreement with suppliers can be calculated with following equations:

$$agc_t = an_t * nn_t + ac_t * nc_t \quad t \in T$$

where agc is the agreement cost, an is signing a new agreement cost, nn is number of new agreements in a year, ac is cancelling an agreement cost, nc is the number of cancelled agreements and t is the planning period.

Total cost function

Considering these cost parameters, total cost function can be written as follows:

$$tc_t = wc_t + mc_t + whc_t + agc_t \quad t \in T$$

where tc is total cost, wc is suppliers purchase cost, mc it the free market purchase market cost, whc is the warehouse holding cost, agc is the agreements cost, and t is planning period.

These steps are showing the cost calculation for one scenario. Therefore, in order to consider a set of scenarios, the average cost value is being considered while creating the designs.

$$dc = \frac{1}{scn} * \sum_{sc=1}^{scn} \sum_{t=1}^{T} tc_{tsc} \quad t \in T$$

where dc is the design average cost, scn is the number of analysed scenarios, sc is the scenario variable, tc is the total cost and t is the planning period.

Robustness value is calculated by considering demand and the amount of product purchased to the free market. Firstly, robustness value for one scenario is calculated. Then the average value of robustness is considered for a set of scenarios.

$$robustness_{sc} = \frac{\sum d_\tau - \sum mo_\tau}{\sum d_\tau} \quad \tau \in T^u$$

$$robustness = \frac{1}{scn} * \sum_{sc=1}^{scn} robustness_{sc}$$

where, d is demand quantity, mo is the amount of product purchased to the free market, sc is a specific scenario and τ is the working period.

Designs are created by minimizing the design cost. Due to the fact that design cost is the average of scenario costs, created design may not be the best design for some particular scenarios. However, this design is assumed to be more reliable as a whole than single best designs. It is proven that it has more response capability by minimizing the average total costs than a single best design.

5.4. Creation of Covid-19 scenario

In addition to created scenarios, a Covid-19 scenario is created to test candidate designs. In order to create this scenario, total active cases are used as total affected people. Table 1 is considered to determine the hazard types. For example, if the number of total active case is less than 0.01% of population of a country, it is considered as hazard type 1. Covid-19 data are obtained from www.worldometers.info in December 2020. The average total active cases and hazard types are presented in Table 1.

Table 1. Covid-19 case data by December 2020

	India									
month	february	march	april	may	jun	july	august	september	october	november
avg. active cases	0	619,5	12940	58995	156947,5	392701	674991,5	863339,5	758040,5	505764,5
hazard type	1	1	1	1	2	2	2	2	2	2
	USA									
month	february	march	april	may	jun	july	august	september	october	november
avg. active cases	30	92639	530526,5	998570	1283803	1857861	2448148	2600824	2835568	4266968
hazard type	1	2	3	3	3	3	3	3	3	4
	Pakistan									
month	february	march	april	may	jun	july	august	september	october	november
avg. active cases	0	918	6916	27341,5	74524	65651	16783	8639,5	10257,5	30218,5
hazard type	1	1	1	2	2	2	1	1	1	2
	Thailand									
month	february	march	april	may	jun	july	august	september	october	november
avg. active cases	7	656,5	756	137	59	92	114,5	116,5	131	133
hazard type	1	1	1	1	1	1	1	1	1	1
	Brazil									
month	february	march	april	may	jun	july	august	september	october	november
avg. active cases	0	2694,5	24466,5	161262	418884,5	624234	690665,5	590450	441475	477505,5
hazard type	1	1	2	2	3	3	3	3	3	3

Covid-19 may happen any time in the studied scenarios, and it is considered a biological hazards. Therefore, to create the Covid-19 scenario, a random year in a random scenario is

selected and the Covid-19 effect is added to this year. An example of this procedure can be seen in Table 2.

Table 2. Example of covid-19 case creation

India										
random year in scenario	1	0	2	1	0	0	1	4	0	0
covid-19 hazard type	1	1	1	1	2	2	2	2	2	2
covid-19 case	2	1	3	2	2	2	3	6	2	2

All the other parameters are assumed as the same than a regular year. Only 10 months are simulated for the Covid-19 case due to the limited available data. In order to observe the Covid-19 effect better, 100 scenarios are selected randomly, and Covid-19 years are selected randomly. For example, Covid-19 may occur in year 5 in scenario 78, or in year 1 in scenario 5. Then, all created designs are sent to the evaluation step.

6. Candidate results and discussion

6.1. Candidate analyses and selection

In this step, supply chain designs are simulated for all scenarios, and they are evaluated according to average cost and robustness values. Seven supply chain designs are created by using 50 randomly chosen scenarios and they are evaluated for 2000 scenarios. The simulation period is 10 years. Created candidate supply chain designs are shown in Table 3.

Table 3. Candidate supply chain designs

	Design 1						Design 2						Desing 3					
years/ suppliers	1	2	3	4	5	warehouse capacity	1	2	3	4	5	warehouse capacity	1	2	3	4	5	warehouse capacity
1	1	0	0	0	1	2,43E+09	1	0	0	0	1	2,66E+09	1	0	0	0	1	2,65E+09
2	1	0	0	0	1		1	0	0	0	1		1	0	0	0	1	
3	1	0	0	0	1		1	0	0	0	1		1	0	0	0	0	
4	1	0	0	0	1		1	0	0	0	1		1	0	0	0	1	
5	1	0	0	0	0		1	0	0	0	1		1	0	0	0	1	
6	1	0	0	0	1		1	0	0	0	1		1	0	0	0	1	
7	1	0	0	0	1		1	0	0	0	1		1	0	0	0	1	
8	1	0	0	0	1		1	0	0	0	1		1	0	0	0	1	
9	1	0	0	0	1		1	0	0	0	1		1	0	1	0	1	
10	1	0	0	0	1		1	0	0	0	1		1	0	0	0	1	

	Design 4						Design 5						Design 6					
years/ suppliers	1	2	3	4	5	warehouse capacity	1	2	3	4	5	warehouse capacity	1	2	3	4	5	warehouse capacity
1	1	0	0	0	0	2,35E+09	1	0	0	0	1	2,08E+09	1	0	0	0	1	2,25E+09
2	1	0	0	0	1		1	0	0	0	0		1	0	1	0	0	
3	1	0	1	0	0		1	0	0	0	1		1	0	0	0	1	
4	1	0	0	0	1		1	0	0	0	1		1	0	0	0	0	
5	1	0	1	0	0		1	0	0	0	1		1	0	0	0	1	
6	1	0	0	0	1		1	0	0	0	1		1	0	0	0	0	
7	1	0	0	0	1		1	0	0	0	1		1	0	0	0	1	
8	1	0	0	0	1		1	0	0	0	1		1	0	0	0	1	
9	1	0	0	0	1		1	0	0	0	1		1	0	0	0	1	
10	1	0	0	0	1		1	0	0	0	1		1	0	0	0	1	

	Design 7					
years/ suppliers	1	2	3	4	5	warehouse capacity
1	1	0	0	0	1	2,13E+09
2	1	0	0	0	1	
3	1	0	0	0	1	
4	1	0	1	0	0	
5	1	0	0	0	1	
6	1	0	0	0	1	
7	1	0	0	0	1	
8	1	0	0	0	1	
9	1	0	1	0	0	
10	1	0	0	0	1	

The cost and robustness evaluation of the candidates' designs are presented in Table 4.

Table 4. Candidate supply chain designs results

Design number	1	2	3	4	5	6	7
Cost	1,09787E+12	1,09781E+12	1,0986E+12	1,09857E+12	1,09837E+12	1,09865E+12	1,09865E+12
Robustness	0,999508376	0,999659662	0,999629133	0,99958523	0,999249328	0,9993938	0,999457156

The covid-19 case results are presented in Table 5 for the same supply chain designs.

Table 5. Covid-19 case results

Design number	1	2	3	4	5	6	7
Cost	1,92872E+11	1,91332E+11	1,92175E+11	1,90692E+11	1,94552E+11	1,92727E+11	1,93549E+11
Robustness	0,889371595	0,891392736	0,890167207	0,892906868	0,887271928	0,889885078	0,888771607

According to Table 4 and Table 5, the robustness results are very close for all candidate supply chain designs. However, if demand quantity is considered, the difference between two robustness values can be observed. For example, in some cases the differences between robustness values are at the third place. If the demand quantity is considered as $149*10^9$ kg, the purchased quantity to the free market can be calculated as 0.001 times $149*10^9$kg which is equal to $149*10^6$kg per year. Therefore, small differences in the robustness value may create big differences in the free market purchased quantity.

Candidate design results are simulated for 10 years. Therefore, in order to find the annual average cost, the cost value for a supply chain design should be divided by 10. As a result, it can be concluded that the supply chain costs of Covid-19 case are much higher than average cost of created scenarios. In addition, the robustness values for the Covid-19 case decreased dramatically when the demand scale is considered. According to Table 4 results, supply chain design 2 shows both the minimum cost and the maximum robustness values when there is no Covid-19. On the other hand, according to Table 5, design 4 shows both the minimum cost and maximum robustness values for Covid-19 case. Design parameters of design 2 and design 4 are presented in Table 6.

Table 6. Designs results of design 2 and 4

	Design 2						Design 4					
years/ suppliers	1	2	3	4	5	warehouse capacity	1	2	3	4	5	warehouse capacity
1	1	0	0	0	1	2,66E+09	1	0	0	0	0	2,35E+09
2	1	0	0	0	1		1	0	0	0	1	
3	1	0	0	0	1		1	0	1	0	0	
4	1	0	0	0	1		1	0	0	0	1	
5	1	0	0	0	1		1	0	1	0	0	
6	1	0	0	0	1		1	0	0	0	1	
7	1	0	0	0	1		1	0	0	0	1	
8	1	0	0	0	1		1	0	0	0	1	
9	1	0	0	0	1		1	0	0	0	1	
10	1	0	0	0	1		1	0	0	0	1	

As it can be seen in the Table 6, in supply chain design 2, India makes agreement with Brazil during all 10 years' period. Also, warehouse capacity is high. On the other hand, in supply chain design 4, India makes agreements with Brazil most the years and Pakistan for some years. Although the results of design 4 are worse than results of design 2 for non Covid-19 scenarios, design 4 provides better results for the Covid-19 case. While making judgment about the robustness values, the scale of demand must be considered. Therefore, small changes in robustness may represent huge increase in the amount purchased at the free market, in other words unmet demand with agreed suppliers.

Increasing warehouse capacity is a common technique to improve robustness. The effects of this technique can be observed in the results of created scenarios. For the predictable hazardous events, increasing warehouse capacity may increase the supply chain robustness. On the other hand, less warehouse capacity may perform better than high warehouse capacity in case of catastrophic events. The explanation is that a catastrophic event has a long impact for several months and this cannot be supplied from the warehouse. Hazardous events have short term impacts so the demand can be supplied from the warehouse.

The main difference between supply chain designs 2 and 4 is that India makes agreement with Pakistan in some years and Brazil the rest of the years. Pakistan has more capacity than Brazil in rice exports. However, rice from Pakistan is more expensive and India should buy more those years because there is a rule that demand zone must buy at least 50% of net capacity of an agreed supplier. The reason that in case of catastrophic events, demand increase unexpectedly and the suppliers' capacity decrease dramatically, means that having suppliers that have more capacity can keep the robustness at a high level. However, having agreements with this kind of supplier every year results in high costs while keeping the robustness at similar levels.

The main problem is that likelihood of catastrophic events is very low and unpredictable. Therefore, changing agreed suppliers in some years may be one of the cautions to keep robustness high level while not increasing total costs. If it is assumed as the Covid-19 scenario occurs at the 11th year, the following results can be obtained.

Table 7. Simulation results considering Covid-19 at the 11th year

Design number	1	2	3	4	5	6	7
Cost	1,29074E+12	1,28914E+12	1,29078E+12	1,28926E+12	1,29292E+12	1,29137E+12	1,29219E+12
Robustness	0,944439985	0,945526199	0,94489817	0,946246049	0,943260628	0,944639439	0,944114381

According to Table 7, supply chain design 2 has the minimum cost but design 4 has the maximum robustness value. Therefore, choosing the best design depends on the objectives priority. It can be claimed that design 2 is the best design in terms of cost, and design 4 is the best design in terms of robustness.

7. Conclusions and recommendations

Supply chain networks are vulnerable to disasters but Covid-19 pandemic reveals that the degree of vulnerability is much higher than expected. There are several strategies developed to reduce the effects of disasters and deal with supply chain network problems such as location, supplier selection, inventory on hand or order quantity and frequency. The purpose of these strategies is increasing the robustness and resilience while trying to decrease the total cost. This study considers the supplier selection problem and aims to contribute to existing methods using hazards simulation. The study is composed of three main steps: The first step is simulating hazards. For this step, future scenarios are created by balancing historical data and randomness. Then, according to created future scenarios, candidate supply chain designs are created by optimizing the robustness and cost values. In the third step, these candidate designs are evaluated, and best design is chosen by considering performance measures. These performance measures can show variety according to future purposes. Mathematical models are created to execute and evaluate these three steps. In this study, general purposes, which are low cost and

high robustness, are applied, and a real case of a food product supply across countries is simulated with available data.

According to the study results, there is no single design that has both lowest cost and highest robustness. In addition, some further observations can be made. For example, increasing the warehouse capacity can increase robustness in low impact hazards, and the results for expected disasters are supporting this method. However, for the catastrophic disasters that can affect for several months, like Covid-19 pandemic, the benefits of increasing warehouse capacity are limited. The reason is that inventory on hand cannot meet demand for several months in case of long-term lack of supplies. High warehouse capacity can increase the revenue during catastrophic disasters, however, in long term, the holding cost can be higher than the additional revenue during catastrophic disasters. Therefore, according to results, the maximum warehouse capacity can be limited by considering expected random hazards.

Having agreements with more suppliers increase the robustness of the supply chain. The robustness term becomes more important when size of demand and catastrophic events are considered. On the other hand, always having agreement with more suppliers than needed may result in unnecessary extra cost because catastrophic events occur very rare. Because catastrophic disasters can occur randomly, the years with higher number of agreed suppliers can be chosen randomly. Increasing the number of agreed suppliers randomly for some years can increase robustness while it may result in small cost increase.

Further research can take this simulation model and modify it to investigate more detailed and complex supply chain networks. For example, new agreement conditions can be applied such as special discount conditions and guarantees. In addition, Covid-19 case can be extended with new data. New performance measures can be added for environmental purposes such as carbon emission and the scenario creation model can be improved by considering currency risks too.

References list

Aryanezhad, M., Jalali, S.G., Jabbarzadeh, A., (2010). An integrated supply chain design model with random disruptions consideration. African Journal of Business Management 4: 2393–2401

Azad, N., Davoudpour, H., Saharidis, G. K., & Shiripour, M. (2014). A new model to mitigating random disruption risks of facility and transportation in supply chain network design. The International Journal of Advanced Manufacturing Technology, 70(9): 1757–1774.

Azad, N., Saharidis, G. K., Davoudpour, H., Malekly, H., & Yektamaram, S. A. (2013). Strategies for protecting supply chain networks against facility and transportation disruptions: an improved Benders decomposition approach. Annals of Operations Research, 210(1): 125–163.

Azadegan, A., Patel, P.C., Zangoueinezhad, A., & Linderman, K. (2013), "The effect of environmental complexity and environmental dynamism on lean practices", Journal of Operations Management, 31(4): 193-212

Behzadi, G., O'Sullivan, M. J., Olsen, T. L., & Zhang, A. (2018). Agribusiness supply chain risk management: A review of quantitative decision models. Omega, 79: 21–42

Brandon-Jones, E., Squire, B., Autry, C. W., & Petersen, K. J. (2014). A contingent resource-based perspective of supply chain resilience and robustness. The Journal of Supply Chain Management, 50(3): 55-73.

Chopra, S. & Sodhi, M.S. (2004). Managing risk to avoid supply-chain breakdown. MIT Sloan Management Review, 46: 52–61

Christopher, M. & Peck, H. (2004). Building the resilient supply chain. The International Journal of Logistics Management, 15(2): 1-13

Christopher, M. & Rutherford, C. (2004). Creating supply chain resilience through agile six sigma. Critical Eye, June/August: 24-28

Durach, C.F., Wieland, A. & Machuca, J.A.D. (2015). Antecedents and dimensions of supply chain robustness: a systematic literature review. International Journal of Physical Distribution & Logistics Management, 45(1/2): 118–137.

Goh, M., Lim, J.Y.S., & Meng, F., (2007). A stochastic model for risk management in global supply chain networks. European Journal of Operational Research, 182: 164–173.

Govindan, K., Fattahi, M., & Keyvanshokooh, E. (2017). Supply chain network design under uncertainty: A comprehensive review and future research directions. European Journal of Operational Research, 263(1): 108–141.

Gurnani, H., Akella, R., & Lehoczky, J., (2000). Supply management in assembly systems with random yield and random demand. IIE Transactions, 32(8): 701–714.

Hasani, A., & A. Khosrojerdi. (2016). Robust Global Supply Chain Network Design Under Disruption and Uncertainty Considering Resilience Strategies: A Parallel Memetic Algorithm for a Real-life Case Study. Transportation Research Part E: Logistics and Transportation Review, 87: 20–52.

Hohenstein, N. O., Feisel, E., Hartmann, E., & Giunipero, L. (2015). Research on the phenomenon of supply chain resilience: a systematic review and paths for further investigation. International Journal of Physical Distribution & Logistics Management, 45(1-2): 90-117.

Inderfurth, K. &Vogelgesang, S., (2013). Concepts for safety stock determination under stochastic demand and different types of random production yield. European Journal of Operational Research, 224(2): 293-301.

ISM (2020). Institute for Supply Management, https://weareism.org/coronavirus-ism.html (Last accessed: 15 December 2020).

Ivanov, D. & Dolgui, A. (2020). OR-methods for coping with the ripple effect in supply chains during COVID-19 pandemic: Managerial insights and research implications. International Journal of Production Economics.

Jones, P.C., Lowe, T.J., Traub, R.D. & Kegler, G. (2001). Matching supply and demand; the value of a second chance in producing hybrid seed corn. Manufacturing and Service Operations Management, 3(2): 122–137.

Klibi, W. & A. Martel, (2011). Scenario-Based Supply Chain Networks Risk Modeling, CIRRELT Research Paper CIRRELT-2011-30, Universite´ Laval, Canada.

Klibi, W., Martel, A., & Guitouni, A. (2010). The design of robust value-creating supply chain networks: a critical review. European Journal of Operational Research, 203(2): 283–293.

Klibi, W. & Martel, A. (2012a). Modeling approaches for the design of resilient supply networks under disruptions Int. J. Prod. Econ., 135: 882-898

Klibi, W. & Martel, A. (2012b). Scenario-based supply chain network risk modeling European Journal of Operational Research, 223(3): 644-658

Mulvey, J. M., Vanderbei, R. J., & Zenios, S. A. (1995). Robust optimization of large-scale systems. Operations Research, 43(2): 264–281.

Peng, P., Snyder, L.V., Lim, A., & Liu, Z. (2011). Reliable logistics networks design with facility disruptions. Transport. Res. Part B, 45: 1190-1211

Rosenhead, J., Elton, M., & Gupta, S.K., (1972). Robustness and optimality as criteria for strategic decisions. Operational Research Quarterly, 23(4): 413–431

Saltelli, A., Ratto M., Tarantola S., Campolongo F., et al. (2006). Sensitivity analysis practices: Strategies for model-based inference. Reliab. Eng. Syst. Saf., 91 (10–11): 1109-1125

Santoso, T., Ahmed, S., Goetschalckx, M., & Shapiro, A., (2005). A stochastic programming approach for supply chain network design under uncertainty. European Journal of Operational Research, 167: 96–115.

Scawthorn, C., Shneider, P.J., & Shauer, B.A. (2006). Natural hazards – the multihazard approach. Natural Hazards Review, 7(2): 39.

Sen, S., & Higle, J. L. (1999). An introductory tutorial on stochastic linear programming models. Interfaces, 29(2): 33-61.

Shapiro, A., (2007). Stochastic programming approach to optimization under uncertainty. Mathematical Programming: Series A and B, 112(1): 183–220.

Tang, C. (2006). Robust strategies for mitigating supply chain disruptions. International Journal of Logistics: Research and Applications, 9(1): 33–45.

Wieland, A. & Wallenburg, C.M. (2013). The influence of relational competencies on supply chain resilience: a relational view. International Journal of Physical Distribution & Logistics Management, 43(4): 300-320.

Yano, C.A. & Lee, H.L. (1995). Lot sizing with random yields: a review. Operations Research, 43(2): 311-334.