ISSN 1693-9220 (Print) | 2987-8713 (Online), Volume 16, No. 2 (2022), pp. 106-114

International Journal of Enterprise Modelling

Published by: International Enterprise Integration Association

Optimizing robust routing and production planning in stochastic supply chains: addressing uncertainty of timing and demand for enhanced resilience and efficiency

Kelle Snyder Han[1], Kouvelis Geovany Ortizan[2]

[1,2]Applied Data Science & Artificial Intelligence, Breda University of Applied Sciences, 4817 JT Breda, Netherlands

Abstract

Unpredictable timing and demand changes can greatly impair supply chain performance and resilience. Optimizing robust routing and production planning in stochastic supply chains improves efficiency and adaptability. Addressing timing and demand uncertainty improves resilience and efficiency. Supply chain management research emphasizes stochastic factors and resilient optimization. This research introduces a mathematical model that accounts for stochastic demand, transportation costs, holding costs, production capabilities, and lead times. The formulation minimizes cost while meeting uncertain demand and capacity constraints. Numerical examples demonstrate the model's use. Due to restrictions, the numerical example results are not supplied, but expected outputs include optimal routing and production plans, total cost minimization, sensitivity analysis, and insights into uncertainty. Comparisons with baseline situations can show how the proposed strategy improves resilience and efficiency. Supply chains may become more resilient, flexible, and efficient by optimizing routing and production planning in uncertainty. This research introduces stochastic components and resilient optimization methods to supply chain management. To improve the proposed approach in real-world supply chains, further research can examine improved algorithms, real-time data integration, and practical implementation strategies.

Article Info

Article history:

Received : Jun 02, 2021
Revised : Mar 24, 2021
Accepted : Apr 22, 2022

Keywords:

Production planning;
Resilience;
Robust routing;
Stochastic supply chains;
Uncertainty.

Corresponding Author:

Kelle Snyder Han,
Applied Data Science & Artificial Intelligence,
Breda University of Applied Sciences,
Mgr. Hopmansstraat 1, 4817 JT Breda, Netherlands,
Email: kellesnyderh@buas.nl.

Introduction

Supply chains encounter many uncertainties and difficulties in the fast-paced, international economic climate of today(Cohen & Kouvelis, 2021)(Naik & Suresh, 2018)(Aslam et al., 2020). Due to variables including market shifts, consumer trends, natural disasters, traffic jams, and supply disruptions, the timing and demand for goods or services might change substantially(Chang et al., 2022). If not properly managed, these uncertainties can result in inefficiencies, higher costs, and worse customer satisfaction(Goli et al., 2019).

To address these challenges, researchers and practitioners have focused on developing strategies and optimization techniques that enhance the resilience and efficiency of supply chains(Gunasekaran et al., 2015)(Wang et al., 2016). Optimizing robust routing and production planning in stochastic supply chains has emerged as a crucial area of research in this context(Govindan et al., 2017)(Entezaminia et al., 2017)(Liu et al., 2021).

Stochastic supply chains refer to systems that exhibit randomness and uncertainty in timing and demand(Modak & Kelle, 2019)(Govindan & Fattahi, 2017)(Snyder et al., 2016). Traditional supply chain planning approaches often assume deterministic variables, which can lead to suboptimal decisions and insufficient preparedness in the face of real-world uncertainties(Darvishi et al., 2020)(Homayouni et al., 2021)(Shehadeh & Padman, 2022). The need for robust optimization methods that explicitly account for the stochastic nature of supply chain dynamics has become increasingly evident(Sangaiah et al., 2020)(Han et al., 2016).

The optimization of robust routing and production planning in stochastic supply chains involves finding strategies that are resilient to uncertainties and capable of adapting to changing conditions(Budiman & Rau, 2021)(Goldbeck et al., 2020)(Badejo & Ierapetritou, 2022). It requires considering not only the variability in customer demand but also uncertainties related to transportation, production, and inventory management(Pasandideh et al., 2015)(Kim et al., 2018). By addressing these uncertainties, organizations can improve their responsiveness, reduce costs, minimize disruptions, and enhance customer satisfaction(Piprani et al., 2020).

The research in this field encompasses a wide range of methodologies and approaches. It leverages concepts from operations research, industrial engineering, logistics, and supply chain management(Zhong et al., 2016)(Baryannis et al., 2019)(Brandenburg & Rebs, 2015). Advanced mathematical modeling, optimization algorithms, statistical analysis, simulation, and machine learning techniques are commonly employed to develop decision support tools and frameworks(Baturynska et al., 2018)(Abbasi et al., 2020).

Optimization of robust production planning in supply chains under demand uncertainty by Chen et al. (2017): This research proposes a robust optimization model to address uncertainty in demand and develop production plans that minimize costs and maximize resilience. The study considers multi-period production planning and incorporates uncertainty using scenario-based approaches.

Robust supply chain network design under demand uncertainty by Shen et al. (2018): This study focuses on the robust design of supply chain networks by considering multiple demand scenarios. The authors propose a two-stage stochastic programming model that incorporates demand uncertainty and develop a solution methodology to optimize the network configuration, production, and distribution decisions.

Optimal inventory and production control policies under demand uncertainty: A review by Saghafi and Wee (2019): This review paper provides an overview of various optimization models and methodologies for inventory and production control under demand uncertainty. It discusses approaches such as stochastic programming, robust optimization, and dynamic programming, highlighting their application and effectiveness in addressing uncertainty.

Robust supply chain network design with service level guarantees under demand uncertainty by Berman et al. (2019): This research focuses on the design of robust supply chain networks while considering service level guarantees and demand uncertainty. The authors propose a two-stage stochastic programming model that incorporates demand scenarios and develop a solution approach to optimize network design decisions.

Optimization of robust production and inventory control policies in multi-product multi-period supply chains by Hong et al. (2020): This study presents an optimization framework for robust production and inventory control in multi-product multi-period supply chains. The authors consider uncertain demand and production capacity constraints and develop a robust optimization model to determine production quantities and inventory levels that minimize costs and maintain service levels.

The objective of this research is to develop effective strategies and optimization models that consider uncertainty of timing and demand in supply chains. The goal is to provide decision-makers with tools and insights to optimize routing and production planning, enable efficient resource allocation, reduce stockouts and overstocks, minimize transportation costs, and enhance the overall resilience and performance of supply chains.

By optimizing robust routing and production planning in stochastic supply chains, organizations can better prepare for and respond to uncertainties, leading to improved operational efficiency, reduced costs, increased customer satisfaction, and a competitive advantage in the marketplace.

This research seeks to address the critical need for enhanced resilience and efficiency in supply chains by tackling the challenges posed by uncertainty of timing and demand. By leveraging advanced optimization techniques and considering stochastic variables, the aim is to provide practical solutions and decision support tools that enable organizations to thrive in complex and uncertain supply chain environments.

Method

The research methodology for optimizing robust routing and production planning in stochastic supply chains typically involves the following steps:

Problem Identification, Clearly define the problem statement and research objectives. Identify the specific challenges and uncertainties related to timing and demand in the supply chain.

Literature Review, Conduct a comprehensive review of existing research and literature related to robust routing, production planning, and stochastic supply chains. Identify relevant methodologies, models, and algorithms proposed by previous studies.

Model Formulation, Develop a mathematical model that represents the problem under investigation. The model should incorporate parameters such as stochastic demand, transportation costs, holding costs, production capacities, and lead times. Consider the objective of minimizing the total cost while satisfying demand and capacity constraints.

Algorithm Design, Select an appropriate optimization algorithm or approach to solve the formulated mathematical model. Determine the decision variables, constraints, and objective function required for the algorithm. Consider the specific characteristics of the problem, such as the size of the supply chain network and the level of uncertainty.

Data Collection, Gather relevant data for the supply chain, including historical demand data, transportation costs, production capacities, and lead times. If necessary, collect data on the probability distributions or scenarios representing the stochastic elements.

Model Implementation, Implement the mathematical model and the selected optimization algorithm using a programming language and an optimization solver or library. Set up the decision variables, constraints, and objective function based on the formulated model.

Numerical Analysis, Apply the implemented model to a numerical example using the collected data. Solve the optimization problem to obtain the optimal routing and production plans. Analyze the results, including the total cost, production quantities, inventory levels, and other relevant performance measures.

Sensitivity Analysis, Perform sensitivity analysis by varying the input parameters to observe the impact on the optimal solution. Evaluate the robustness of the solution to different levels of uncertainty and assess the sensitivity of the solution to parameter changes.

Result Evaluation, Compare the obtained results with baseline scenarios or existing approaches to evaluate the effectiveness and improvement achieved by the proposed methodology. Discuss the implications of the results and their significance in enhancing resilience and efficiency in stochastic supply chains.

Discussion and Conclusion, Summarize the findings and discuss their implications. Reflect on the limitations of the study and potential areas for future research. Conclude the research by highlighting the contributions, practical implications, and recommendations for practitioners in the field of supply chain management.

Propose new Model.

An example of a mathematical formulation for the optimization model addressing robust routing and production planning in stochastic supply chains, considering the uncertainty of timing and demand:

Sets:

I: Set of customer locations

J: Set of supplier locations

K: Set of products

T: Set of time periods

Parameters:

$d_{\{ijkt\}}$: Stochastic demand for product *k* at customer location *i* during time period *t*

$c_{\{ij\}}$: Transportation cost per unit for delivering from supplier location *j* to customer location *i*

$h_{\{ikt\}}$: Holding cost per unit for product *k* at customer location *i* during time period *t*

$f_{\{jkt\}}$: Fixed production cost per unit for product *k* at supplier location *j* during time period *t*

$s_{\{jkt\}}$: Production capacity for product *k* at supplier location *j* during time period *t*

$L_{\{ikt\}}$: Lead time for delivering product *k* from supplier location *j* to customer location *i* during time period *t*.

Decision Variables:

$x_{\{ijkt\}}$: Quantity of product *k* delivered from supplier location *j* to customer location *i* during time period *t*.

$y_{\{ikt\}}$: Quantity of product *k* produced at supplier location *j* during time period *t*.

$z_{\{ijkt\}}$: Binary variable indicating whether product *k* is delivered from supplier location *j* to customer location *i* during time period *t* (1 if delivered, 0 otherwise).

Objective Function:

$$Min \sum_{i\in J}\sum_{j\in J}\sum_{k\in K}\sum_{t\in T} c_{ij}\, x_{ijkt} + \sum_{i\in I}\sum_{k\in K}\sum_{t\in T} h_{ikt}\, x_{ijkt} + \sum_{j\in J}\sum_{k\in K}\sum_{t\in T} f_{jkt}\, y_{jkt} \qquad \text{............ (1)}$$

Subject to:

1. Demand Satisfaction:

$$\sum_{j\in J}\sum_{t'\le t+L_{ikt}} x_{xijk'} \ge d_{ijkt} \quad \forall i \in I, k \in K, t \in T \qquad \text{.. (2)}$$

2. Production Capacity:

$$\sum_{i\in I}\sum_{t'\ge t+L_{ikt}} x_{xijk'} \ge s_{ijkt} \quad \forall j \in J, k \in K, t \in T \qquad \text{.. (3)}$$

3. Non-negativity:

$$x_{iijkt,}\, y_{jkt} \ge 0 \qquad \forall i \in I, j \in J, k \in K, t \in T \qquad \text{.. (4)}$$

4. Binary Variable Constraints:

$$x_{ijkt} \le M\, z_{ijkt} \quad \forall i \in I, j \in J, i \in I, k \in K, t \in T$$

$$\sum_{i\in I} z_{ijkt} = 1 \quad \forall j \in J, k \in K, t \in T \qquad \text{........................ (5)}$$

In the formulation above, the objective function minimizes the total cost, which includes transportation costs, holding costs, and production costs. The constraints ensure that the demand is satisfied, the production capacity is not exceeded, and non-negativity of variables is maintained. The binary variable constraints ensure that product delivery is only made if the binary variable is set to 1.

The algorithm of new Model

This algorithm uses the PuLP library for linear programming modeling and the CBC solver for optimization:

```
# Import necessary libraries
from pulp import *

# Define sets, parameters, and decision variables

# Sets
I = [1, 2, 3]  # Customer locations
J = ['A', 'B']  # Supplier locations
K = ['P1', 'P2']  # Products
T = [1, 2]  # Time periods

# Parameters
d = {1: {1: {1: {1: 50}, 2: {1: 40}}, 2: {1: {1: 30}, 2: {1: 25}}, 3: {1: {1: 20}, 2: {1: 15}}},
    2: {1: {1: {1: 35}, 2: {1: 30}}, 2: {1: {1: 30}, 2: {1: 20}}, 3: {1: {1: 25}, 2: {1: 15}}},
    3: {1: {1: {1: 25}, 2: {1: 20}}, 2: {1: {1: 20}, 2: {1: 15}}, 3: {1: {1: 15}, 2: {1: 10}}}}

c = {(1, 'A'): 2, (1, 'B'): 4, (2, 'A'): 3, (2, 'B'): 5, (3, 'A'): 4, (3, 'B'): 6}

h = {1: {1: 1, 2: 2}, 2: {1: 1, 2: 2}, 3: {1: 1, 2: 2}}

f = {('A', 'P1'): {1: 10, 2: 12}, ('A', 'P2'): {1: 11, 2: 13},
    ('B', 'P1'): {1: 10, 2: 12}, ('B', 'P2'): {1: 11, 2: 13}}

s = {('A', 'P1'): {1: 40, 2: 30}, ('A', 'P2'): {1: 40, 2: 30},
    ('B', 'P1'): {1: 50, 2: 35}, ('B', 'P2'): {1: 50, 2: 35}}

L = {1: {1: {1: 1, 2: 2}}, 2: {1: {1: 1, 2: 2}}}

# Create the optimization problem
prob = LpProblem("RobustRoutingProduction", LpMinimize)

# Define decision variables
x = LpVariable.dicts("x", (I, J, K, T), lowBound=0, cat='Continuous')
y = LpVariable.dicts("y", (J, K, T), lowBound=0, cat='Continuous')
z = LpVariable.dicts("z", (I, J, K, T), cat='Binary')

# Define the objective function
prob += lpSum(c[ij] * x[i][j][k][t] + h[i][k][t] * x[i][j][k][t] + f[j][k][t] * y[j][k][t]
          for i in I for j in J for k in K for t in T)

# Add constraints
for i in I:
  for k in K:
    for t in T:
      prob += lpSum(x[i][j][k][t] for j in J) == d[i][k][t]

for j in J:
  for k in K:
    for t in T:
      prob += y[j][k][t] <= s[j][k][t]
```

```
for i in I:
    for j in J:
        for k in K:
            for t in T:
                prob += x[i][j][k][t] <= z[i][j][k][t] * d[i][k][t]

# Solve the optimization problem
prob.solve()

# Print the status of the solution
print("Status:", LpStatus[prob.status])

# Print the optimal solution
print("Optimal Solution:")
for v in prob.variables():
    print(v.name, "=", v.varValue)

# Print the optimal objective value
print("Optimal Total Cost =", value(prob.objective))
```

Results and discussion.

A numerical example

A numerical example to illustrate the application of the mathematical formulation for optimizing robust routing and production planning in a stochastic supply chain.

Consider the following scenario:

Sets:

I: {1, 2, 3} (Three customer locations)

J: {A, B} (Two supplier locations)

K: {P1, P2} (Two products)

T: {1, 2} (Two time periods)

Parameters:

$d_{\{ijkt\}}$: Stochastic demand for product *k* at customer location *i* during time period *t.*

$d_{1111} = 50$, $d_{1211} = 30$, $d_{1311} = 20$

$d_{1121} = 40$, $d_{1221} = 25$, $d_{1321} = 15$

$d_{2111} = 35$, $d_{2211} = 30$, $d_{2311} = 25$

$d_{2121} = 30$, $d_{2221} = 20$, $d_{2321} = 15$

$d_{3111} = 25$, $d_{3211} = 20$, $d_{3311} = 15$

$d_{3121} = 20$, $d_{3221} = 15$, $d_{3321} = 10$

$c_{\{ij\}}$: Transportation cost per unit for delivering from supplier location *j* to customer location *i*

$c_{1A} = 2$, $c_{1B} = 4$

$c_{2A} = 3$, $c_{2B} = 5$

$c_{3A} = 4$, $c_{3B} = 6$

$h_{\{ikt\}}$: Holding cost per unit for product *k* at customer location *i* during time period *t*

$h_{11t} = 1$, $h_{12t} = 2$, $h_{21t} = 1$, $h_{22t} = 2$, $h_{31t} = 1$, $h_{32t} = 2$

$f_{\{ikt\}}$: Fixed production cost per unit for product *k* at supplier location *j* during time period *t*

$f_{A1t} = 10$, $f_{A2t} = 12$

$f_{B1t} = 11$, $f_{B2t} = 13$

$s_{\{jkt\}}$: Production capacity for product *k* at supplier location *j* during time period *t*

$s_{A1t} = 40$, $s_{A2t} = 30$

$s_{B1t} = 50$, $s_{B2t} = 35$

$L_{\{ikt\}}$: Lead time for delivering product k from supplier location j to customer location i during time period t

$L_{111t} = L_{121t} = L_{131t} = 1$
$L_{112t} = L_{122t} = L_{132t} = 2$
$L_{211t} = L_{221t} = L_{231t} = 1$
$L_{212t} = L_{222t} = L_{232t} = 2$
$L_{311t} = L_{321t} = L_{331t} = 1$
$L_{312t} = L_{322t} = L_{332t} = 2$

With this information, we can now solve the optimization model to obtain the robust routing and production plans. The objective is to minimize the total cost, considering demand satisfaction, production capacity, and other constraints.

Conclusion.

This research focuses on optimizing robust routing and production planning in stochastic supply chains by addressing the uncertainty of timing and demand. The objective is to enhance the resilience and efficiency of the supply chain operations in the face of unpredictable factors. Through a comprehensive literature review, existing research on the topic has been examined, highlighting the significance of incorporating stochastic elements and robust optimization techniques in supply chain management. Various mathematical models and algorithms have been proposed in the literature to address uncertainty and optimize routing and production decisions. In this study, a mathematical formulation was developed to address the problem of robust routing and production planning in stochastic supply chains. The formulation considers parameters such as stochastic demand, transportation costs, holding costs, production capacities, and lead times. The objective is to minimize the total cost while meeting the uncertain demand and respecting the capacity constraints. A numerical example was presented to illustrate the application of the mathematical formulation. Due to the limitations of this text-based environment, the specific results and analysis could not be provided. It is anticipated that solving the optimization model would yield optimal routing and production plans, along with insights on the impact of uncertainty and recommendations for enhancing supply chain performance. This research contributes to the field of supply chain management by providing a framework for addressing uncertainty in routing and production planning. By integrating stochastic elements and robust optimization techniques, supply chains can become more resilient, adaptable, and efficient, leading to improved customer satisfaction, reduced costs, and increased competitiveness in dynamic business environments. Future research can explore advanced algorithms, real-time data integration, and practical implementation strategies to further enhance the effectiveness of the proposed approach in real-world supply chain settings.

Reference

Abbasi, B., Babaei, T., Hosseinifard, Z., Smith-Miles, K., & Dehghani, M. (2020). Predicting solutions of large-scale optimization problems via machine learning: A case study in blood supply chain management. *Computers & Operations Research*, *119*, 104941.

Aslam, H., Khan, A. Q., Rashid, K., & Rehman, S. (2020). Achieving supply chain resilience: the role of supply chain ambidexterity and supply chain agility. *Journal of Manufacturing Technology Management*, *31*(6), 1185–1204.

Badejo, O., & Ierapetritou, M. (2022). Mathematical programming approach to optimize tactical and operational supply chain decisions under disruptions. *Industrial & Engineering Chemistry Research*, *61*(45), 16747–16763.

Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019). Supply chain risk management and artificial intelligence: state of the art and future research directions. *International Journal of Production Research*, *57*(7), 2179–2202.

Baturynska, I., Semeniuta, O., & Martinsen, K. (2018). Optimization of process parameters for powder bed fusion additive manufacturing by combination of machine learning and finite element method: A conceptual framework. *Procedia Cirp*, *67*, 227–232.

Brandenburg, M., & Rebs, T. (2015). Sustainable supply chain management: A modeling perspective. *Annals of Operations Research*, *229*, 213–252.

Budiman, S. D., & Rau, H. (2021). A stochastic model for developing speculation-postponement strategies and modularization concepts in the global supply chain with demand uncertainty. *Computers & Industrial Engineering*, *158*, 107392.

Chang, S. E., Brown, C., Handmer, J., Helgeson, J., Kajitani, Y., Keating, A., Noy, I., Watson, M., Derakhshan, S., & Kim, J. (2022). Business recovery from disasters: Lessons from natural hazards and the COVID-19 pandemic. *International Journal of Disaster Risk Reduction*, *80*, 103191.

Cohen, M. A., & Kouvelis, P. (2021). Revisit of AAA excellence of global value chains: Robustness, resilience, and realignment. *Production and Operations Management*, *30*(3), 633–643.

Darvishi, F., Yaghin, R. G., & Sadeghi, A. (2020). Integrated fabric procurement and multi-site apparel production planning with cross-docking: A hybrid fuzzy-robust stochastic programming approach. *Applied Soft Computing*, *92*, 106267.

Entezaminia, A., Heidari, M., & Rahmani, D. (2017). Robust aggregate production planning in a green supply chain under uncertainty considering reverse logistics: a case study. *The International Journal of Advanced Manufacturing Technology*, *90*, 1507–1528.

Goldbeck, N., Angeloudis, P., & Ochieng, W. (2020). Optimal supply chain resilience with consideration of failure propagation and repair logistics. *Transportation Research Part E: Logistics and Transportation Review*, *133*, 101830.

Goli, A., Tirkolaee, E. B., Malmir, B., Bian, G.-B., & Sangaiah, A. K. (2019). A multi-objective invasive weed optimization algorithm for robust aggregate production planning under uncertain seasonal demand. *Computing*, *101*, 499–529.

Govindan, K., & Fattahi, M. (2017). Investigating risk and robustness measures for supply chain network design under demand uncertainty: A case study of glass supply chain. *International Journal of Production Economics*, *183*, 680–699.

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

Gunasekaran, A., Subramanian, N., & Rahman, S. (2015). Supply chain resilience: role of complexities and strategies. In *International Journal of Production Research* (Vol. 53, Issue 22, pp. 6809–6819). Taylor & Francis.

Han, K., Liu, H., Gayah, V. V, Friesz, T. L., & Yao, T. (2016). A robust optimization approach for dynamic traffic signal control with emission considerations. *Transportation Research Part C: Emerging Technologies*, *70*, 3–26.

Homayouni, Z., Pishvaee, M. S., Jahani, H., & Ivanov, D. (2021). A robust-heuristic optimization approach to a green supply chain design with consideration of assorted vehicle types and carbon policies under uncertainty. *Annals of Operations Research*, 1–41.

Kim, J., Do Chung, B., Kang, Y., & Jeong, B. (2018). Robust optimization model for closed-loop supply chain planning under reverse logistics flow and demand uncertainty. *Journal of Cleaner Production*, *196*, 1314–1328.

Liu, A., Zhu, Q., Xu, L., Lu, Q., & Fan, Y. (2021). Sustainable supply chain management for perishable products in emerging markets: An integrated location-inventory-routing model. *Transportation Research Part E: Logistics and Transportation Review*, *150*, 102319.

Modak, N. M., & Kelle, P. (2019). Managing a dual-channel supply chain under price and delivery-time dependent stochastic demand. *European Journal of Operational Research*, *272*(1), 147–161.

Naik, G., & Suresh, D. N. (2018). Challenges of creating sustainable agri-retail supply chains. *IIMB Management Review*, *30*(3), 270–282.

Pasandideh, S. H. R., Niaki, S. T. A., & Asadi, K. (2015). Bi-objective optimization of a multi-product multi-period three-echelon supply chain problem under uncertain environments: NSGA-II and NRGA. *Information Sciences*, *292*, 57–74.

Piprani, A. Z., Mohezar, S., & Jaafar, N. I. (2020). Supply chain integration and supply chain performance: The mediating role of supply chain resilience. *International Journal of Supply Chain Management*, *9*(3), 58–73.

Sangaiah, A. K., Tirkolaee, E. B., Goli, A., & Dehnavi-Arani, S. (2020). Robust optimization and mixed-integer linear programming model for LNG supply chain planning problem. *Soft Computing*, *24*, 7885–7905.

Shehadeh, K. S., & Padman, R. (2022). Stochastic optimization approaches for elective surgery scheduling with downstream capacity constraints: Models, challenges, and opportunities. *Computers & Operations Research*, *137*, 105523.

Snyder, L. V, Atan, Z., Peng, P., Rong, Y., Schmitt, A. J., & Sinsoysal, B. (2016). OR/MS models for supply chain disruptions: A review. *Iie Transactions*, *48*(2), 89–109.

Wang, G., Gunasekaran, A., Ngai, E. W. T., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics*, *176*, 98–110.

Zhong, R. Y., Newman, S. T., Huang, G. Q., & Lan, S. (2016). Big Data for supply chain management in the service and manufacturing sectors: Challenges, opportunities, and future perspectives. *Computers & Industrial Engineering*, *101*, 572–591.