Deriving a global production network type in times of uncertainty – a simulation based approach

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Abstract: Global production networks are highly complex to manage and constantly to optimize. Recent developments such as political power changes, pandemic crises or increasing trade hurdles have significantly altered the risk exposure of global production set-ups. We use optimization and simulation tools to derive a suitable network type. We develop a global cross-shipping strategy with an integrated approach combining heuristics and simulation. We quantify the impacts of different uncertainties, such as plant closure and high demand variation with simulation, and it to compare to a local-to-local production network. Our approach makes the model easy to implement and close to real-world processes.

This paper provides support for production network decision-making. We present a scientifically sound and practically feasible approach to an important actual business management problem. The developed integrated approach does not require assumptions about the production network structure or policies and is therefore applicable to a wide range of settings. In our case study, we quantify the positive impact of a global cross-shipping production network in comparison to a local-to-local approach. The result of our study helps to adjust the needed strategic and operational measures to manage a global production network.

Keywords: Production, production network, strategy, operations, simulation, decision-making, industrie 4.0, smart factory

Ableitung eines globalen Produktionsnetzwerk-Typs in Zeiten von Unsicherheit – ein simulationsbasierter Ansatz

Zusammenfassung: Globale Produktionsnetzwerke sind hochkomplex zu führen und ständig zu optimieren. Jüngste Entwicklungen wie politische Machtwechsel, Pandemiekrisen oder zunehmende Handelshürden haben die Risikoexposition von Produktionsverbünden signifikant verändert. Wir verwenden Optimierungs- und Simulationswerkzeuge, um einen geeigneten Netzwerktyp abzuleiten. Wir entwickeln eine globale Cross-Shipping-Strategie mit einem integrierten Ansatz, der Heuristik und Simulation kombiniert. Zusätzlich quantifizieren wir die Auswirkungen verschiedener Unsicherheiten, wie Werksschließungen und hohe Nachfrageschwankungen, mit Hilfe von Simulationen, um die Cross-Shipping-Strategie mit einem Local-to-Local-Produktionsnetzwerk zu vergleichen. Unser Ansatz macht das Modell einfach zu implementieren und ist nahe an realen Prozessen.

Diese wissenschaftliche Arbeit bietet Unterstützung für die Entscheidungsfindung in Produktionsnetzwerken. Wir präsentieren einen wissenschaftlich fundierten und praktisch umsetzbaren Ansatz für ein wichtiges und aktuelles Problem in der Unternehmensführung. Der entwickelte integrierte Ansatz erfordert keine Annahmen über die Struktur oder die Richtlinien des Produktionsnetzwerks und ist daher auf eine breite Palette von Einstellungen anwendbar. In unserer Fallstudie quantifizieren wir die positiven Auswirkungen eines globalen Cross-Shipping-Produktionsnetzwerks im Vergleich zu einem Local-to-Local-Ansatz. Das Ergebnis unserer Studie hilft dabei, die notwendigen strategischen und operativen Maßnahmen zur Steuerung eines globalen Produktionsnetzwerks anzupassen.

Stichwörter: Produktion, Produktionsnetzwerk, Strategie, Betrieb, Simulation, Entscheidungsfindung, Industrie 4.0, Smarte Fabrik

1 Introduction

1.1 Motivation

Most producers today have established several plants abroad and operate in global supply chains to better address different market needs and optimize cost. Due to this increasing willingness to outsource steps of the production network on a global scale, the development of transport sectors and the setup of bilateral and international trading agreements have followed suit. In addition, by operating in global production networks, companies can bypass trade barriers such as customs duties and optimize transport and labor costs (*Friedli et al.* 2014). However, the complexity of operating the resulting production networks is raised due to the many diverse components and an increasing need of coordination to deal with costs factors, logistics lead-times, risks and variability.

Given the complex nature of a global production network, it is difficult to manage risks such as natural disasters, pandemics, political power changes and terrorism. Moreover, production strategies like lean inventories, just-in-time delivery schedules, centralized distribution, sourcing from developing countries and global production strategies have been widely applied. These strategies are most often neither openly debated nor transparent until an event leads to a supply chain failure. Quantifying the costs and assessing the risks of a production strategy with a global production network is very difficult due to the complex interconnection of all stakeholders (*Manners-Bell* 2017).

Faced to the two main challenges of production network design and operations, complexity and uncertainty, previous research papers have developed sophisticated approaches such as search algorithms (SA), simulation with design of experiments (DoE), combined SA and simulation, or closed form solutions for simplified formulations which are far from real-world processes. However, in many cases, small and medium enterprises (SMEs) who don't necessarily have capacity in statistics or search algorithms, need fast and easy-to-implement approaches which achieve sound performance for real-world problems. This paper responds to this need in decision-making support, by combining heuristics and simulation. To the best of our knowledge, very little has been done in this area (*Paul et al.* 2016).

In this paper, we use optimization and simulation tools to derive a suitable production network type. The management decisions are at strategic (e.g., opening new plants) and operative (e.g., production, procurement and delivery plans) levels. A deterministic mathematical model and a discrete-event simulation (DES) model considering uncertainties have been developed. First, a heuristic approach that ignores certain constraints is applied to the mathematical model to obtain an initial strategy and an upper bound on the total profit. The DES model then improves the initial strategy by considering all constraints and uncertainties and evaluates the performance of the final strategy with respect to the upper bound. The simulation model also evaluates the impacts of different uncertainties and the performances of different production network settings under various conditions.

Our integrated approach improves operational efficiency and provides reasonable model performance. In our case study, we see that our solution achieves 90 % total profit comparing to the upper bound obtained. This approach has a high practical contribution for industrial decision makers. It provides insight into current business management problems from practice.

1.2 Structure of the paper

The remainder of this paper is organized as follows. Section 2 summarizes the state-of-art. Section 3 introduces the research question, formulates the problem, explains the problem complexity and presents our integrated approach. Section 4 presents a real-world use case. Section 5 presents conclusions and findings.

2 State of the Art

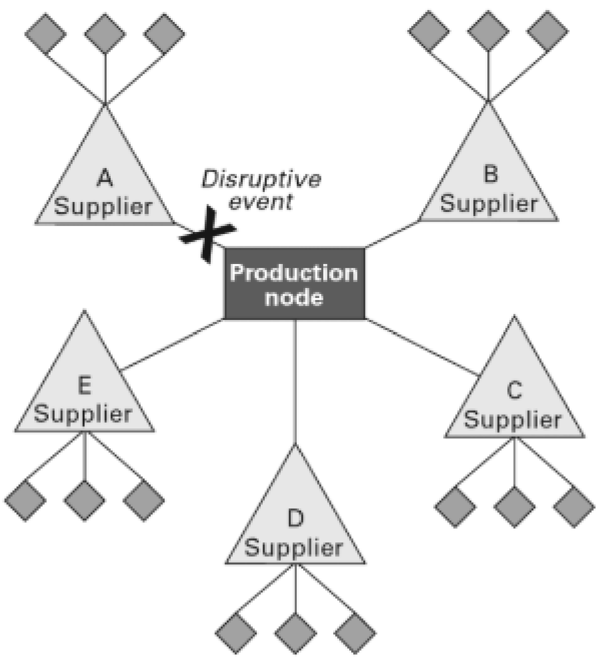


Figure 1: Multi-Supplier Network

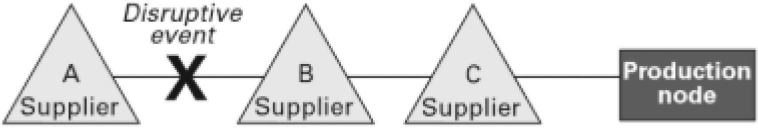


Figure 2: Single-Supplier Network

Risk and disruption management have recently become important topics for production networks and supply chains. There are many ways to categorize risk types. One relevant way (*Manners-Bell* 2017) is to classify risks into internal risks (such as process and control) and external risks (demand or supply uncertainty, environment disasters, weather, etc.) Globalization has led to increased risks due to longer lead times, less agile responses to market conditions, currency fluctuations, labor disputes and shipping costs. A production network with multiple suppliers (*Figure 1*) is more complex to manage but has lower probability of a total disruption compared to a single supplier network (*Figure 2*). However, as *Manners-Bell* (2017) stated, "it is very difficult to measure the impact of an event on a supply chain and even harder to attempt to forecast the impact of a potential event."

2.1 Solution approaches and research gap

Quantitative approaches solving supply chain network (SCN) problems are mainly divided into two groups: optimization and simulation.

Optimization methods can be further classified as (i) traditional optimization approaches, (ii) heuristic approaches and (iii) search algorithms (metaheuristics). Traditional optimization approaches can solve simple supply chain management problems using methods such as branch and bound (*Timpe/Kallrath* 2014), linear programming (*Kabak/Ülengin* 2011) or quadratic programming (*Xia et al.* 2004). However, the supply chain network risk and disruption management problem are usually large-scale, multi-stage and non-linear. Traditional optimization approaches thus have limits of applicability. Heuristics are approximate strategies for decision-making and problem-solving that do not guarantee an optimal solution but that typically yield a reasonable solution (*Todd* 2001). Heuristics are simple to understand, easy to apply, and very inexpensive in terms of computing effort, thus speeding up the process of finding a satisfactory solution (*Talbot/Patterson* 1979). Search algorithms use different random-search and parallelization paradigms to obtain solutions. Examples include genetic algorithms (e.g. *Nezamoddini et al.* 2020), simulated annealing (e.g. *Diabat* 2014), ant colony algorithm (e.g. *Bottani et al.* 2019), particle swarm optimization (e.g. *Goodarzian et al.* 2020), etc.

While optimization methods have been mostly applied to simplified scenarios of real-life processes, simulation deals with complex processes without mathematical sophistication but with details and accuracy (*Figueira/Almada-Lobo* 2014). Simulation is especially suitable for complex production networks (*Lanza et al.* 2019). DES can be defined as an interacting set of entities that evolve through different states as internal or external events happen (*Robinson* 2004). DES is able to produce valid representations of a real system incorporating the system's uncertainty and dynamics. *Semini et al.* (2006) reviewed 52 applications of DES to support manufacturing logistic decision-making.

Simulation is not an optimization tool, however. It needs help from other methods such as DOE or SA to identify promising solution areas. Hybrid sim-opt methods refer to the interaction between optimization and simulation "to find near-optimal solutions to complex or stochastic optimization problems". A few examples can be found in the production network management literature. *Ding et al.* (2009) combined a multi-objective genetic algorithm (MOGA) and simulation in order to support decisions in the production distribution network structure and its operation strategies and related control parameters. DES is used to estimate the operational performance of solutions suggested by the optimizer MOGA. *He et al.* (2015) dealed with the modeling and optimization problem of a multi-echelon container supply chain network, where a genetic algorithm (GA) and a particle swarm optimization (PSO) algorithm are integrated for searching near-optimal solutions, and simulation is used for evaluating solutions and repairing unfeasible solutions. *Aqlan/Lam* (2016) proposed an approach combining goal programming and simulation for supply chain optimization under risk and uncertainty. *Chiadamrong/Piyathanavong* (2017) supported decisions for supply chain network design using a combination of analytical model and DES models, where decisions are split to be separately and iteratively determined by the two models. *Keizer et al.* (2015) identifed a cost-optimal network design under product quality requirements by combining MILP (for strategic optimization) and simulation (for production quality evalution). *Tordecilla et al.* (2021) reviewed the existing literature on the use of simulation-optimization methods in the design of resilient supply chain networks (SCNs). They stated that applications of hybrid sim-opt methods are still scarce in the topic of supply chain network design.

Hybrid sim-opt methods usually run the optimization and simulation models iteratively, solving the analytical part by search or exact algorithms, with parameters or evaluation results obtained from a simulation model (*Juan et al.* 2015). In this study, we take a different approach. We combine a heuristic with simulation, where the heuristic is used to deterimine an initial strategy and a profit upper bound and the simulation is used to improve this strategy by taking into account uncertainties and complex constraints. The upper bound obtained from the heuristic approach serves as a reference for the strategy's performance.

Paul et al. (2016) reviewed the mathematical models and the solution approaches used to solve models for managing risk and disruption in production-inventory systems and supply chains. They stated that, "It is observed that, most studies focused on using search algorithm to solve the models. A good number of works also have been found which developed heuristic and simulation approach to solve the complex models. In case of dynamic and complex problem, it is worth to develop a combined heuristic and simulation approach to make the model easy to implement and closer to a real-world process." They further pointed out that, "Some papers developed a heuristic to solve their models, but very little has been done to develop a combined heuristic and simulation approach to operate a model as a real-world process".

2.2 Conceptual model

In this paper we analyze a production network design and operation problem. The objective is to maximize total profit while maintaining a specified on-time-delivery rate (OTD) and fill rate under certain constraints. Questions to be answered include:

- What production network type is proposed? What are the procurement plan, production plan and delivery plan over the considered time horizon for this production network?
- Under deterministic /uncertain conditions, how does the performance of the proposed global production network (where materials and products are distributed across continents) comparing to the existing local production network?
- What would be the financial impact of an event (uncertainty) on the (proposed) global vs. (existing) local production networks?

We propose a new solution approach combining a heuristic and simulation. This approach describes a new way that can be widely used in production network decision-making for SMEs. It brings a practical contribution to companies facing supply chain disruption risks and an academic contribution in filling the research gap mentioned above.

This approach is based on in-depth data analysis and process understanding. Prior to the development of the optimization and simulation model, extensive data collection took place and valuable insights into the case company were gained. Our work could benefit from direct access to all relevant data and people in the company. The model was constantly tested and challenged. This research methodology results in a high degree of congruence between the simulation results and reality.

3 Research Design

In this paper we consider a single product production network with multiple globally located plants, suppliers and customers. To receive raw materials from suppliers, the plants pay raw material, transportation and import costs. Each supplier has its own capacity and commercial limits. Similarly, by delivering product to customers, the plants receive revenue per batch and pay transportation costs (per shipment) and export taxes. Each delivery path (supplier-plant or plant-customer) has a maximum volume and a transportation time. The OTD rate for each customer is required to achieve a target level.

The product is produced and delivered in full batches. Different machine versions are available which possess different production times (and production costs) per batch, where the more advanced machine version has higher production priority. Each plant has its own planned yearly production time, numbers of different machine versions and overall equipment efficiency (OEE). The capacity utilization of each plant is bounded above. Production and overhead costs occur in the plants. Inventory costs are included in the logistic overhead. In each plant, inventory levels of both raw material and product are required to stay between the available corresponding inventory space and safety stock (SS) levels.

We now present the full mixed integer program (MIP) formulation of the multi-period production network. See Appendix I for the model notation.

Objective function:

$$\max_{x_{ijt},\, y_{jt},\, z_{jkt}} \sum\nolimits_{j=1}^{J} \sum\nolimits_{k=1}^{K} \sum\nolimits_{t=1}^{T} c_k \times z_{jkt} \quad - \sum\nolimits_{j=1}^{J} Cost_j(x_{ijt}, y_{jt}, z_{jkt}) \tag{1}$$

$$Cost_j(x_{ijt}, y_{jt}, z_{jkt}) = \quad \sum\nolimits_{i=1}^{I} \sum\nolimits_{t=1}^{T} r_i \times x_{ijt}\,(1 + TC_{ij} + ImTax_{ij})$$
$$+ \quad POCost_j \; + \; \sum\nolimits_{k=1}^{K} \sum\nolimits_{t=1}^{T} \left(ExTax_{jk} \times c_k \times z_{jkt} + DLC_{jk} \times \left\lceil \frac{z_{jkt}}{\overline{V}max_{jk}} \right\rceil \right)\;, \tag{2}$$
$$\forall j$$

Suppliers' capacity and commercial limits:

$$\sum\nolimits_{j=1}^{J} \sum\nolimits_{t=1}^{T} x_{ijt} \leq Cmax_i\,,\ \forall i \tag{3}$$

$$\sum\nolimits_{j=1}^{J} \sum\nolimits_{t=1}^{T} x_{ijt} \leq CL_i\,,\ \forall i \tag{4}$$

$$CL_i \leq \alpha_i \sum\nolimits_{i=1}^{I} \sum\nolimits_{j=1}^{J} \sum\nolimits_{t=1}^{T} x_{ijt},\ \forall i \tag{5}$$

Plants' raw material inventory level constraints:

$$\mathbf{MSS}_j \leq IM_{jt} \leq \ \mathbf{MSpace}_j,\ \forall j,\ t \tag{6}$$

$$IM_{jt} = \ IM_{j(t-1)} - BOM \times \frac{y_{jt}}{Quality_j} + \sum\nolimits_{i=1}^{I} x_{ij(t-L_{ij})},\ \forall j,\ t \tag{7}$$

Plants' finished product inventory level constraints:

$$IP_{jt} = \ IP_{j(t-1)} + y_{j(t-PLT_j)} - \sum\nolimits_{k=1}^{K} z_{jkt},\ \forall j,\ t \tag{8}$$

$$\mathbf{PLT}_j = \frac{\max\limits_{v}(\,VT_v\,)}{OEE_j},\ \forall j \tag{9}$$

$$PSS_j \leq IP_{jt} \leq \ PSpace_j,\ \forall j,\ t \tag{10}$$

Plant's capacity utilization constraints:

$$\frac{\sum\nolimits_{t=1}^{T} y_{jt}}{\sum\nolimits_{v=1}^{V} \frac{B_{vj} \times PT_j \times OEE_j}{VT_v}} \leq \ \beta_j,\ \forall j \tag{11}$$

Production and overhead costs:

$$POCost_j = \Bigg\{ p_{1j} \times min\left(\sum\nolimits_{t=1}^{T} y_{jt},\ \frac{B_{1j} \times PT_j \times OEE_j}{VT_1}\right)$$
$$+ \sum\nolimits_{v=2}^{V} p_{vj} \times min\left(max\left(\sum\nolimits_{t=1}^{T} y_{jt} - \sum\nolimits_{\tilde{v}=1}^{v-1} \frac{B_{\tilde{v}j} \times PT_j \times OEE_j}{VT_{\tilde{v}}}, 0\right),\right. \tag{12}$$
$$\left.\frac{B_{vj} \times PT_j \times OEE_j}{VT_v}\right) \Bigg\} \times (1 + OPDALS_j),\ \forall j$$

OTD constraints:

$$\widehat{\boldsymbol{D}}_{\boldsymbol{k}1} = \mathbf{min}\left\{\boldsymbol{D}_{\boldsymbol{k}1}, \sum_{\boldsymbol{j}=1}^{\boldsymbol{J}} \boldsymbol{z}_{\boldsymbol{jk}\left(1-\overline{L}_{jk}\right)}\right\},\ \forall \boldsymbol{k} \tag{13}$$

$$\widehat{\boldsymbol{D}}_{\boldsymbol{kt}} = \mathbf{min}\left\{\boldsymbol{D}_{\boldsymbol{kt}}, \boldsymbol{max}\left(\sum_{\tilde{\boldsymbol{t}}=1}^{\boldsymbol{t}} \sum_{\boldsymbol{j}=1}^{\boldsymbol{J}} \boldsymbol{z}_{\boldsymbol{jk}\left(\tilde{\boldsymbol{t}}-\overline{L}_{jk}\right)} - \sum_{\tilde{\boldsymbol{t}}=1}^{\boldsymbol{t}-1} \boldsymbol{D}_{\boldsymbol{k}\tilde{\boldsymbol{t}}}, 0\right)\right\},\ \forall \boldsymbol{k},\ \boldsymbol{t} = 2, \ldots,\ \boldsymbol{T} \tag{14}$$

$$\frac{\sum_{\boldsymbol{t}=1}^{\boldsymbol{T}} \widehat{\boldsymbol{D}}_{\boldsymbol{kt}}}{\sum_{\boldsymbol{t}=1}^{\boldsymbol{T}} \boldsymbol{D}_{\boldsymbol{kt}}} \geq \boldsymbol{\gamma}_{\boldsymbol{k}},\ \forall \boldsymbol{k} \tag{15}$$

Variable restrictions:

$$\boldsymbol{y}_{\boldsymbol{jt}},\ \boldsymbol{z}_{\boldsymbol{jkt}} \in \boldsymbol{Z}_0^+,\ \ \boldsymbol{x}_{\boldsymbol{ijt}} \geq 0, \quad \forall \boldsymbol{i},\ \boldsymbol{j},\ \boldsymbol{k},\ \ \boldsymbol{t} \in \left[1, \boldsymbol{T}\right] \tag{16}$$

The objective is to maximize the total profit over the considered periods, which is the difference between the total revenues and total costs of all plants. Equation (2) indicates the three parts of total cost: purchasing, production and delivery costs. Constraints (3)-(5) enforce that each supplier cannot deliver more than its capacity and commercial limits. Constraints (6)-(10) require inventory levels to stay between the corresponding inventory space and SS level. Constraint (11) bounds the capacity utilization of each plant to be the actual output divided by the potential output of all machine versions. Equation (12) defines the production and overhead costs in a plant. The machine versions with small value (v) have higher priority. Equations (13) and (14) define the OTD amount for each customer at each period: when new batches arrive to a customer in period t, they first fill the pending demand from previous periods (if it exists) and then fill the demand of the actual period. Constraint (15) bounds the target OTD level of each customer. Constraint (16) is the variable constraint. We assume that the initial amounts purchased, produced and delivered are zero $\left(y_{jt} = 0,\ z_{jkt} = 0,\ x_{ijt} = 0,\ t < 0\right)$ in the periods that are outside our considered scope.

Note that in order to keep the model a reasonable size, we simplified the product inventory levels and production costs. In functions (8) and (9), the biggest processing time among all machines PLT_j is used to approximate the production time for one batch in plant j. Similarly, in function (12), the yearly production cost is estimated by assuming that old version machines work only when new version machines are all fully busy, while in reality, older machines may continue to work when new machines have completed their jobs. Thus, the real production cost might be slightly higher than our definition in (12).

We can see that even with the above-mentioned simplifications, it is already very complex to find an optimal solution for our problem. Firstly, it is a multistage dynamic problem with $\mathrm{J} \times \mathrm{T} + \mathrm{J} \times \mathrm{K} \times \mathrm{T}$ integer and $\mathrm{I} \times \mathrm{J} \times \mathrm{T}$ real variables. The state of future stages depends on the decision variable values in previous stages. Expensive computer processing capacity and long solution times are necessary if we wish to solve it using a dynamic programming approach. Furthermore, randomness such as demand variability needs to be considered. Its size also proves problematic should we wish to use stochastic programming to search for an optimal solution under uncertainty. Adjustable robust optimization can be utilized to solve dynamic (multi-stage) production-inventory problems under uncertainty. For tractability, however, it requires constraints to be linear or convex in the decision variables (*Yanıkoğlu et al.* 2019) and constraint (12) doesn't fulfill this requirement.

As discussed in *Lanza et al.* (2019), optimization relies on simplifying assumptions. Finding optimal solutions is ambitious for real-life problems due to their complexity. Simulation is a widely used methodology for decision support in global production networks, as it facilitates the analysis of the system's behavior under a variety of operating conditions. However, assuming that we consider *n=10* variations of each parameter for a production network with three suppliers, three plants and three customers, over 52 periods (weeks), there are $n^{3\times 52+3\times 3\times 52+3\times 3\times 52}=10^{1092}$ possible combinations. It is simply not practical to apply Design of Experiments and use pure simulation to get insights for our problem due to the vast number of parameter combinations.

We propose a combined heuristic and simulation approach to obtain an approximate solution to our problem. The heuristic model relaxes the requirements of the original optimization model and quickly provides a solution as the starting point for the simulation model, which keeps all settings close to the original problem and improves the solution with iterations. Our approach greatly reduces the solution time but keeps the model close to reality.

Step 1: Approximate the original mathematic model and obtain an initial strategy.

1) The multi-stage problem is transferred into a single stage problem. We search for yearly allocation decisions $\left(y_{j,}\ z_{jk}\in Z_0^+,\ \ x_{ij}\geq 0,\quad \forall i,\ j,\ k\right)$ instead of weekly allocation decisions as in constraint (16).
2) In constraint (2), $\left\lceil\frac{z_{jkt}}{\overline{V}max_{jk}}\right\rceil$ is approximated by $\frac{z_{jk}}{\overline{V}max_{jk}}$, and all integer constraints in (16) are relaxed. We also ignore the inventory and OTD constraints, (6)–(10) and (13)–(15).
3) Using Excel solver, we get an optimal solution for the relaxed problem.
4) We find the nearest integer point to the Excel solve solution and use it as the base of the yearly decisions.
5) Dividing the yearly decision variables by period and rounding when necessary, we get the weekly decision variables.

All the above simplifications underestimate the total costs of the production network. The resulting total profit provides an upper bound on the real optimal total profit.

Step 2: Build a DES model considering inventory, OTD and integer constraints and improve the initial strategy.

We use the program SIMIO (version 12, *Vieira et al.* 2020) to build a discrete-event simulation model (DESM1) for our production network. We use the initial strategy from Step 1 as a starting point and develop a local search technique to improve the strategy. In this step, all constraints which were ignored in Step 1 apply. We improve the cross-shipping strategy by iteratively adjusting the delivery frequency and amount until the inventory and OTD constraints are met. The total profit upper bound from Stage 1 serves as a reference to judge the performance of the improved cross-shipping strategy.

Step 3: Add uncertainty to our simulation model and add adaptation measures to the cross-shipping strategy.

To the discrete-event simulation model (DESM2) for our production network, we add three types of uncertainties: demand variation, supplier failure and plant breakdown. For each type of uncertainty, we propose adaptation measures to the cross-shipping strategy from Step 2.

Concerning demand variations, we assume that the weekly demands of all customers vary with a certain percentage, but the total yearly demands keep constant. The customers communicate their variation in advance (frozen window, e.g., 4 weeks) and the plants adjust their original production plan accordingly. We add the following adaptation measures:

- Delivery plan: At the beginning of each week, the expected OTD rate of each customer in the next frozen window time is calculated. If it is lower than 100 %, the nearest plant delivers the missed batches just-in-time using backward scheduling.
- Production plan: The production plan of the plant which has delivered the missed batches is adjusted accordingly.
- Purchasing plan: No change.

Concerning supplier failure, we assume different failure rate for each supplier. We add the following adaptation measures:

- Delivery plan: When a small supply failure occurs, the corresponding plants reduce their delivery amount for their farthest customer and the missed amount for the customer is delivered by a local plant. If the supplier failure rate is rather high, the corresponding plants only deliver the portion that they can. The other plants produce the missed batches and deliver to all customers.
- Production plan: The production plan is adapted to the delivery plan accordingly.
- Purchasing plan: The other suppliers provide the needed material accordingly.

Plant breakdown: Inspired by the actual COVID-19 pandemic, plant breakdown is considered by decreasing plant availability within a defined time frame. The adaptation measures use the same rules as with supplier failures.

Using simulation, we then evaluate the performance of the above developed cross-shipping comparing to other strategies (e.g., local-to-local strategy) and gain useful insights.

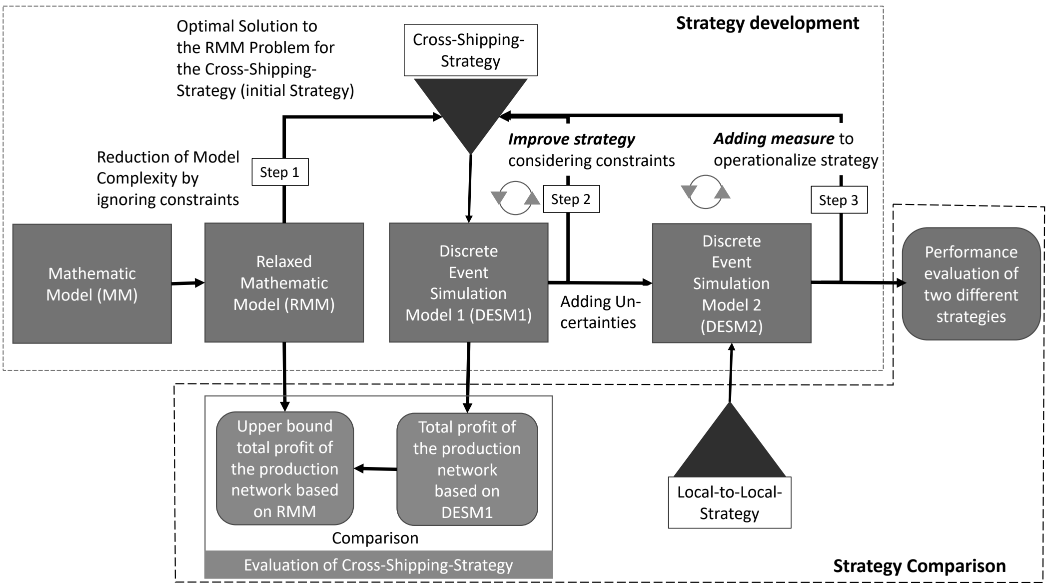


Figure 3: Overview of our approach

Figure 3 provides an overview of our approach with two different focus areas. One focus area shows the development steps of the cross-shipping strategy, as explained above. The second focus area features a comparison of the strategies' performances. As mentioned above, the total profit upper bound obtained from the heuristic approach (Step 1) is used as a reference to evaluate the performance of the improved strategy (Step 2).

4 Case Study

The developed approach in Section 3 is applied in a SME. A product is produced in several plants located in the US and Europe following the same production process with three different versions of machines available. Raw materials are provided by three suppliers, one in the US and two in Europe. Three customers are demanding products, two in the US and one in Europe. We refer to "local-to-local" vs. "cross-shipping" production networks depending on whether materials and products are distributed within or across continents.

We build a simulation model as in *Figure* 4, using all the parameters and constraints described in Section 3. KPIs such as revenues, costs, OTD rate, and capacity utilization are displayed numerically. The inventory levels comparing inventory spaces and SS levels are displayed graphically (see Appendix II-IV).

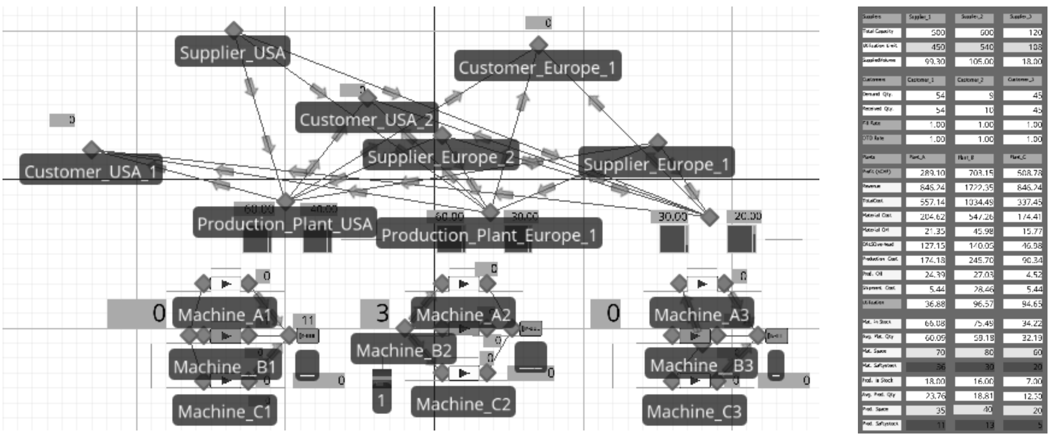


Figure 4: Simulation model

We compare the performance of two networks under various conditions (scenarios): the actual network with two sites and a local-to-local supply strategy (*Figure* 5) and a global network with three sites and a global cross-shipping supply strategy (*Figure* 6). For the local-to-local strategy, each plant uses the backward scheduling method (just-in-time) to deliver to its corresponding customers, produce the exact required amount, and purchase raw material according to the production plan. The cross-shipping strategy is developed as in Section 3.

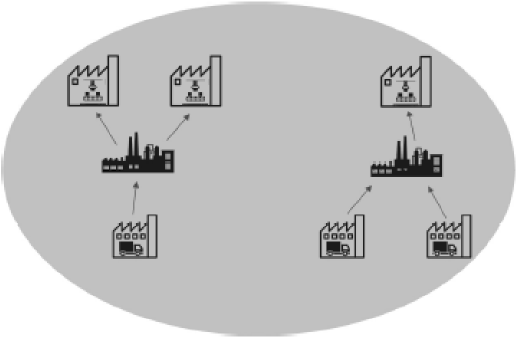


Figure 5: Local-to-local network

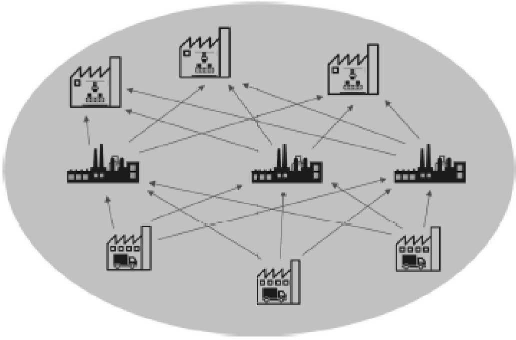


Figure 6: Global cross-shipping network

In the first scenario, all parameters are deterministic. Weekly demand from each customer is assumed to be stable and known from the beginning of the year. In the next three scenarios, demand variation, supplier failure and plant breakdown are considered with the cross-shipping strategy applying the adaptation measures (presented in Section 3) accordingly. In Scenario 2, the local-to-local network does not apply a supply-chain adaptation since the transport time is shorter than the frozen window. In Scenario 3, different supplier failure rates have been applied for the supplier in the US. Under this condition, the local-to-local network can't make any adaptation since the US-plant relies on its only supplier located in the US. In Scenario 4, the US-production plant availability has been reduced. In this case, the local-to-local network adapts the raw material purchasing amount according to the new plant availability.

4.1 Results

In this section we discuss the results of the four scenarios simulated.

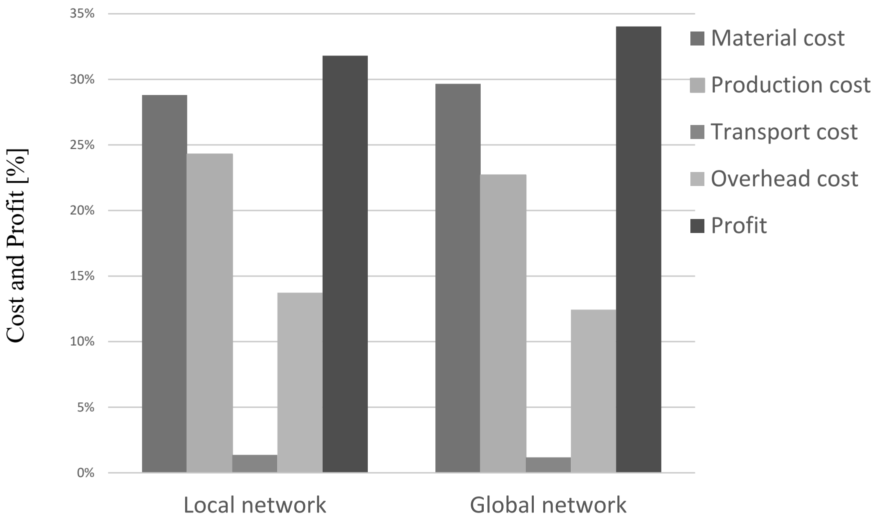


Figure 7: Costs and Profits local vs. global network for Scenario 1

In Scenario 1, both local and global networks achieve 100 % OTD and fill rates. Within the local set up, both plants' utilizations are under 75 %. Within the global network, all three plants are well below 80 % utilization. A financial comparison (*Figure* 7) shows that the global network has a 2.2 % higher profit margin than the local setup, driven by lower production and overhead costs, but higher material costs.

It is worth mentioning that the total profit of our global cross-shipping network based on the discrete-event simulation model is 90 % of the total profit upper bound we get from the relaxed mathematical model in Section 3, Step 1. This upper bound provides a reference for judging how well a strategy behaves financially.

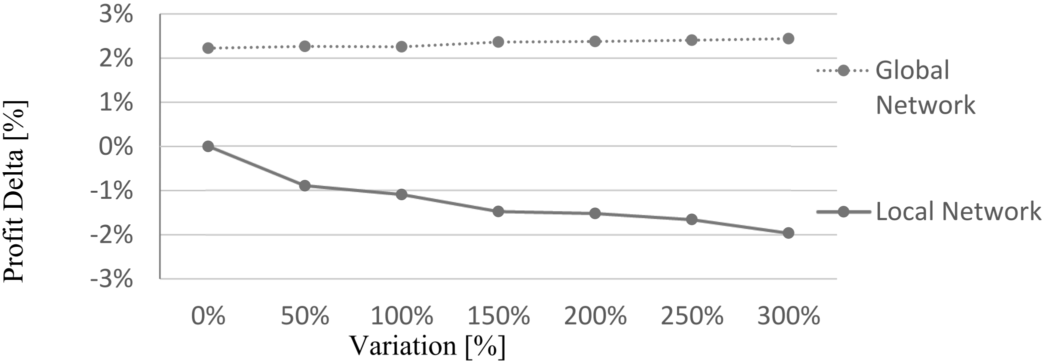


Figure 8: Profit vs. Demand Variation for Scenario 2

Scenario 2 simulates demand variations from 50 % to 300 %. Within the local network they are compensated with underutilized, older and more expensive machine versions. Whereas, in the global network, demand variations are compensated by cross-shipping within the network. Demand variation has more significant negative impacts on profit for both local and global networks (*Figure* 8). Deliveries start to be late within the global

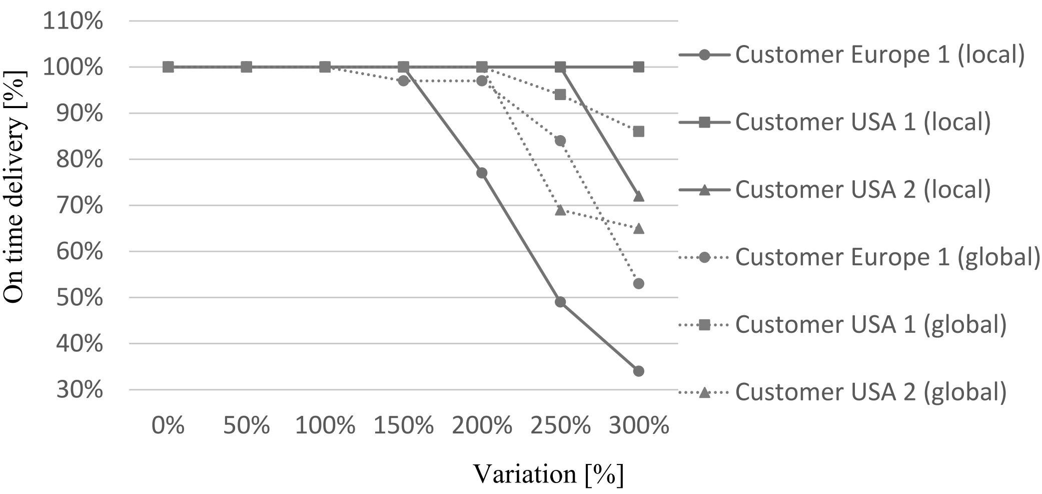


Figure 9: OTD vs. Demand Variation for Scenario 2

network at a demand variation of 100 % (*Figure 9)*. However, the OTD rate is only slightly impacted up to a demand variation of 200 % and concerns only one customer site. On the other hand, the local network's OTD rate falls steeply from variations over 150 %. We can conclude that, in our case, the global network is more stable in terms of OTD under demand variation.

Generally, both networks could achieve a 100 % fill rate at demand variation of 300 %. Only at 300 % demand variation within the global set up does the fill rate fall slightly below target at 97 %.

Except for a few negligible SS violations, product inventories for the local network are kept well within the required borders below 100 % demand variation. Within the global network, product is kept to acceptable levels up to 150 % variation. At higher variations product stocks fall critically low for both networks. Conversely, with quite small variations, raw material storage gets very low (global set up) and extremely high (local set up). This could be improved by adjusting the purchasing plan (which was not a part of this model). An example of the inventory development can be found in *Appendix* II.

In Scenario 3, supplier failures and raw material rejections of the US-raw material supplier were simulated. As rejected raw material is not paid, and raw material stocks are just consumed, the total profit of the local network increases for failure rates of up to 15 % (*Figure* 10). At higher failure rates the profit decreases as the fill rates decrease and fewer products are sold (*Figure* 12). Consequently, deliveries are late and the OTD rate drops (*Figure* 11).

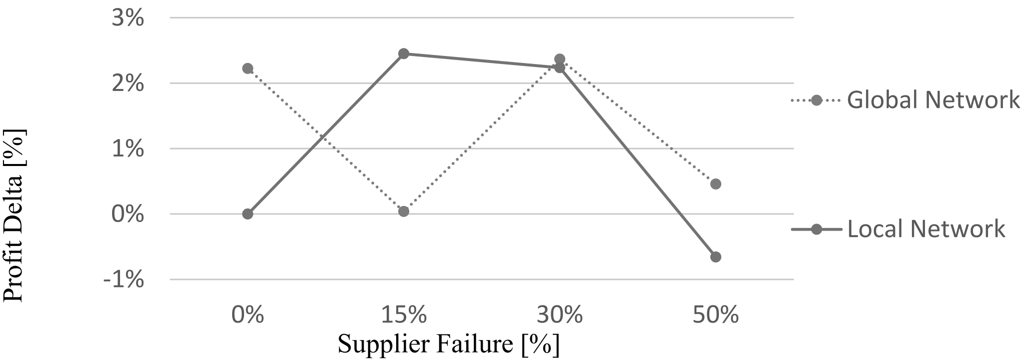


Figure 10: Profit vs. Supplier Failure Rate for Scenario 3

The global network is more affected at failure rates below 15 %. Profits decrease (*Figure* 10), deliveries are late (*Figure* 11) and demands cannot be fulfilled (*Figure* 12). Increasing failure rates from 15 % to 50 %, demonstrates the strategy adaptation's positive impact. The plant Europe 1 takes over short-delivered orders from the US-plant. The US-plant only executes local deliveries. With changed strategies the total profit increases as the failure rate goes up to 30 % from 15 % (*Figure* 10). In the worst case, at a 50 % failure rate, the profit is less impacted than that of the local network. The OTD rates are stabilizing (*Figure* 11) except for customer Europe 1. More important is the fill rate development (*Figure* 12). At a failure rate of 30 %, two of three customers still receive the full demand. Furthermore, the overall fill rate at failure rates larger than 30 % is better than with the local network set up.

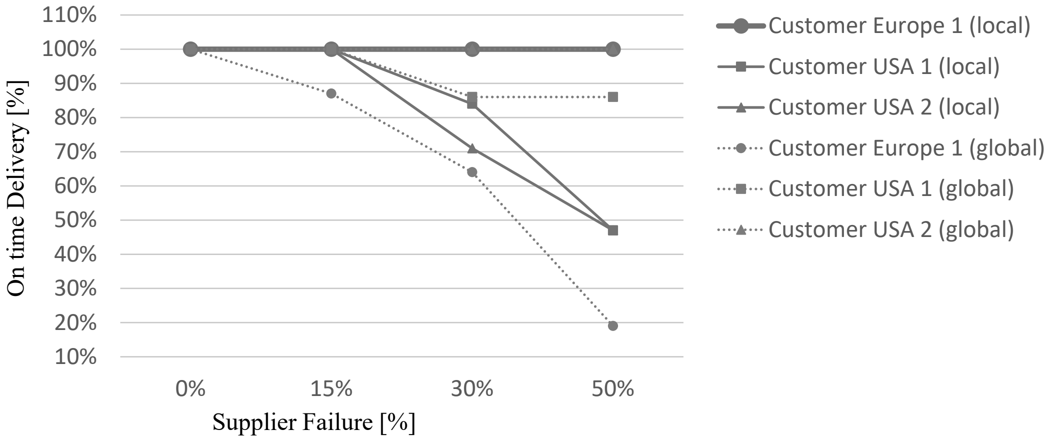


Figure 11: OTD vs. Supplier Failure Rate for Scenario 3

In summary, at low failure rates the local set up is better in terms of profit, OTD and fill rates. At higher failure rates the global network absorbs some of the financial loss and can flatten the negative OTD and fill rate trends.

The inventories at a failure rate of 50 % are presented in *Appendix* III. Within the local strategy, the raw material and product at the US-plant are just run to zero. There is no possibility to take counter measures to avoid a supply shortage. Comparatively, in the global network set up, by adapting delivery, production and procurement strategies, the product stocks in the US-plant can be kept on an acceptable level. Taking over the deliveries of the disturbed US-plant causes product stocks at plant Europe 1 to run at a low but stable level. The temporarily very high raw material stock can improve with a better procurement strategy. Hence, a smaller order lot size or longer delivery intervals should be applied.

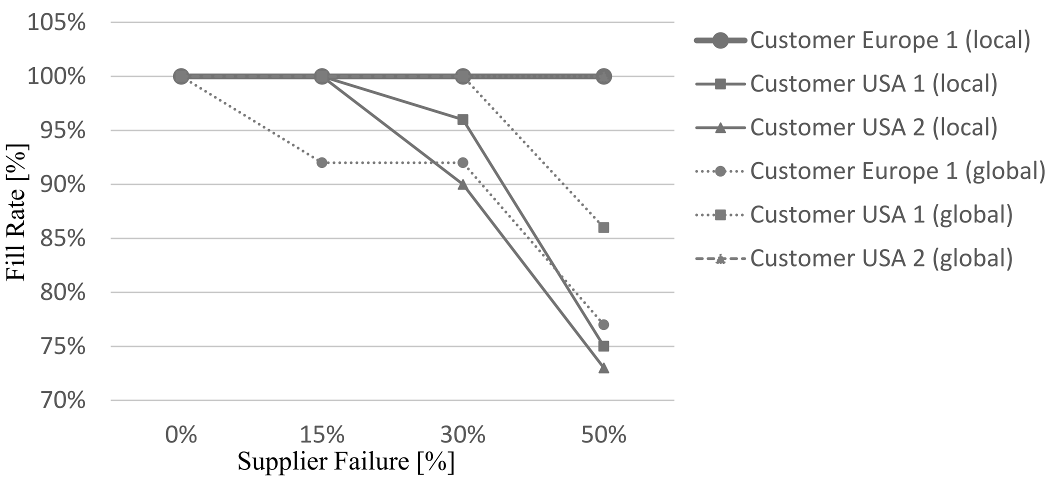


Figure 12: Fill Rate vs. Supplier Failure Rate for Scenario 3

Scenario 4 simulates plant breakdown with different levels. The adaptation rules for the cross-shipping strategy in Scenario 4 are very similar to those in Scenario 3 (as described in Section 3). Scenario 4 thus shows results similar to Scenario 3. For same reasons, the local network shows an increased profit at lower breakdown rates and then steadily decreases (*Figure* 13).

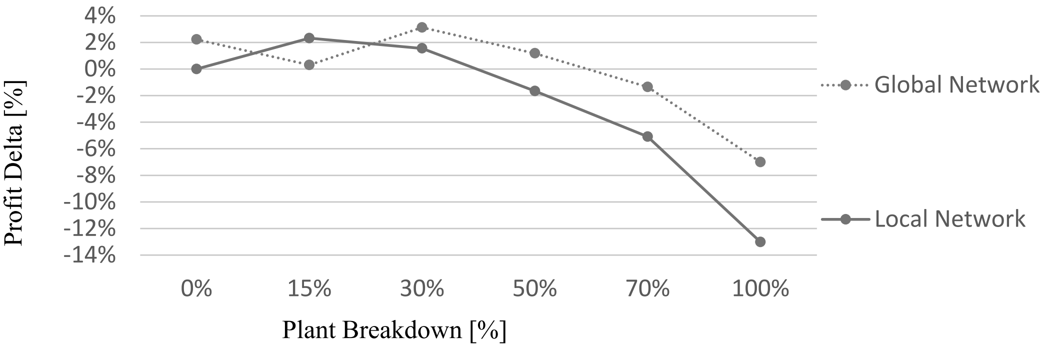


Figure 13: Profit vs. Plant Breakdown for Scenario 4

As we have simulated a wider range in this scenario, the higher robustness of the global network regarding profit is more obvious. At breakdown rates higher than 30 % the global network results in less financial loss. Furthermore, the OTD performance of the global network is better. For example, at a breakdown rate of 70 % the global network still on average delivers 62 % of the parts on time, whereas only 46 % of parts are on time within the local set up (*Figure* 14).

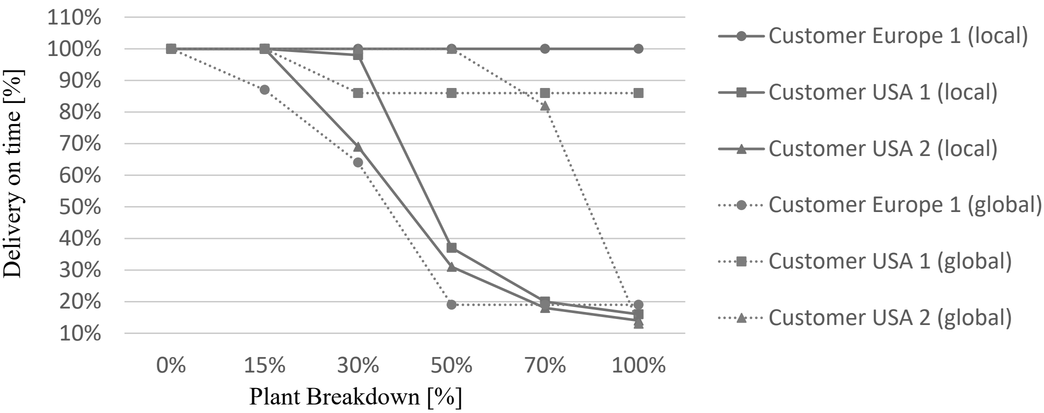


Figure 14: OTD vs. Plant Breakdown for Scenario 4

Crucial is the fill rate, which indicates how much demand could be fulfilled at the end of the simulation period (*Figure* 15). Between a 30 % to 70 % breakdown rate the global network significantly outperforms the local network. For example, with a 70 % breakdown rate, 85 % of the products can still be delivered, whereas the local network correspondingly delivers only 68 %.

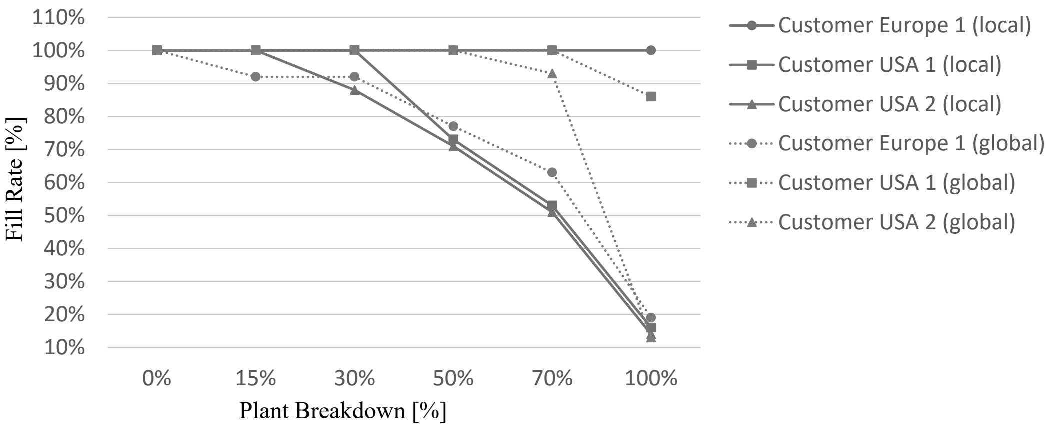


Figure 15: Fill Rate vs. Plant Breakdown for Scenario 4

Concerning the inventories, a similar development is seen as in Scenario 3 (*Appendix* IV). In both scenarios, the inventories of the disturbed plant (the US-plant) are running low. They recover at the end of the simulation period in the global network.

Similar statements can be made as in scenario 3. The global network is more sensitive in terms of profits, OTD and fill rates at breakdown rates up to 15 %. Its performance increases with higher breakdown rates from 30 % to 70 %. At a 100 % breakdown rate both networks show poor OTD and fill rate performance but the financial loss within the global set up is smaller.

In summary, within the settings of our use-case, the local network has advantages when disruptions are small while the global network performs better under larger disruptions. With more sophisticated procurement, production and delivery strategies, the performance of the global production network could be further improved. Improvement potentials within the local network to counter steer the impacts of uncertainties are limited.

5 Conclusion

In this work, we consider a complex multi-stage production network problem, originating in a real case of a Swiss SME. The objective is to maximize the total profit of the whole production network with respect to various constraints such as OTD rate, fill rate, inventory levels, and capacities. We have developed a new integrated approach combining heuristics and simulation to solve the dynamic, complex, large-scale MIP problem under uncertainty. This approach can be widely and generically used for operational problems in production networks and supply chain management.

In our case-study, we develop a global cross-shipping strategy using optimization and simulation tools. With the developed simulation model, under various conditions, we evaluate the performance of the new cross-shipping strategy as compared to the actual local-to-local strategy. The results in our case study show that, within our problem setting, a global network is less vulnerable to selected uncertainties. For large variations of uncertainties, the global network outperforms (in profit, OTD and fill rate) the local network setup in all scenarios. Further development of optimal strategies and timings for strategy adaptions could even further improve the results of the global network set up. An interlinked, cross-shipping global network with multiple suppliers, production plants and customers offers many more possibilities regarding operational adjustments in uncertain times.

We emphasize that the above discovery is based on the parameter settings of our specific case study. It doesn't necessarily generalize. However, the integrated approach that we developed can be widely used to gain insights for other production networks. We believe that decision-makers in industry could significantly benefit from this easy-to-implement approach to making prompt and reasonable decisions for constantly optimizing production networks at a strategic and operational level. At the same time, our work fills the research gap of developing combined heuristic and simulation approaches with models that are both easy to implement and close to real-world processes (*Paul et al.* 2016), not only in production networks but also in supply chain optimization research.

6 Appendix

I Notations

Parameters

Index

$\boldsymbol{i} = 1, \ldots, \boldsymbol{I}$	Supplier
$\boldsymbol{j} = 1, \ldots, \boldsymbol{J}$	Plant
$\boldsymbol{k} = 1, \ldots, \boldsymbol{K}$	Customer
$\boldsymbol{t} = 1, \ldots, \boldsymbol{T}$	Time period (week)
$\boldsymbol{v} = 1, \ldots, \boldsymbol{V}$	Machine version
Purchasing	
$\boldsymbol{Cmax_i}$	Capacity limit of supplier *i*
$\boldsymbol{ImTax_{ij}}$	Import tax (%) when plant *j* purchases from supplier *i*
$\boldsymbol{L_{ij}}$	Transportation time from supplier *i* to plant *j*
$\boldsymbol{r_i}$	Raw material price per ton from supplier *i*
$\boldsymbol{TC_{ij}}$	Transportation cost (%) from supplier *i* to plant *j*
$\boldsymbol{Vmax_{ij}}$	Maximum volume (tons) per delivery from supplier *i* to plant *j*
$\boldsymbol{\alpha_i}$	Maximum commercial share for supplier *i*
Production	
$\boldsymbol{Availability_j}$	Availability factor in plant *j*
$\boldsymbol{B_{vj}}$	Amount of machines version *v* in plant *j*
BOM	Raw material (tons) needed to produce one batch of product
$\boldsymbol{IM_{j0}}$	Initial raw material inventory level in plant *j*
$\boldsymbol{IP_{j0}}$	Initial product inventory level in plant *j*
$\boldsymbol{OPDALS_j}$	Overhead costs (production, development, administration, logistic overhead and sales, %) in plant *j*
$\boldsymbol{p_{vj}}$	Production cost for one batch of product made by machine version *v* in plant *j*
$\boldsymbol{Performance_j}$	Performance factor in plant *j*
$\boldsymbol{PSpace_j}$	Product space in plant *j*
$\mathbf{PSS_j}$	Product SS level in plant *j*
$\boldsymbol{PT_j}$	Planned production time over one year in plant *j*
$\boldsymbol{Quality_j}$	Quality factor in plant *j*
$\boldsymbol{MSpace_j}$	Raw material space in plant *j*

Parameters

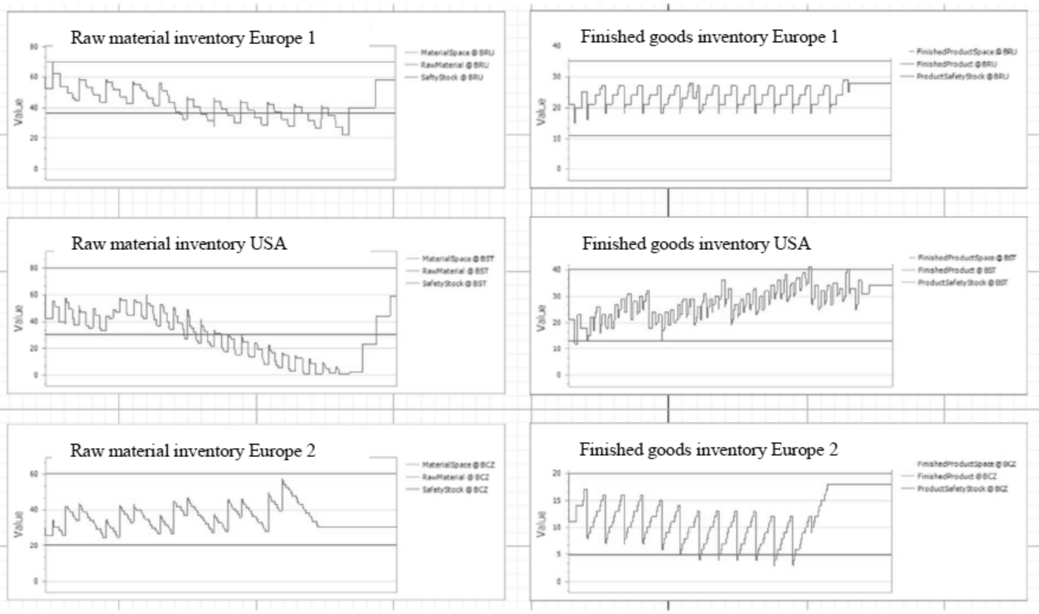
$\boldsymbol{MSS_j}$	Raw material SS level in plant *j*
$\boldsymbol{VT_v}$	Production time to produce one batch, by machine version *v*
$\boldsymbol{\beta_j}$	Capacity utilization of plant *j*
Delivery	
$\boldsymbol{c_k}$	Sale price per batch to customer *k*
$\boldsymbol{D_{kt}}$	The demand from customer *k* at period *t*
$\boldsymbol{DLC_{jk}}$	Shipment cost per delivery from plant *j* to customer *k*
$\boldsymbol{ExTax_{jk}}$	Export tax (%) paid when plant *j* delivers to customer *k*
$\boldsymbol{\overline{L}_{jk}}$	Transportation time from plant *j* to customer *k*
$\boldsymbol{\overline{V}max_{jk}}$	Maximum volume (batches) per delivery from plant *j* to customer *k*
$\boldsymbol{\gamma_k}$	Target OTD rate of customer *k*

Variables

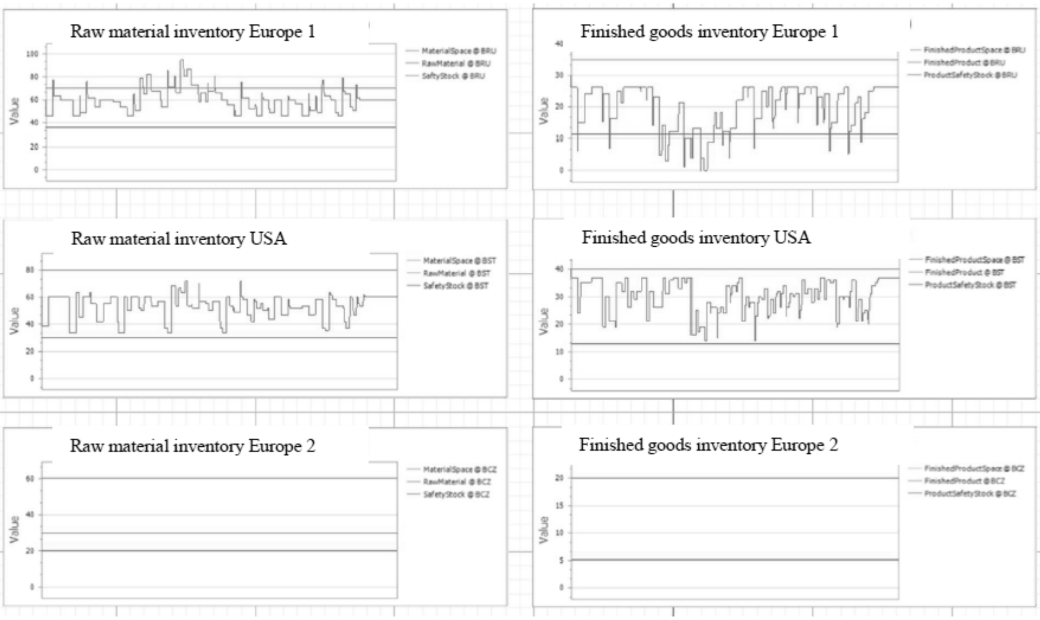
$\boldsymbol{CL_i}$	Commercial limit of supplier *i*
$\boldsymbol{Cost_j}$	Total cost for plant *j*
$\boldsymbol{\widehat{D}_{kt}}$	OTD amount for customer *k* in period *t*
$\boldsymbol{IM_{jt}}$	Inventory level of raw material in plant *j* at the beginning of period *t*
$\boldsymbol{IP_{jt}}$	Inventory level of product in plant *j* at the beginning of period *t*
$\mathbf{PLT_j}$	Maximum production time per batch in plant *j*
$\boldsymbol{POCost_j}$	Production and overhead costs for plant *j*
$\boldsymbol{x_{ijt}}$	The raw material amount (tons) delivered from supplier *i* to each plant *j*
$\boldsymbol{y_{jt}}$	The production amount (batches) at plant *j*
$\boldsymbol{z_{jkt}}$	The product amount (batches) delivered from plant *j* to customer *k*

II Inventory Demand variation

Global network – Demand variations 150%:

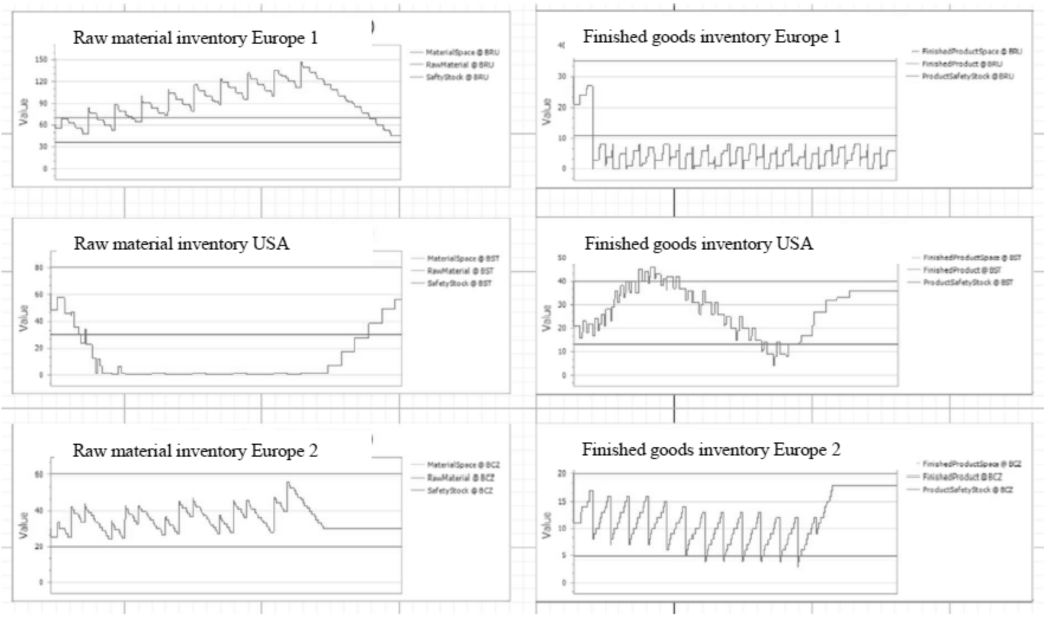


Local network – Demand variations 150%:

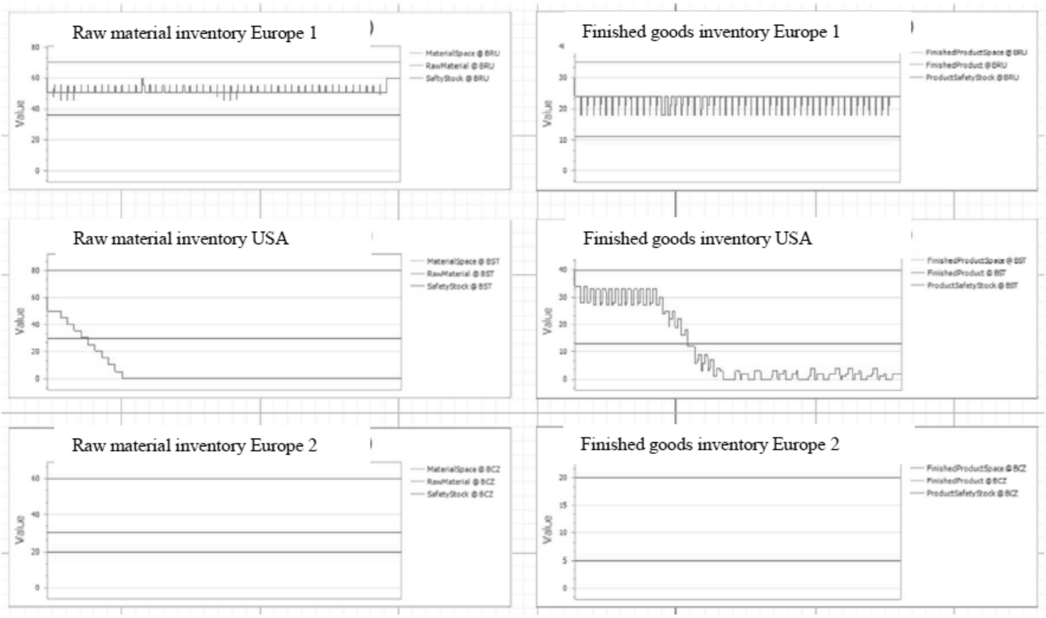


III Inventory Supplier failure

Global network – Supplier failure 50%:

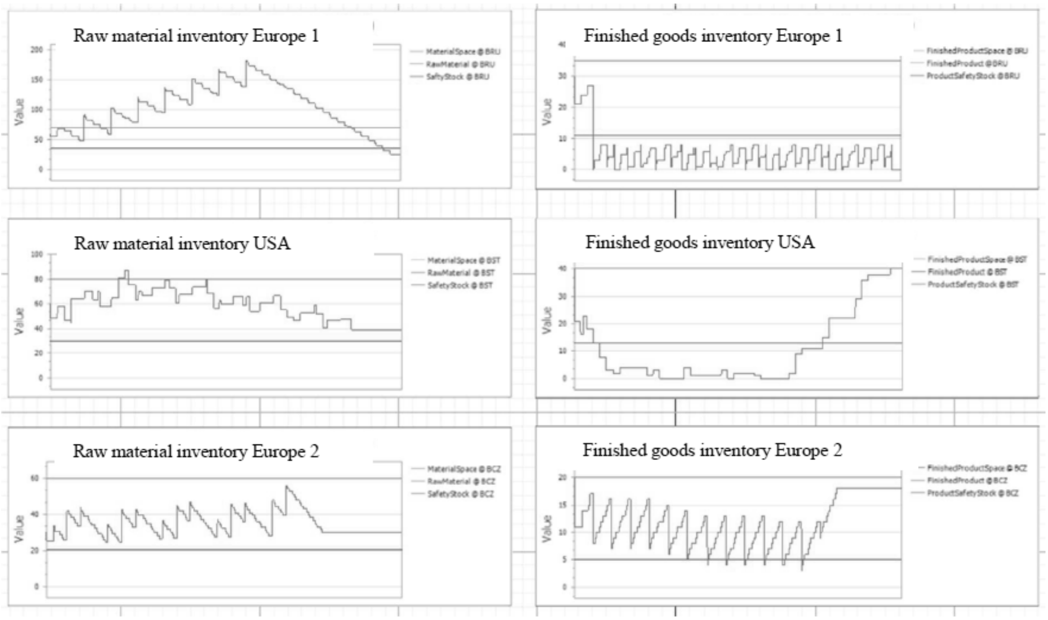


Local network – Supplier failure 50%:

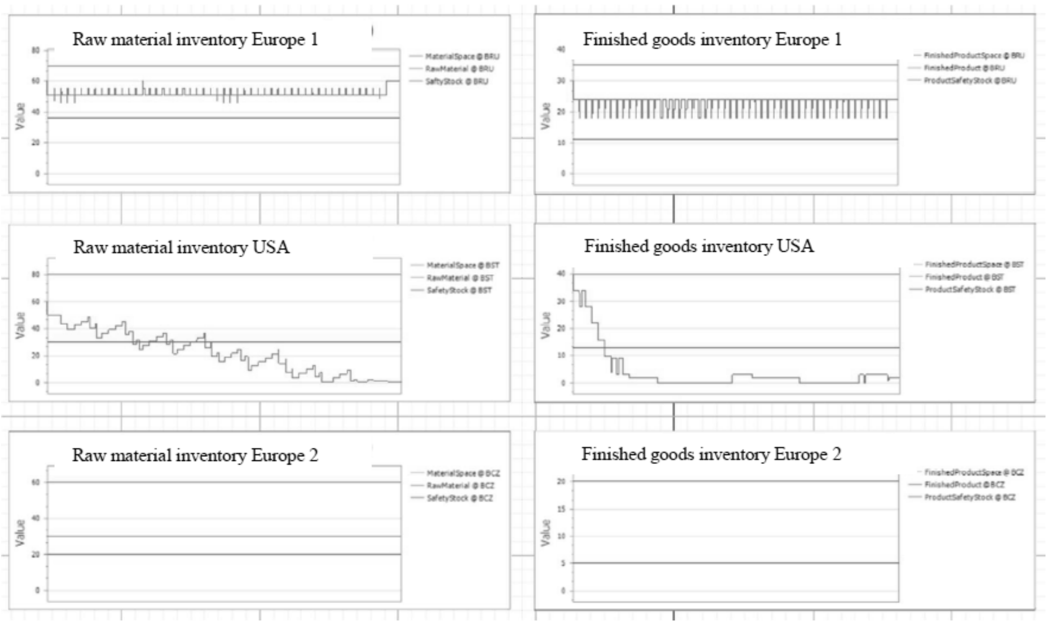


IV Inventory Plant failure

Global network – Plant failure 70%:



Local network – Plant failure 70%:



References

Aqlan, F./Lam, S. S. (2016): Supply chain optimization under risk and uncertainty: A case study for high-end server manufacturing, in: Computers & Industrial Engineering, Vol. 93, pp. 78–87.

Bottani, E., et al. (2019): Resilient food supply chain design: Modelling framework and metaheuristic solution approach, in: Computers & Industrial Engineering, Vol. 135, pp. 177–198.

Chiadamrong, N./Piyathanavong, V. (2017): Optimal design of supply chain network under uncertainty environment using hybrid analytical and simulation modeling approach, in: Journal of Industrial Engineering International, Vol. 13, No. 4, pp. 465–478.

Diabat, A. (2014): Hybrid algorithm for a vendor managed inventory system in a two-echelon supply chain, in: European Journal of Operational Research, Vol. 238, No. 1, pp. 114–121.

Ding, H., et al. (2009): Stochastic multi-objective production-distribution network design using simulation-based optimization, in: International Journal of Production Research, Vol. 47, No. 2, pp. 479–505.

Figueira, G./Almada-Lobo, B. (2014): Hybrid simulation–optimization methods: A taxonomy and discussion, in: Simulation modelling practice and theory, Vol. 46, pp. 118–134.

Friedli, T., et al. (2014): Strategic management of global manufacturing networks: Aligning strategy, configuration, and co-ordination.

Goodarzian, F., et al. (2020): A multi-objective pharmaceutical supply chain network based on a robust fuzzy model: A comparison of meta-heuristics, in: Applied Soft Computing, Vol. 92, pp. 106331.

He, J., et al. (2015): Simulation-based heuristic method for container supply chain network optimization, in: Advanced Engineering Informatics, Vol. 29, No. 3, pp. 339–354.

Juan, A. A., et al. (2015): A review of simheuristics: Extending metaheuristics to deal with stochastic combinatorial optimization problems, in: Operations Research Perspectives, Vol. 2, pp. 62–72.

Kabak, Ö./Ülengin, F. (2011): Possibilistic linear-programming approach for supply chain networking decisions, in: European Journal of Operational Research, Vol. 209, No. 3, pp. 253–264.

Keizer, M. de, et al. (2015): Hybrid optimization and simulation to design a logistics network for distributing perishable products, in: Computers & Industrial Engineering, Vol. 88, pp. 26–38.

Lanza, G., et al. (2019): Global production networks: Design and operation, in: CIRP Annals, Vol. 68, No. 2, pp. 823–841.

Manners-Bell, J. (2017): Supply chain risk: Understanding emerging threats to global supply chains.

Nezamoddini, N., et al. (2020): A risk-based optimization framework for integrated supply chains using genetic algorithm and artificial neural networks, in: International Journal of Production Economics, Vol. 225, p. 107569.

Paul, S. K., et al. (2016): Managing risk and disruption in production-inventory and supply chain systems: A review, in: Journal of Industrial and Management Optimization, Vol. 12, No. 3, pp. 1009–1029.

Robinson, S. (2004): Simulation: The Practice of Model Development and Use, Chichester.

Semini, M./Fauske, H./Strandhagen, J. (Hrsg.) (2006): Applications of Discrete-Event Simulation to Support Manufacturing Logistics Decision-Making: A Survey.

Talbot, F. B./Patterson, J. H. (1979): Optimal methods for scheduling projects under resource constraints, in: Project Management Quarterly, Vol. 10, No. 4, pp. 26–33.

Timpe, C. H./Kallrath, J. (2014): Optimal planning in large multi-site production networks, in: European Journal of Operational Research, Vol. 126, pp. 422–435.

Todd, P. M. (2001): Heuristics for Decision and Choice, in: International Encyclopedia of the Social & Behavioral Sciences, pp. 6676–6679.

Tordecilla, R. D., et al. (2021): Simulation-optimization methods for designing and assessing resilient supply chain networks under uncertainty scenarios: A review, in: Simulation modelling practice and theory, Vol. 106, p. 102166.

Vieira, A. A., et al. (2020): Are Simulation Tools Ready For Big Data? Computational Experiments with Supply Chain Models Developed in Simio, in: Procedia Manufacturing, Vol. 42, pp. 125–131.

Xia, Y., et al. (2004): Real-time disruption management in a two-stage production and inventory system, in: IIE Transactions, Vol. 36, No. 2, pp. 111–125.

Yanıkoğlu, İ., et al. (2019): A survey of adjustable robust optimization, in: European Journal of Operational Research, Vol. 277, No. 3, pp. 799–813.

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