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Simulation-based single vs dual sourcing analysis in the supply chain with consideration of capacity disruptions, Big Data and demand patterns

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Abstract

Sourcing strategy analysis in the settings of supply chain flexibility in regard to single vs dual sourcing has been a well explored area over the last two decades. In recent years, single vs dual sourcing analysis has been increasingly introduced in supply chain disruption management. Since most of the decision-support models for supply chain sourcing strategy adaptation in the case of disruptions presume real-time information and coordination, the issues of Big Data and business intelligence needs to be included into the consideration. A supply chain simulation model with consideration of capacity disruption and Big Data along with experimental results are presented. Based on both literature analysis and modelling example, managerial insights are derived. A set of sensitivity experiments allows to illustrate the model's behaviour. The analysis suggest recommendation on using single sourcing, capacity flexibility, and dual sourcing for different combinations of demand and inventory patterns. The paper is concluded by summarizing the most important insights and outlining future research agenda.

Keywords: supply chain flexibility, risk management, simulation, capacity disruption, Big Data

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Introduction

Sourcing strategy analysis in light of supply chain (SC) flexibility regarding single vs dual sourcing decisions has been a well explored area over the last two decades (Das 2001, Nair et al.2015). In recent years, single vs dual sourcing analysis has also been increasingly introduced in SC severe disruption management (Yu et al. 2009, Iakovou et al. 2010, Lu et al. 2011, Yang et al. 2012, Ivanov et al. 2016b, Tsai 2016). Severe disruptions in SCs are low-frequency-high-impact disruptions such fires, tsunamis, political crisis, etc.

Strategies to cope with such severe disruptions are frequently analysed in light of SC resilience that correlates to SC sourcing flexibility (Ambulkar et al. 2015, Gupta et al. 2016, Ivanov et al. 2016a, Ransikarbum and Mason 2016). Snyder et al. (2016) consider sourcing strategy as one of the key drivers for SC resilience. Fundamental concepts comprise proactive sourcing strategy design and reactive sourcing strategy adaptation in case of disruptions. Basic areas of SC *flexibility* include system, process and product (Simchi-Levi and Wei 2015). Inventory and capacity buffers can be considered as *process redundancy* (Govindan et al. 2015). Back-up facilities and suppliers belong to *system redundancy* (Ivanov et al. 2014b).

Focusing on single sourcing provides many efficiency advantages. However, a number of recent disruptions have forced SC managers to rethink this lean sourcing strategy since the cost savings can be wiped out by disruption impacts (Chopra and Sodhi 2014, Ivanov et al. 2014a). Companies which used single sourcing with suppliers in Japan or Thailand were drastically affected by tsunami and floods in 2011. Many production factories worldwide were halted for several months. Intel claimed to have lost $1 billion in sales during the fourth quarter of 2011 (MacKenzie et al. 2014). Such performance decreases force many companies to invest in system redundancy (e.g., Toyota extends its SC subject to multiple sourcing and building new facilities on the supply side).

Another example is online fashion retailer ASOS that was badly affected by a fire in their UK warehouse in 2005 when operations were almost stopped for one month. They developed a contingency policy for such disruptions. Among others, an additional warehouse was established in Asia. This helped the company to recover within two days in June 2014 when a new fire occurred in the UK warehouse.

Dependencies of sourcing strategy from demand patterns can be observed. For example, Amazon prefers holding fast-moving items in distribution centres while slow-moving items tend to be stored centrally. ZARA produces their trendiest items in Europe close to highly dynamic and changing demand.

Alternatively, slow-moving items are produced in Turkey and Asia since lead-time is not crucial and cost reduction can be achieved in manufacturing. Such SC segmentation helps to reduce disruption risk implications (Chopra and Sodhi, 2014).

The risks related to product standardization should also be named. If the sole supplier produces items which are used in many different models of a product, the impacts of a disaster can ripple very fast in the SC as in the case at Toyota in 2011. That is why many companies, such as Samsung, tend to have at least two suppliers even if the second one provides only 20% of the volume (Sodhi and Lee 2007).

Different quantitative approaches to protect and control SCs in regard to severe disruptions and to coping with uncertainty have been developed in recent years. While mathematical and stochastic optimization dominate the research domain in this field (Cui et al. 2010, Li et al. 2013, Ivanov et al. 2015, Sawik 2016), the potential of simulation modelling still remains underexplored. At the same time, simulation modelling is generally a recognized approach to SC and logistics (Tako and Robinson 2012, Meisel and Bierwirth 2014).

In addition, a research gap can be identified in regard to the parametric content of the models and filling these models with data (Choi 2013). Since most of the decision-support models for SC sourcing strategy adaptation in the case of disruptions presume real-time information and coordination, the issues of Big Data (Hofmann 2015) and business intelligence such as demand and inventory pattern recognition (Chong et al. 2015) needs to be included into the consideration.

The objective of this study is to extend the exiting body of literature on proactive and reactive sourcing strategy in the SC in regard to single vs dual sourcing analysis by incorporating the considerations of capacity disruptions, Big Data and different demand and inventory patterns using simulation modelling approach.

The reminder of this paper is organized as follows. In Section 2, recent literature on sourcing strategies and simulation modelling in light of capacity disruptions as well as on Big Data and analytics application to SC is analysed. Section 3 is devoted to the problem statement and research methodology. In Section 4, a SC simulation model with consideration of capacity disruption and Big Data along with experimental results are presented. Based on both literature analysis and modelling example, managerial insights are derived in Section 5. Section 6 concludes the paper by summarizing most important insights and outlining future research agenda.

2. State-of-the-art

The literature review comprises analysis in three relevant areas:

- Proactive and reactive studies on single vs dual sourcing strategies in light of capacity disruptions
- Simulation modelling studies on SC disruptions and
- Big Data and analytics applications to SCs

2.1 Single vs dual sourcing strategies in light of capacity disruptions

Research on single vs dual sourcing strategies in light of capacity disruptions can be grouped into proactive and reactive studies. Mixed-integer programming (MIP) has been widely used to model proactive SC sourcing decisions with capacity disruption considerations (Cui et al. 2010). Lim et al. (2010, 2013) incorporated a totally reliable back-up supplier that can be used if a primary supplier is destroyed. The related costs are incorporated into the objective function but the fortification budget remains incapacitated. In addition, inventory considerations have been included.

Rafiei et al. (2013) considered multiple products and many periods along with the levels of inventory, back-ordering, available machine capacity and labour levels for each source, transportation capacity at each transshipment node and available warehouse space at each destination. This study also considered the facility fortification by taking into account the back-up supplier with reserved capacity and a back-up transshipment node that satisfied demands at higher prices without disruption facility. The solution to the model is based on a priority-based genetic algorithm.

Sawik (2016) developed a stochastic programming model to integrate supplier selection, order quantity allocation and customer order scheduling in the presence of SC disruption risks. Torabi et al. (2015) propose a bi-objective mixed two-stage stochastic programming model for supplier selection and order allocation problem under operational and disruption risks. The model considers several proactive strategies such as suppliers' business continuity plans, fortification of suppliers and contracting with backup suppliers.

Different studies incorporated reactive policies. Melo et al. (2005) introduced gradual recovery strategies as part of their modeling framework in the context of capacity relocation in case of SC disruption. Liberatore et al. (2012) study the problem of optimally protecting a capacitated median system with a limited amount of protective resources subject to disruptions. The authors use a single-level mixed-integer program to analyse disruption propagation in the SC.

Qi (2013) developed a continuous review inventory model with random disruptions at the primary supplier. Hishamuddin et al. (2013) presented a recovery model for a two-echelon serial SC with consideration of transportation disruption. Their model is capable of determining the optimal ordering and production quantities during the recovery period to minimize total costs.

Hasani and Khosrojerdi (2016) develop a non-linear MIP model and use it to model resilience strategies to mitigate the risk of correlated disruptions. Solution is implemented as a Taguchi-based memetic algorithm that incorporates a customized hybrid parallel adaptive large neighborhood search. The model is solved for a real-life case of a global medical device manufacturer.

In addition, competition, pricing and contracting issues attracted wide attention from researchers in the inventory management and game theory fields. Serel (2008) models the inventory and pricing decisions in a single-period problem faced by one retailer and two suppliers, where one supplier encounters supply disruption risks. Li et al. (2010) investigate the sourcing strategy of a retailer and the pricing strategies of two suppliers in the case of a supply disruption. They derive a coordination mechanism to maximize supplier profits.

Shao and Dong (2012) analyse an assemble-to-order system with a backup source to offer on-time delivery and compensation policy to compensate customers for waiting in each period during a disruption. The findings suggest that the backup sourcing strategy is preferred at the beginning of the supply disruption, while the compensation strategy is preferred as time elapses. Hu et al. (2013) analyse incentive mechanisms to motivate a supplier's investment in the capacity restoration. They consider the cases when the incentive is committed to *ex-ante* (prior to disruption) as well as when it is committed to *ex-post* (after disruption). The analysis indicates if the buyer offers incentives, both the buyer and supplier (weakly) prefer the ex-ante commitment over the ex-post one. Choi et al. (2013) consider coordination of multi-suppliers single-warehouse-operator single-manufacturer SCs with variable production rates and storage costs.

Gupta et al. (2015) study from game-theoretical perspective the implications of the contingent sourcing strategy under competition and in the presence of a possible supply disruption. The time of the occurrence of the supply disruption is uncertain and exogenous, but the procurement time of components is in the control of the firms. The results imply that supply disruption and procurement times jointly impact the firms' buying decisions, optimal order quantities and their expected profits. Subsequently, this study considers the impact endogenizing equilibrium sourcing strategies of asymmetric and symmetric firms, and of capacity reservation to mitigate disruption.

2.2 Simulation modelling in SC disruption management problems

Simulation approaches have been proved to be a suitable tool for analysis of SC dynamics and disruptions. Wu et al. (2007) presented a Petri net-based modelling approach to show how disruptions propagate through an SC and evaluated the impact of the disruption on SC performance. Another application of Petri net-based simulation to SCs is presented by Tuncel and Alpan (2010) in order to evaluate the impact of multiple disruption scenarios (disruptions in demand, transportation and quality) and possible mitigation actions on SC performance.

A Monte Carlo approach based on a generalized semi-Markov process is taken to assess the disruptions caused by a specific type of hazard on an SC (Deleris and Erhun, 2011). This model estimates the probability distribution of the loss in SC output caused by the occurrence of hazards within the SC. Zegordi and Davarzani (2012) present an SC disruption analysis model based on colored Petri nets for better visual representation. Schmitt and Singh (2012) presented a quantitative estimation of the disruption risk in a multi-echelon SC using simulation. The disruption risk is measured by "weeks of recovery" as the amplification of the disruption. The modelled strategies include satisfying demand from an alternate location in the network, procuring material or transportation from an alternative source or route, and holding strategic inventory reserves throughout the network.

Wilson (2007) presented a system dynamics model for a multi-stage SC. Different transportation disruptions are modelled and their impact on customer orders fulfilment rate and inventory fluctuations are evaluated. The greatest impact occurs when transportation is disrupted between the Tier-1 supplier and the warehouse. Carvalho et al. (2012) analysed impacts of disruptions on lead times and overall SC costs using ARENA-based simulation model. To study the impact of transportation disruptions on SC performance, Ivanov et al. (2010, 2015) developed a structure dynamics control approach to SCD with the simultaneous consideration of multiple SC structures (i.e., material, information, product, technology and finance) and their dynamics. They presented solution methods based on a combination of optimal control and mathematical programming. Xu et al. (2014) used AnyLogic software and modelled SC as an agent system to study the disruption at suppliers and recovery policies on the SC service level. Ivanov et al. (2016b) take into account disruptions in the Australian food SC and analyse the performance impact of disruptions at distribution centres with the usage of optimal control-based simulation with the help of anyLogistix software.

2.3 Big Data and analytics applications to SCs

The importance of Big Data and analytics applications to SCs has been underlined in numerous studies (Waller and Fawcett 2013, Chae et al. 2014, Schoenherr and Speier-Pero 2015, Wamba and Akter 2015, Huang et al. 2015). We restrict ourselves to the studies dealing with uncertainty, risks and simulation. Chong et al. (2015) consider the issues of demand uncertainty and demand pattern analysis by predicting consumer product demands via Big Data in light of online promotional marketing and online reviews. Similarly, the demand pattern recognition issues are considered by Li and Wang (2015). They study dynamic SC decisions based on networked sensor data with an application in the chilled food retail chain. The research investigates the potential benefits of the chilled food chain management innovation through sensor data driven pricing decisions. Data generated and recorded through the sensor network are used to predict the remaining shelf-life of perishable foods.

In regard to operational risks, Hofmann (2015) studies impact of volume, variety and velocity properties on the bullwhip effect using Big Data and applying a system dynamics simulation model. Fan et al. (2015) present a framework of a SC risk management system under uncertain environments by using Big Data technologies and analytics. The process-oriented framework serves as a guideline to integrate and analyze big data as well as to implement SC risk management system.

It can be observed from literature analysis that proactive and reactive sourcing strategies have been extensively studied in light of disruption risks whereas optimization studies dominate this research domain. Simulation has also been used for disruption risks analysis in the SC but its potential still remains underdeveloped. Big Data and analytics have been recognized by research community as powerful and promising techniques for demand pattern recognition, SC simulation and risks but disruption risks have not been considered in this research domain so far.

Research gaps can be identified therefore on the interfaces sourcing strategy-simulation and simulation model-data. To the best of our knowledge, there is no published research on simulation-based single vs dual sourcing analysis in the SC with consideration of capacity disruptions, Big Data and different demand patterns. We consider it as a research opportunity that can enlarge the existing body of knowledge on decision-support systems for SCs using modern technologies.

3. Modelling approach

3.1 Problem statement

We consider a three-stage SC that comprises a supplier, a distribution center (DC1), a back-up distribution center (DC2), and a customer (Fig. 1).

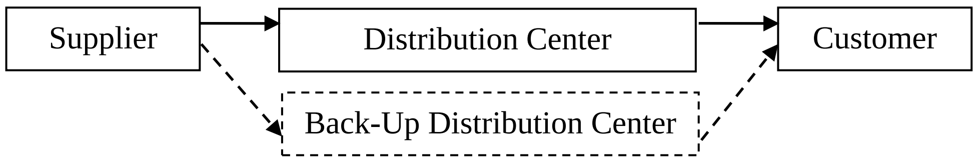

Fig. 1. Three-stage supply chain

Under normal conditions, the back-up DC is not used. The problem consists in the analysis of single vs dual sourcing strategy selection with disruption consideration in DC1 capacity using different inventory and demand patterns. We include the following parameters in the problem statement:

- One-month period is considered
- Capacity at DC1 can be disrupted
- DC2 is backup DC
- At the beginning of the period, DC1's has some beginning inventory subject to an inventory pattern
- Period demand at the customer can be described by different patterns
- Shipment time is computed automatically subject to real routes and fixed average truck speed
- Transportation costs is subject to weight and distance
- Inbound and outbound processing costs are known
- Fixed facility operating costs are known
- Inventory holding costs are known
- Unit price is known

We are interested to quantify the impact of capacity disruptions at DC1 for different inventory and demand patterns and subject to overall financial, customer, and operational performance in the SC. The following KPI (key performance indicators) are included in the analysis:

Financial SC performance:

- Total revenue (i.e., turnover at DCs)
- Total costs (i.e., sum of production, transportation and inventory costs)
- Profit (i.e., difference between total revenue and total costs)

Customer performance:

- B-Service level (i.e., the percentage of total sales in regard to maximum customer demand during the lead-time)
- Total sales (i.e., delivered products to customers)

Operational performance:

- Inventory holding costs

3.2 Modelling approach

Motivated by the fact that Big Data and analytics provide sound basis for demand and inventory pattern recognition, we propose in this research to include those patterns into proactive and reactive sourcing decisions in the SC with capacity disruption consideration by utilizing simulation modelling. Two fundamental approaches to hedging SC against the negative impacts of different disruptions – proactive and reactive are used in this study. Reactive approach aims at adjusting SC processes and structure in the presence of unexpected events. Proactive approach creates certain protection and takes into account possible perturbations while generating SC structures and execution plans. The basis of the proposed methodology is scenario approach.

A large discrete-event simulation model has been developed using software anyLogistix. Simulation modeling methods allow us considering the details and specific traits of the SC elements. This allows not only visualizing network operations but also tracing every process inside. In addition, using simulation allows us to observe the impact of different disruptions and recovery policies in time and consider gradual capacity degradation and recovery.

Developed simulation model is based on the following Big Data structure (Fig. 2):

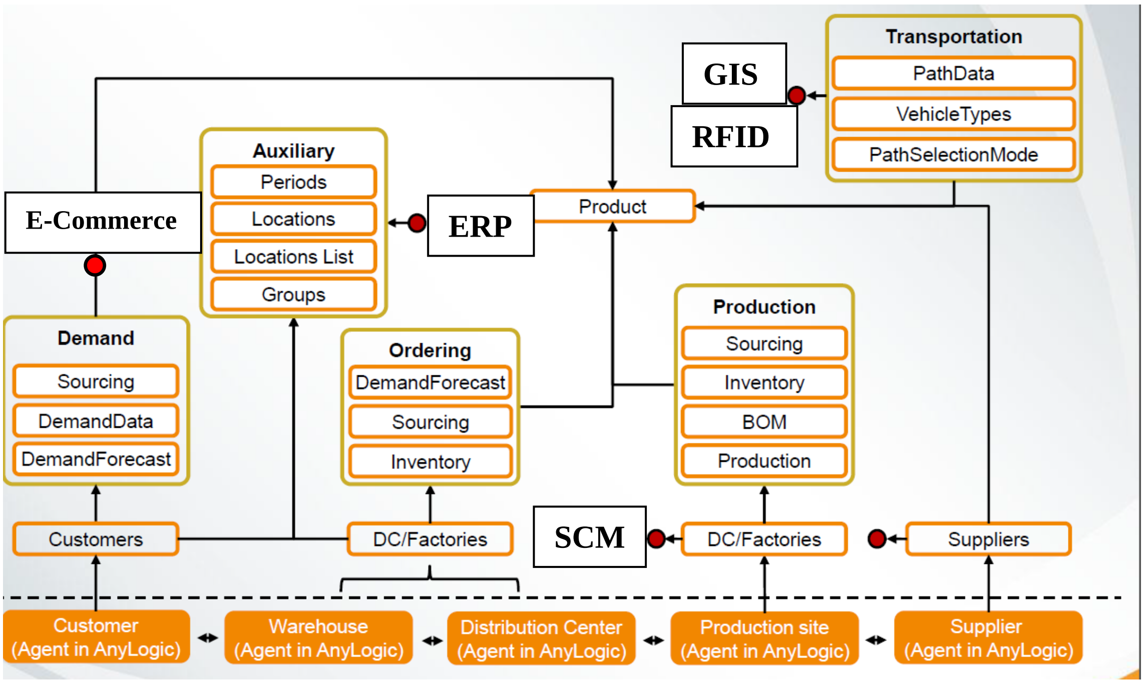

Fig. 2. Simulation model data structure (adopted with changes from Popkov 2015)

The developed simulation model and experimental environment exhibit the following characteristics:

- Discrete-event simulation model
- Each structural model object in AnyLogistix is an agent in AnyLogic multimethod simulation software
- Standard AnyLogistix functionality has been used
- Experiments have been performed using a standard notebook with 2.40 GHz CPU and 8.00 GB RAM.

In the block “demand”, customers are created and demand forecasts are setup based on either historical data or periodic demand. In the block “Ordering”, sourcing policies from DCs to customers (e.g., single or multiple sourcing) and inventory control policies (e.g., *s,S* or *r,q*) at DCs are setup and matched logically with demand forecasts and production. Similar, in the blocks “Production”, sourcing policies from factories to DCs and inventory policies at factories are setup and matched logically with production policy with the possibility to use BOM (bill-of-materials). In the block “Transportation”, vehicle types and path data are setup. Path data define parameters for shipments in the SC.

Fig. 2 also depicts interfaces of simulation software and different components of SC Big Data infrastructure such as GIS (geographic information systems), RFID (Radio Frequency Identification), ERP (enterprise resource planning) system, E-commerce, and SCM (supply chain management) system. By decreasing capacities at different points of time and for different duration, performance impacts are observed for different strategies.

4. Experiments

4.1. Input data for single sourcing experiment

For single-sourcing experiments, the following data was used:

- One-month period is considered
- Inbound capacity at DC1 is disrupted and no shipments can be received from the supplier within the one-month period
- Outbound capacity is not disrupted
- DC2 is not used
- At the beginning of the period, DC1’s inventory on-hand is 20, 40 or 60 units
- Period demand at the customer can be low (7 units per 10 days), medium (20 units per 10 days) or high (33 units per 10 days).
- Shipment time is computed automatically subject to real routes and fixed average truck speed of 80 km/h
- Transportation costs is computed as 0.01 x weight x distance
- Inbound and outbound processing costs at DCs is each $2 for a product unit
- Fixed facility costs is $5 per day
- Inventory holding costs is $0.1 per day
- Price is $100 per unit

The experimental part comprises consideration of the following disruption and reconfiguration scenarios (Table 1)

Table 1 Simulation scenarios

Scenarios	Monthly Demand 1 (low)	Monthly Demand 2 (medium)	Monthly Demand 3 (High)
Low Beginning Inventory (20 Units)	*Scenario 1_20*	*Scenario 2_20*	*Scenario 3_20*

Medium Beginning Inventory (40 Units)	*Scenario 1_40*	*Scenario 2_40*	*Scenario 3_40*
High Beginning Inventory (60 Units)	*Scenario 1_60*	*Scenario 2_60*	*Scenario 3_60*

The simulation results for performance impact analysis of the inbound capacity disruption at DC1 in the single sourcing case for nine scenarios (cf. Table 1) are depicted in Figs 3 and 4.

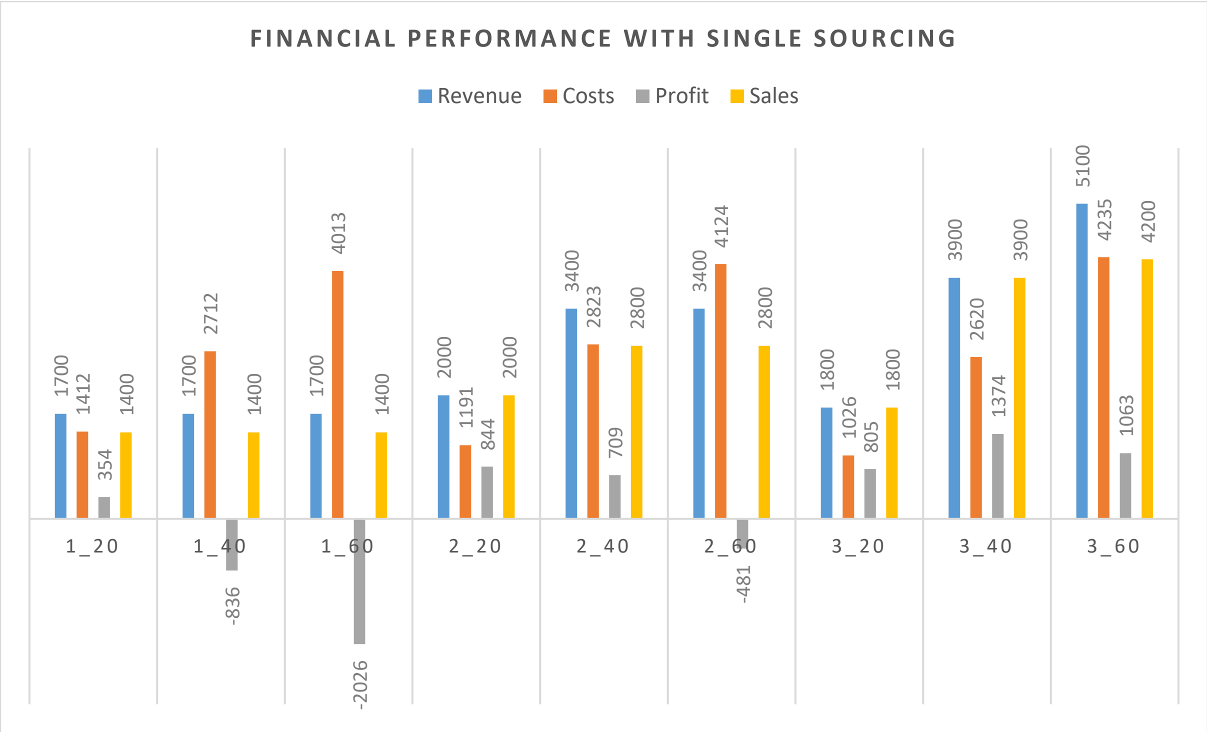

Fig. 3. Financial performance impact analysis of inbound capacity disruption at DC1 in the single sourcing case for nine scenarios

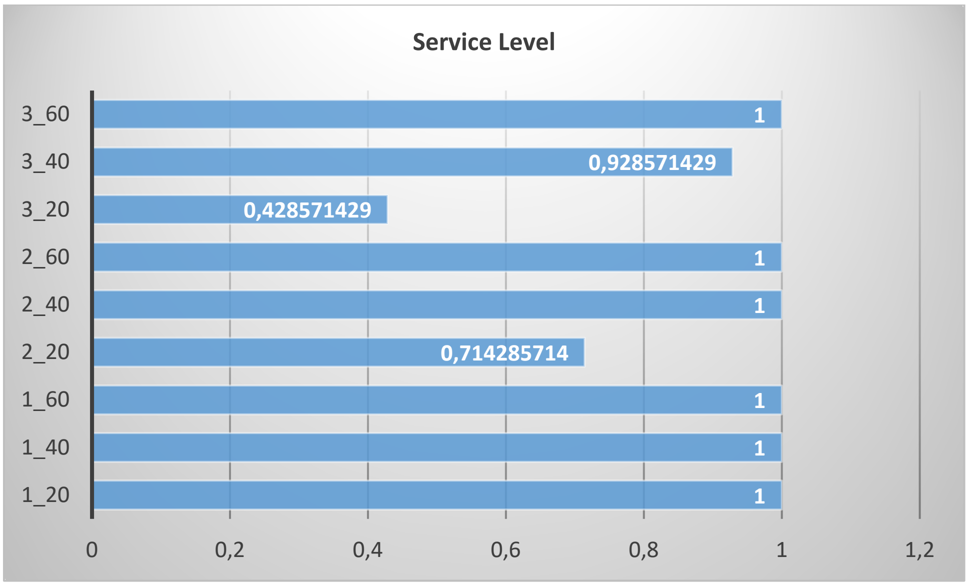

Fig. 4. Service level impact analysis of inbound capacity disruption at DC1 in the single sourcing case for nine scenarios

It can be observed from Fig. 3 that the highest profit can be achieved using medium inventory quantity in the periods with medium and high demand and using low inventory policy in the period with low demand. Losses can be observed in three scenarios (1_60, 2_40 and 2_60). From the sales point of view, it can be observed that medium and high inventory policies allow achieving higher sales as compared with low inventory policy in the periods with high and medium demand, while low inventory policy is preferred solution for the low demand period.

In Fig. 4, service level impact analysis of the inbound capacity disruption at DC1 is shown in the single sourcing case for nine scenarios. It can be observed that the service level decreases to the highest extents in the medium and high demand scenarios if applying low and medium inventory policy respectively.

The simulation results (Figs 3 and 4) allow a recommendation to use low inventory policy in the low demand periods and high inventory policy in medium and high demand periods if considering possible inbound capacity disruption at DC1. For scenarios 2_20, 3_20 and 3_40, dual sourcing may be recommended in regard to service level decrease.

4.2. Input data for dual sourcing experiment

For dual-sourcing experiments, the following data was used:

- One-month period is considered
- Inbound capacity at DC1 is disrupted and no shipments can be received from the supplier within the one-month period
- Outbound capacity is not disrupted
- DC2 is used for scenarios 2_20, 3_20 and 3_40
- DC2’s beginning inventory on-hand is 20, 40 or 60 units
- Costs and lead times at DC2 are higher as at DC1

The simulation results for performance impact analysis of inbound capacity disruption at DC1 in the dual sourcing case are depicted in Figs 5-7.

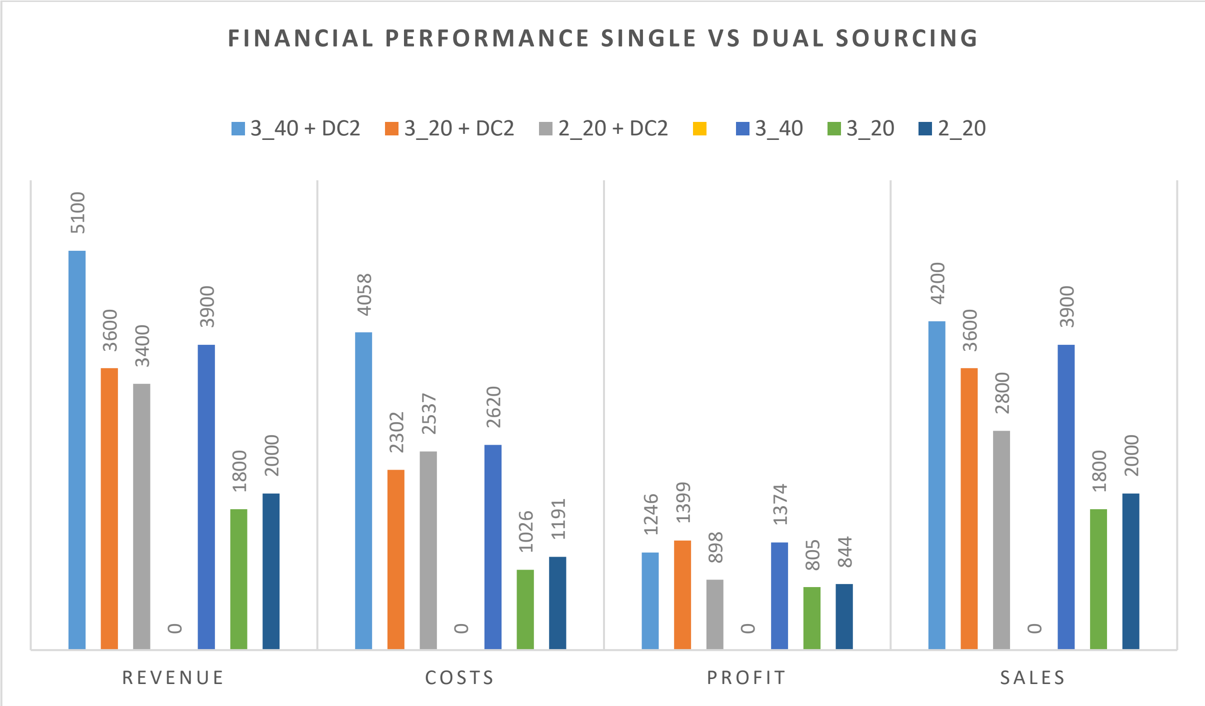

Fig. 5. Financial performance impact analysis of inbound capacity disruption at DC1 in the dual sourcing case

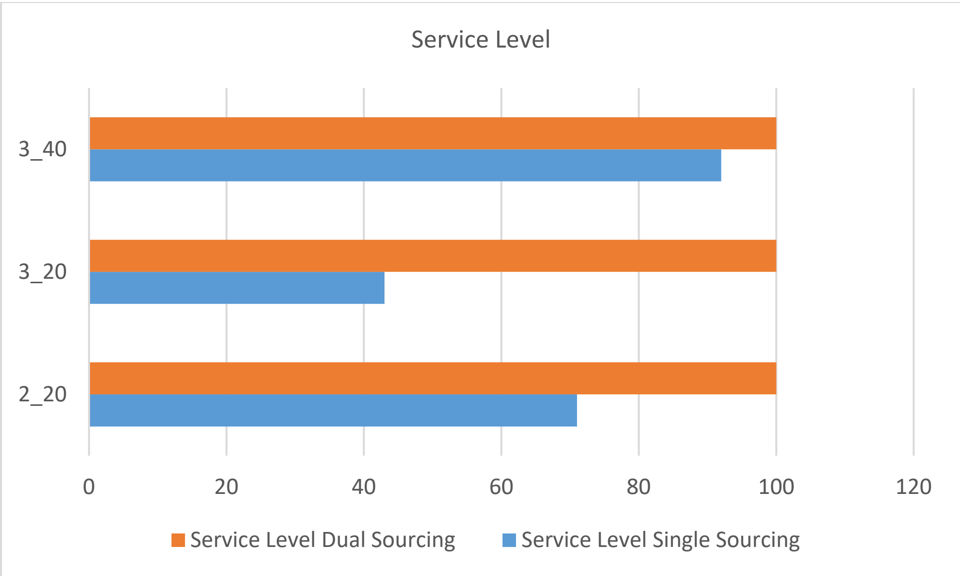

Fig. 6. Service level impact analysis of the inbound capacity disruption at DC1 in the dual sourcing case

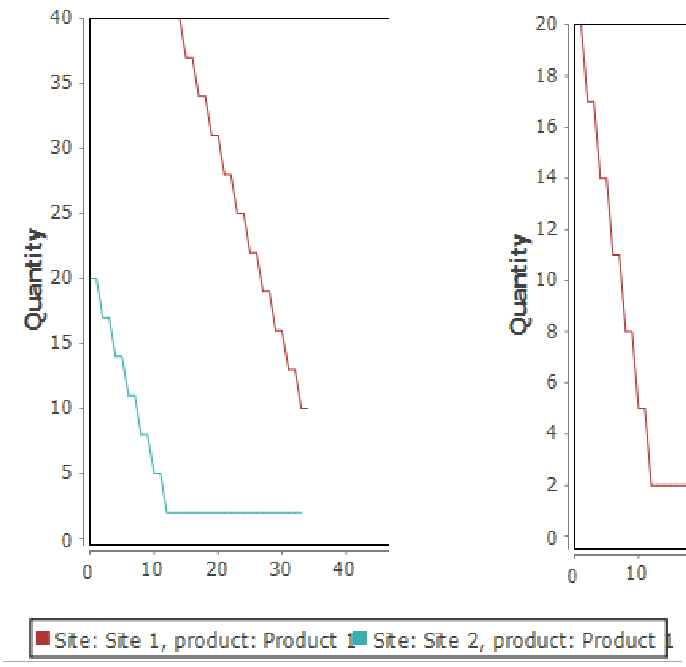

Fig 6. Inventory dynamics in single and dual sourcing cases

It can be observed from Fig. 5 that dual sourcing allows achieving higher profits for scenarios 2_20 and 3_20, i.e., for the cases with low inventory policy and high/medium demand whereas in 3_40 scenario, profit decreases in dual sourcing case if compared to single sourcing. This can be explained by the fact that the service levels in scenarios 2_40 and 3_20 were 71% and 43% respectively whereas service level in scenario 3_40 was 92% (Fig. 6). Fig. 7 depicts inventory dynamics in single and dual sourcing cases. Computational results from Figs 5-7 allow a conclusion that dual sourcing can be recommended for the scenarios with significant reductions in service level in disruption case.

5. Managerial insights

Literature analysis and numerical experimental results allow drawing some important managerial insights.

5.1 Theoretical observations

In many cases where disruption probabilities can be fairly estimated, most of the MIP solutions suggest opening new facilities. That increases total costs even if transportation costs are not increased. However, as pointed out in recent articles by Chopra and Sodhi (2014) and Simchi-Levi et al. (2014) it is almost impossible to determine probability of factory fires, natural disasters, or piracy in certain regions. That is why one has to concentrate mostly on mitigation strategies and identification of the impact of disruption on financial and operational performance regardless of what caused the disruption.

In addition, a general shortcoming of existing studies, as pointed out by Cui et al. (2010) and Li et al. (2013a) is that the dynamics of SC execution is not considered. The disruptions are mostly considered as static events, without taking into account their duration, stabilization/ recovery policies.

Similar to MIP, the assumptions on known reliability of suppliers and parametric probabilities make the stochastic programming models generally difficult to handle and implement. In addition, a scenario-based approach exponentially increases the number of variables and constraints in stochastic formulations. For some practical challenges and solutions in this direction, we refer to van Delft and Vial (2004).

Generally the application of fuzzy and robust optimization is related mostly to operational risks (e.g., demand fluctuations) and the tactical planning level with some episodic interfaces to SCD. In addition, as a general shortcoming of robust optimization, the tendency for quite pessimistic solutions has to be pointed out. In practice, it is hardly to assume that managers will accept SCDs with low efficiency and high fixed costs just in anticipation of the worst case.

Summarizing, investment in SC protection can help to avoid many problems with disruptive events. However, it is impossible to avoid disruption completely. Simchi-Levi et al. (2014) and Ambulkar et al. (2015) emphasise that focus should be directed to the recovery policies regardless of what caused the disruption. Therefore, adaptation is needed to change SC plans, schedules or inventory policies in order to achieve the desired output performance. Management science and operations research along with system dynamics and control theory contain a number of useful methods that can be used for analysis and for mitigating severe disruptions in the SC. While mathematical and stochastic optimization has its place at the SC design and planning stages without recovery considerations, they fail to throw much light on the dynamic behaviour of the SC. The implications of strategic SC design and tactical plans on SC performance at the execution and recovery stage can be enhanced by using models based on the dynamics of the execution processes.

Reactive approaches can be based either on purely recovery policies without any SC proactive protection or integrated in or with proactive approaches. We focus on the second case. Many proactive techniques actually include reactive elements. MIP formulations with facility fortification consider product shift to back-up suppliers if primary suppliers are disrupted. Inventory control models also suggest policies for recovery. Simulation techniques consider “what-if” scenarios which can be used by SC managers in the case of a disruption occurrence to quickly estimate the recovery policies and impacts on operational and financial performance.

The main challenge in this domain is to extend resilience strategies providing adequate protection from disruptions without reducing SC effectiveness in business-as-usual situations. The costs of adaptation should also be considered along with the costs of redundancy creation. It is observed that research on reactive policies is much limited, as in the proactive domain. We regard this as a future research opportunity.

5.2 Experimental observations

It can be observed from Sect. 4 that both inventory quantity and demand parameters influence the performance and the decision on single vs dual sourcing. Therefore, for different constellations of demand and inventory patterns, recommendation on single vs dual sourcing can be obtained in the form of a matrix (Fig. 8).

Single Sourcing Production smoothing	Single Sourcing Capacity flexibility	*High*	**Inventory Level**
Single Sourcing	Dual Sourcing	*Low*	
Low	*High*		
Demand			

Fig. 8. Sourcing strategies with supply chain disruption considerations

It can be observed from Figs 3-6 that the highest profit can be achieved using medium inventory quantity in the periods with medium and high demand and using low inventory quantity in the period with low demand. Losses can be observed in the scenarios where demand patterns have significant discrepancies with inventory patterns (e.g., scenarios 1_60, 2_40 and 2_60). Similarly, from the sales point of view, it can be observed that medium and high inventory policies allow achieving higher sales as compared with low inventory policy in the periods with high and medium demand, while low inventory policy is preferred solution for the low demand period.

It can be observed from Fig. 5 that dual sourcing allows achieving higher profits for scenarios 2_20 and 3_20, i.e., for the cases with low inventory policy and high/medium demand whereas in 3_40 scenario, profit decreases in dual sourcing case if compared to single sourcing. The explanation if these effect is the service levels in scenarios 2_40 and 3_20 which were 71% and 43% respectively whereas service level in scenario 3_40 was 92% (Fig. 6). Scenarios 3_40 and 3_60 make it evident that in the cases of high demand pattern and medium/high inventory pattern, the recommendation is rather to maintain some level of capacity flexibility in DCs and in contracts of DCs with factories rather than to invest in dual sourcing.

The computational results allow a conclusion that dual sourcing can be recommended for the scenarios with significant discrepancies between demand and inventory patterns and significant reductions in service level (about 30-60%) in disruption case. The simulation results also allow a recommendation to use low inventory policy in the low demand periods and high inventory policy in medium and high demand periods if considering possible inbound capacity disruption at DC1. For scenarios 2_20, 3_20 and 3_40, dual sourcing may be recommended in regard to significant service level decrease in disruption case.

In light of the considered reflections and literature analysis, some directions for simulation application to modelling the SC with disruption considerations can be derived. The possibility to change parameters dynamically during the experiment and observe performance impact of these changes in real-time allow closing some research gaps, e.g.:

- consider dynamic recovery policies
- consider gradual capacity degradation and recovery
- consider multiple performance impact dimensions including financial, service level, and operational performance

Such simulation analysis is of vital importance for SC operations planners and dispatchers at tactical and operative decision-making levels while optimization methods provide rigor decision-making support for SC executives at the strategic level. By making changes to the simulated SC, one expects to gain understanding of the dynamics of the physical SC. Simulation is an ideal tool for further analysing the performance of a proposed SC design derived from an optimization model. Simulation-based optimization can be considered in this regard as a technique that can integrate decision-making at strategic and tactical-operative level.

6. Conclusion

This study focused on low-frequency-high-impact disruptions in the SC in light of capacity disruptions and considering Big Data issues within a simulation framework. Sourcing strategy analysis in the settings of SC flexibility in regard to single vs dual sourcing has been a well explored area over the last two decades. This study extends the exiting body of literature on proactive and reactive sourcing strategy in the SC in regard to single vs dual sourcing analysis by incorporating the considerations of capacity disruptions, Big Data and different demand and inventory patterns using simulation modelling approach.

A SC simulation model with consideration of capacity disruption and Big Data along with experimental results has been developed. The observations from the literature review allow the conclusion that while optimization modelling dominated the research field of SC disruption management, the potential of simulation modelling still remains underexplored. This potential lies in the dynamic analysis of both proactive strategies and recovery contingency plans.

In light of the considered reflections, some directions for simulation application to SC modelling in the presence of disruptive risks and using Big Data can be derived. First, the possibility to change parameters dynamically during the experiment and observe performance impact of these changes in real-time has to be named. Second, simulation model allows considering disruption propagation in the SC (e.g., by analyzing inventory dynamics), considering dynamic recovery policies and utilizing gradual capacity degradation and recovery in time.

On an example of a SC simulation model implemented in AnyLogistix multimethod simulation software, we developed a case-study using simulation. Nine scenarios for different inventory and demand patterns have been modelled and evaluated in regard to SC financial, customer, and operational performance. The experimental results can be used by SC managers to analyse performance impact of different disruptions, disruption propagation in the SC (i.e., the ripple effect), and recovery sourcing policies in regard to their dynamics, performance impact and costs.

Future research on simulation-based SC modelling with disruption and Big Data considerations is multi-facet. It may include extensions in both conceptual part and technical side. In the conceptual part, more detailed scenarios and KPI schemes can be explored. On the technical side, the presented model can be extended in different ways in regard to both parameter structure and customization of sourcing and inventory policies as well as to technical data interchange protocols.

7. Literature

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