

Editorial

Special Issue “Modeling of Supply Chain Systems”

Zina Ben Miled 

Electrical and Computer Engineering Department, Indiana University-Purdue University, Indianapolis, IN 46202, USA; zmiled@iupui.edu

Received: 20 October 2020; Accepted: 20 October 2020; Published: 22 October 2020



1. Introduction

Supply chain systems are complex networks of producers, service providers and consumers. Over the years, the complexity of these systems increased due to several economical and geographical drivers. While manufacturing may have been mostly local a few decades ago, market penetration and improved distribution networks have created large global supply chains. This increase in scale and reach coupled with the need for reduced cost and improved services is being matched with heightened challenges [1].

This Special Issue investigates some of the challenges and proposes potential solutions. The primary requirements of current and future supply chain networks are resilience and flexibility. These requirements can only be fulfilled through collaboration and dynamic planning. Unfortunately, different manufacturing sectors operate under different constraints. For example, temperature control constraints in the food sector may not be applicable to the chemical industries. Conversely, the transport of hazardous material in the chemical sector is unlikely to be applicable to the food sector. This heterogeneity makes collaboration among different sectors in the supply chain difficult. It also makes the re-purposing of supply chain resources across the distribution network impractical. Another limitation of supply chain collaboration is information transparency. Digital workflows are needed to enable the sharing of information along the supply chain while respecting the privacy of the participating partners so as not to erode their competitive advantage. Despite these limitations, increased collaboration, when possible, should be considered. This issue explores two case studies of collaborative supply chain frameworks, one between suppliers and manufacturers in the automotive sector and the other among carriers.

Dynamic planning [2] is the second enabler of the resilience and flexibility requirements in supply chain networks. Unfortunately, these requirements are being increasingly tested due to disruptions resulting from extreme weather conditions, unrest and other global events. These events led to changing market patterns. For example, the recent pandemic led to an increase in e-commerce and direct manufacturer to consumer supply. In the long term, these events may also change the structure of supply chain networks [3] by promoting decentralization and dynamic reconfigurability. Two of the papers in this Special Issue cover this topic. The first examines the dynamic routing of vehicles in response to a mixture of static delivery orders and dynamic pick-up orders. The second paper focuses on supporting dynamic planning of outbound shipments based on the probability of occurrence of disruptive events.

2. Summary of Articles

Two collaborative models are presented in this Special Issue. In *Proposing a Supply Chain Collaboration Framework for Synchronous Flow Implementation in the Automotive Industry: A Moroccan Case Study* by Imane Ibn El Farouk et. al. [4], the authors investigate a vertical collaborative model across an automotive constructor and first-tier equipment suppliers. The key factors impacting a successful collaboration are first established. Based on these factors, the model defines decision support rules that

can help assess the feasibility of the collaboration. In the case study investigated by the authors, the key factors to a successful collaboration included proximity, information sharing, and the availability of both human and material resources.

A horizontal collaborative model for supply chain distribution is proposed in *Model for Collaboration among Carriers to Reduce Empty Container Truck Trips* by Majbah Uddin and Nathan Huynh [5]. The authors highlight some of the inefficiencies associated with intermodal transport. While this type of transport offers additional flexibilities compared to the traditional single mode transport, the authors indicate that the former may lead to an increase in empty container movements which can negatively impact both the environment and freight cost. The paper proposes a collaborative model that reduces the movement of empty containers while also reducing freight cost. The model is developed using integer programming and tested using empirical data. Both static and dynamic travel times are considered. In addition, the study includes a review of current approaches to horizontal collaboration.

Dynamic planning is the second theme discussed in this issue. Highly optimized supply chain processes are risk abound. For instance, these processes may not allow for large inventory buffering as in the automotive case study introduced in [4]. Resources and lead times optimization can also result in narrow risk margins [5]. Collaborative supply chain models can help mitigate some of these risks. However, supply chain networks must also have the ability to adjust to variances in the operating conditions.

In *The Effect of Limited Resources in the Dynamic Vehicle Routing Problem with Mixed Backhauls* by Georgios Ninikas and Ioannis Minis [6], the authors focus on the dynamic routing of a fleet of vehicles with mixed backhauls. This type of transport system covers dynamic pick-up orders and static delivery orders that are not necessarily related. The delivery orders are static because they are known beforehand. The pick-up orders are dynamic because they are received during the execution of the delivery orders. The authors propose a multi-objective optimization algorithm for this routing problem with resource constraints. The proposed model attempts to maximize both the service level and the fleet productivity. The authors also investigate several aspects of the routing model, including the prioritization of services, partial planning and the frequency of re-planning. While the main objective of the proposed approach is to optimize the routing of a fleet of vehicles, it can also be extended to the problem of right-sizing of the fleet in terms of number of vehicles and operating times.

Risk Assessment Framework for Outbound Supply-Chain Management by Mark Krystofik et. al. [7] introduces a model that quantifies the risks for delivery delays in outbound shipments. Typically, delivery delays in supply chain are assessed from an inbound perspective. Analyzing delay potentials for outbound shipments provides an opportunity for proactive risk mitigation and planning. The authors propose a probabilistic model that considers both the likelihood of a disruptive supply chain event and the importance of the shipment. The model assigns a risk score to scheduled and en-route shipments in order to support risk mitigation decisions. The study also includes an overview of supply chain risk management (SCRM) and supply chain event management (SCEM) systems.

3. Outlook

The articles of this Special Issue highlight the complexity of supply chain systems and the potential for improvement using collaborative supply chain networks and dynamic planning. They also indicate that current supply chain systems can benefit from improved information transparency and better risk prediction visibility. Information transparency should be extended to facilitate both vertical and horizontal collaboration for a large number of partners while preserving data privacy. Distributed information systems, such as blockchains [8] and Internet of Things (IoT) [9] offer a potential solution.

Dynamic planning and risk prediction models are increasingly necessary to support supply chain resilience and flexibility. Machine learning techniques should be considered when developing these models. However, machine learning has been primarily applied to demand [10,11] and route [12]

planning in supply chain. Extending machine learning to other areas of supply chain may require overcoming two main difficulties. First, these models are trained with large datasets which may not be available to scientists. Second, successful supply chain machine learning models should be capable of operating at different levels of granularity and time scales. These capabilities have yet to be fully developed.

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