

Institut für Wirtschaftsinformatik

Von-Melle Park 5 20146 Hamburg

FLEXIBLE SUPPLY CHAIN PLANNING FOR **STOCHASTIC CATASTROPHIC ENVIRONMENTS** YINGJIE FAN, STEFAN VOSS STATE DETAILTER STY SON STATES TOTAL

Flexible supply chain planning is an efficient way to cope with **future uncertainties**. Our focus lies on low-frequency and high-impact supply chain risks. Future potential catastrophic disruptions are forecasted based on Supply Chain internal and external Big Data analyses. Uncertainties are modeled by a multi-stage scenario tree. An objective function and constraints are defined in a SCENArio-based multi-stage stochastic programming model. After creating the scenario tree and the stochastic programming model, a set of **high-quality** feasible solutions (purchasing plan, production plan, transportation plan, distribution plan, etc. which merge into a supply chain plan) are generated by **PYOMO**. The **Supply** chain plan is adopted into practice on a rolling horizon. Re-planning becomes necessary once new **information** is available.

Assuming possible Disruptions in a Global Supply Chain

External Environments:



Assumption 1: In Country A a coup d'état and its subse-quent civil war might lead to a breakdown in all economic activities.



Stochastic Programming

Scenario Tree



Based on forecasting of potential catastrophic disruptions, a scenario tree

is used to show possible realizations of the future. Each root-leaf-path de-

fines a scenario, which represents one possible realization. An initial deci-

sion has to be made at the root-node. Further decisions are made at other

non-leaf nodes stage by stage by considering future uncertainties.

Objective Function:

 $\min\left\{TC^{1st} + \sum_{s \in S} P_s \cdot TC_s^{2nd}\right\}$ 1st Stage Costs:



2nd Stage Costs (for each scenario $s \in S$:

 $TC_s^{2nd} := \sum C_t^{SC}$ $T_0 + T_{1st} \leq t \leq T_f$

Decision Variables:

1st stage variables: $T_0 \le t < T_0 + T_{1st}$ 2nd stage variables: $T_0 + T_{1st} \le t \le T_f$ Q_{tpi}^{Purc} : Purchasing quantity of material $p \in P^{Material}$ at node $i \in N^{Asm} \cup N^{Pro}$ at time $t \in T$ Q_{tp}^{Proc} : Processing quantity of component $p \in P^{Core}$ at the processing center

 $n \in N^{Pro}$ at time $t \in T$ (2) Q_{toi}^{Asm} : Assembling quantity of the final product $p \in P^{Final}$ at assembling center

 $i \in N^{Asm}$ at time $t \in T$ Q_{toiim}^{lnter} : Transportation quantity of product $p \in P$ on international transportation link $(i, j) \in Conn^{Inter}$ launched at time $t \in T$ with transportation

 Q_{tpij}^{lnland} : Transportation quantity of product $p \in P$ on inland transportation link $(i, j) \in Conn^{lnland}$

launched at time $t \in T$ (3)

A multi-stage stochastic programming model is used to determine a decision for each node of the

scenario tree, given the information available at that node. The example shows a two-stage stocha-

stic programming problem. The objective is to make the first stage supply chain plan taking into ac-

count potential catastrophic disruptions during the second stage to minimize supply chain costs for

the whole considered time horizon.

mode $m \in M$

Supply Chain Cost Functions:

$C_t^{SC} := \sum_{i \in N^{Pro} \cup N^{Asm}} \sum_{p \in P^{Material}} C_{pi}^{Purc} \cdot Q_{tpi}^{Purc}$ (materials purchasing cost)
+ $\sum_{(i,j)\in Conn^{Inter}} \sum_{p\in P^{Core}\cup P^{Final}} \sum_{m\in M} C_{pijm}^{Inter} \cdot Q_{tpijm}^{Inter}$ (international trans cost)
$+ \sum_{(i,j) \in Conn^{Inland}} \sum_{p \in P} C_{pij}^{Inland} \cdot Q_{tpij}^{Inland} $ (inland trans cost)
$+ \sum_{i \in N^{Pro}} \sum_{p \in P_i^{Node}} C_i^O \cdot Q_{tp}^{Proc} $ (processing cost)
$+ \sum_{i \in N^{Asm}} \sum_{p \in P_i^{Node}} C_i^O \cdot Q_{tpi}^{Asm} $ (assembling cost)
+ $\sum_{i \in N^{Pro} \cup N^{Asm}} \sum_{p \in P^{Material}} C_{pi}^{Storage} \cdot I_{tpi}^{Material}$ (materials storage cost)
$+ \sum_{i \in N^{Pro} \cup N^{Asm}} \sum_{p \in P^{Core}} C_{pi}^{Storage} \cdot I_{tpi}^{Core} $ (components storage cost)
+ $\sum_{i \in N^{Asm} \cup N^{Final}} \sum_{p \in P^{Final}} C_{pi}^{Storage} \cdot I_{tpi}^{Final}$ (final products storage cost)
+ $\sum_{(i,j)\in Conn^{Inter}} \sum_{p\in P_i^{Node}} \sum_{m\in M} C^h \cdot V_{pi} \cdot Q_{tpijm}^{Inter}$ (capital holding cost)
$+ \sum_{(i,j) \in Conn^{Inland}} \sum_{p \in P_i^{Node}} C^h \cdot V_{pi} \cdot Q_{tpij}^{Inland} $ (capital holding cost)
$+ \sum_{p \in P^{Final}} \sum_{i \in N^{Dis}} C_p^{Stockout} \cdot I_{tpi}^{-Final} $ (stockout cost of final products)

Stochastic Parameters:

S: Stochastic scenario set

 $T_{s_i}^{bang}$: The disruptive event of scenario $s \in S$ breaks out at node $i \in N$ at time T_{si}^{bang}

 T_{si}^{dur} : The disruptive event of scenario $s \in S$ at node $i \in N$ will last for a time period of T_{si}^{dur}

 Q_{si}^{bang} : The up-bound capacity of scenario $s \in S$ at node $i \in N$ during the time period of disruption when $T_{si}^{bang} \leq t < T_{si}^{bang} + T_{si}^{dur}$

 D_{stpi}^{S} : Predictive demand of final products $p \in P^{Final}$ at distribution center $i \in N^{dis}$ at time $t \in (T_0 + T_{1st}, T_f]$ under scenario $s \in S$

 P_s : The probability of scenario s

Flexible Supply Chain adopted in a Rolling Planning Horizon

For the last step PYOMO, a Python-based, open-source optimization modeling language with a diverse set of optimization

upper bound of predicted demand 1

upper bound of predicted demand 3

References:

capabilities, is used. The high-quality feasible solutions obtained by implementing the structure of the scenario tree and the stochastic model into PYOMO are merged into a supply chain plan. This plan contains sub-plans like the purchasing plan, the production plan, the transportation plan, the distribution plan, etc. The supply chain plan is adopted into practice on a rolling horizon. a rolling horizon consists of a set of adjusted supply chain plans. Whenever there is new information available in forms of big data, the whole process of creating scenario trees and determining decisions via the stochastic programming model has to be repeated in order to obtain the set of supply chain plans. Simulation results show that supply chain plans generated in this way can help to save 5 up to 64 percent of a supply chain's costs. This has been found by analyzing the costs of supply chain plans from multi-scenario modeling by comparing three benchmarks: a pessimistic, an optimistic, and an average scenario.

Rolling Planning Horizon actual demand lower bound of predicted demand 3 upper bound of predicted demand 2 lower bound of predicted demand 1 lower bound of predicted demand 2 Time 2 Time 3 Time o Time 1

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For more information on PYOMO please visit: http://www.pyomo.org/

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