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Discrete Optimization

Hybrid robust and stochastic optimization for closed-loop supply chain network design using accelerated Benders decomposition

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ABSTRACT

Environmental, social and economic concerns motivate the operation of closed-loop supply chain networks (CLSCN) in many industries. We propose a novel profit maximization model for CLSCN design as a mixed-integer linear program in which there is flexibility in covering the proportions of demand satisfied and returns collected based on the firm's policies. Our major contribution is to develop a novel hybrid robust-stochastic programming (HRSP) approach to simultaneously model two different types of uncertainties by including stochastic scenarios for transportation costs and polyhedral uncertainty sets for demands and returns. Transportation cost scenarios are generated using a Latin Hypercube Sampling method and scenario reduction is applied to consolidate them. An accelerated stochastic Benders decomposition algorithm is proposed for solving this model. To speed up the convergence of this algorithm, valid inequalities are introduced to improve the lower bound quality, and also a Pareto-optimal cut generation scheme is used to strengthen the Benders optimality cuts. Numerical studies are performed to verify our mathematical formulation and also demonstrate the benefits of the HRSP approach. The performance improvements achieved by the valid inequalities and Pareto-optimal cuts are demonstrated in randomly generated instances.

1. Introduction

The growing need for remanufacturing and recycling due to resource scarcity and environmental concerns requires firms to coordinate the forward and reverse material flows in their supply chains. This motivates the design of a closed-loop supply chain network (CLSCN) to avoid sub-optimality arising from separate design of forward and reverse networks. As pointed out by Klibi, Martel, and Guitouni (2010), the design of a supply chain network is a crucial strategic decision, the effects of which will persist for many years while the business environment may change. Thus, some important parameters such as demand and costs are significantly uncertain. In addition, because opening or closing a facility is time-consuming and costly, making any change in these decisions in response to parameter oscillations is impossible within a short time frame (Pishvaee, Rabbani, & Torabi, 2011). Uncertainties are intensified in the reverse supply chain network where the quality and quantity of returned products vary unpredictably and fast. Therefore, the design of CLSCN should be robust to the inherent uncertainty in the network parameters.

Of the few recent relevant papers that consider uncertainty in the CLSCN design problem, most estimate the probability distributions for the parameters and then apply scenario-based stochastic programming (SP; e.g., Salema, Barbosa-Povoa, & Novais, 2007; Santoso, Ahmed, Goetschalckx, & Shapiro, 2005). SP is a powerful modeling tool when an accurate probabilistic description of the random variables is known. However, it has three main drawbacks (Bertsimas & Thiele, 2006; Gülpınar, Pachamanova, & Çanakoğlu, 2013). First, in many real-life applications not enough historical data are available to estimate distributions. For instance, predicting demand of a new product is challenging. Secondly, an accurate distribution approximation may require a large number of scenarios. But the more scenarios used for representing uncertainty, the harder it is to solve the problem to optimality. Conversely, if the number of scenarios is limited for computational reasons, the obtained solution may be infeasible for some realizations of uncertain parameters. Even if this occurs with very small probability, it could result in high cost due to the large scale of the CLSCN. Finally, SP models based on expected cost are appropriate when the decision maker worries about the average performance of the system. However, there are situations where the decision maker is concerned with the worst case. We highlight this concern with respect to uncertain demand and return quantities.

To avoid these drawbacks, robust optimization (RO) has emerged as an alternative methodology to cope with uncertainty in the input

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data. The robust counterpart is a deterministic reformulation of the original problem in which the worst case cost is minimized over all possible values the input parameters may take within predefined uncertainty sets. Two main advantages of RO compared with SP are (Alumur, Nickel, Saldanha-da-Gama, & Verter, 2012): first, independently of the number of uncertain parameters, the robust counterpart can remain computationally tractable, and second, rough historical data and decision makers' experiences can be used to derive the boundaries of uncertainty sets, without the need for precise estimates of probability distributions.

The uncertain parameters we consider in our CLSCN design problem differ qualitatively. Historical data for transportation costs can be used to formulate probabilistic scenarios for them, but no such data for demand and return quantities of a new product exist. Because the purpose of the network is to supply products and collect the returns, we design it for the extreme quantities to ensure that its capacity and configuration will suffice in any event. The need to consider both types of uncertainty in an integrated network has been emphasized recently by Klibi and Martel (2012), Melo, Nickel, and Saldanha-da-Gama (2009) and Gabrel, Murat, and Thiele (2014).

This paper contributes to the CLSCN design literature by developing a novel hybrid robust-stochastic optimization approach and also devising an efficient solution procedure. Specifically, a mixed-integer linear program (MILP) is developed for a multi-period, single-product and capacitated CLSCN. The strategic decisions including locations and capacities of facilities as well as the tactical decisions including inventory levels, production amounts, and shipments among the network entities are determined to maximize the expected worst-case profit. The major contributions can be summarized as follows:

- To integrate both strategic and tactical decisions with flexibility to cover varying proportions of demands and customer returns.
- To simultaneously model two different types of uncertainties including stochastic scenarios for transportation costs and polyhedral uncertainty sets for demand and return quantities, via a hybrid robust-stochastic programming (HRSP) approach.
- To obtain a small but representative set of transportation cost scenarios using Latin Hypercube Sampling (LHS) followed by scenario reduction.
- To strengthen the Benders master problem and improve the quality of the lower bound with two sets of valid inequalities (VI). Pareto-optimal cuts are also used to accelerate the convergence of the solution algorithm.

The remainder of this paper is organized as follows. In the next section, we briefly review the literature on the CLSCN design problem and the relevant solution methods. The problem and its stochastic formulation are defined in Section 3. Then, the HRSP approach is presented in Section 4. In Section 5, the scenario generation and reduction algorithm for transportation costs is presented. The stochastic Benders decomposition (BD) algorithm with some acceleration techniques for improving its convergence is provided in Section 6. Section 7 describes computational experiments and sensitivity analyses that allow us to derive managerial insights about this CLSCN. Finally, Section 8 concludes this paper and offers some suggestions for future research.

2. Literature review

The relevant literature follows two separate but complementary streams. We first review studies of the CLSCN design problem and then discuss solution algorithms. A complete literature review for the CLSCN design problem based on problem features, supply chain stages, objective, modeling, uncertainty programming, uncertain parameters, decisions, and solution methods is provided in Keyvanshokooh (2015).

2.1. *Closed-loop supply chain network design problem*

To avoid sub-optimality from modeling and designing forward and reverse networks separately, many researchers have integrated them in the more complex CLSCN (Melo et al., 2009). Many CLSCN models are inspired by facility location theory. In this regard, Melo et al. (2009) and Klibi et al. (2010) presented comprehensive reviews on the facility location models in supply chain planning and on supply chain network design under uncertainty, respectively. Moreover, Pokharel and Mutha (2009) summarized the current developments of reverse supply chains, while Brandenburg, Govindan, Sarkis, and Seuring (2014) and Dekker, Bloemhof, and Mallidis (2012) reviewed quantitative models that address environmental and social aspects in the supply chain.

Originally, Fleischmann et al. (2001) considered the integration of forward and reverse flows as a CLSCN using some case studies. They found that this integrated approach could provide a potential for a significant cost savings compared to a segregated approach. The research that followed was primarily carried out with simple facility location models (e.g. Aras, Aksen, & Gönül Tanuğur, 2008). Then, more complex models were proposed especially by considering the real-life characteristics (e.g. Cruz-Rivera & Ertel, 2009). The field has experienced a strong development over the last decade (e.g. Alumur et al., 2012; Baghalian, Rezapour, & Farahani, 2013; Cardoso, Barbosa-Póvoa, & Relvas, 2013; De Giovanni & Zaccour, 2014; Devika, Jafarian, & Nourbakhsh, 2014; Faccio, Persona, Sgarbossa, & Zanin, 2014; Gao & Ryan, 2014; Keyvanshokooh, Fattahi, Seyed-Hosseini, & Tavakkoli-Moghaddam, 2013; Klibi & Martel, 2012; Niknejad & Petrovic, 2014; Soleimani & Govindan, 2014).

Given that all activities in both forward and reverse supply chains are subject to considerable uncertainty, many works addressed the CLSCN design problem where some network parameters such as demand, return and costs are uncertain. In a pioneering step, Salema et al. (2007) extended the model of Fleischmann et al. (2001) to a multi-product and capacitated CLSCN considering uncertainty in demand and return. SP is the most popular tool applied to the configuration of a CLSCN under uncertainty. However, a limited number of studies employed RO (Pishvaee et al., 2011; Hasani, Zegordi, & Nikbakhsh, 2011). These applied a worst-case robust formulation (Soyster, 1973) which may result in an overly conservative solution. Considering this research gap, we apply a more recent RO approach (Bertsimas & Sim, 2004), which allows a tradeoff between optimality and robustness. To our knowledge, no existing research on CLSCN design combines probabilistic scenarios for some parameters with uncertainty sets for others. Fanzeres, Street, and Barroso (2015) applied a similar hybrid approach in the context of electricity markets.

Minimizing cost has been the primary objective in most CLSCN models. These models typically require that every customer's demand and return has to be satisfied. However, it may not always be optimal to satisfy all demands and returns. Sometimes, there is not much competition in target market, so the cost of losing customers will be very low. Hence, the firm may maximize its profit by losing some customers. On the other hand, sometimes profit is increased with better customer service. This paper includes flexibility to determine what fraction of customers to serve.

2.2. *Solution algorithms*

Because the CLSCN design problem is an NP-hard combinatorial optimization problem, many solution algorithms including metaheuristic, heuristic, and exact methods have been developed. Most solution methods employ standard commercial packages such as CPLEX to solve mixed-integer programming formulations. However, when the number of discrete variables is large, the resulting models can be solved only by using metaheuristic or heuristic methods to