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Distributionally robust optimization of a Canadian healthcare supply chain to enhance resilience during the COVID-19 pandemic

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ABSTRACT

This paper presents a multi-period multi-objective distributionally robust optimization framework for enhancing the resilience of personal protective equipment (PPE) supply chains against disruptions caused by pandemics. The research is motivated by and addresses the supply chain challenges encountered by a Canadian provincial healthcare provider during the COVID-19 pandemic. Supply, price, and demand of PPE are the uncertain parameters. The ε-constraint method is implemented to generate efficient solutions along the trade-off between cost minimization and service level maximization. Decision makers can easily adjust model conservatism through the ambiguity set size parameter. Experiments investigate the effects of model conservatism on optimal procurement decisions such as the portion of the supply base dedicated to long-term fixed contracts. Other types of PPE sources considered by the model are one-time open-market purchases and federal emergency PPE stockpiles. The study recommends that during pandemics health care providers use distributionally robust optimization with the ambiguity set size falling in one of three intervals based on decision makers’ relative preferences for average cost performance, worst-case cost performance, or cost variance. The study also highlights the importance of surveillance and early warning systems to allow supply chain decision makers to trigger contingency plans such as locking contracts, reinforcing logistical capacities and drawing from emergency stockpiles. These emergency stockpiles are shown to play efficient hedging functions in allowing healthcare supply chain decision makers to compensate variations in deliveries from contract and open-market suppliers.

1. Introduction

Throughout the COVID-19 pandemic, healthcare providers have encountered severe shortages and inflated prices of personal protective equipment (PPE) and other medical equipment needed to fight the virus. As of April 2nd, 2020, market prices for 3-ply masks, isolation gowns, and N95 masks had risen 1500%, 2000%, and 6136% respectively compared to their pre-COVID-19 levels (Shopp.org, 2020). Surging PPE prices were also accompanied by insufficient supplies to meet demand. On April 13, 2020, a Canadian news agency reported that Canada had received around 6% of 293 million surgical masks ordered, around 0.5% of 130 million N95 masks ordered, and less than 0.5% of 900 million pairs of gloves ordered (Zimonjic, 2020). The severity of supply chain (SC) disruptions spurred by the COVID-19 pandemic highlights the potential value of a resilience-oriented approach to supply chain design rather than focusing solely on short-term efficiencies.

Even prior to COVID-19, the amount of research on SC resilience had increased significantly in recent years (Hosseini, Ivanov, & Dolgui, 2019). Resilience describes a SC’s capacity to prepare for, absorb, recover from, and adapt to the negative consequences of disruptions (National Research Council, 2012). It contrasts other SC properties like sustainability or robustness with its focus on recuperating losses and returning to normal operations following a disruption (Golan, Jernegan, & Linkov, 2020). Enhancing SC resilience often coincides with decreasing SC risk which Jajja, Chatha, and Farooq (2018) define as both the likelihood and impact of disruption in SC sourcing, transportation, or operations. However, resilience is a property of SCs and risk is an environmental factor. Designing SCs with resilience to long-term SC disruptions like the COVID-19 pandemic has become crucial to maintaining cost and fulfillment performance. The extant literature...
mainly uses simulation, stochastic programming (SP) and robust optimization (RO) modeling to handle uncertainty when formulating these SC disruption problems.

There are numerous points for SC managers to consider when selecting a suitable optimization approach to deal with uncertainty. One factor is the availability of historical data. The certainty regarding future states and probability distribution estimates required for deterministic optimization and SP is generally not possible during pandemics when historical data is scarce or out-of-sample. Distributionally robust optimization (DRO) offers protection against over-fitting SP models by assuming that estimated probabilities can be incorrect. The protection against worst-case expected cost provided by more conservative DRO models comes at the expense of increased expected cost when estimated probabilities are in fact correct.

Although SC disruption, resilience and vitality issues have been investigated in the literature, few of them have been based on actual pandemic conditions (Ivanov & Dolgui, 2021). To fill this gap, we develop a DRO model based on a real healthcare provider’s realities and constraints. We are interested in addressing the following research questions:

- How to reconcile the competing objective functions of cost reduction and improved service level when supply capacity is uncertain?
- How to account for the uncertainty in pandemic evolution during the planning horizon when making healthcare SC decisions?
- What are the trade-offs between the need for less risky decisions (conservatism) and the need to keep costs under control?
- Can emergency stockpiles be effective to protect against variability in deliveries from contract and open-market suppliers?

Therefore, this paper explores novel applications of DRO to improve the resilience of a Canadian provincial healthcare provider’s PPE SC. Canada has a unique public healthcare system that is funded by the federal government but delivered by provincial health authorities with unique regional characteristics. For example, the size of serviced populations can vary between tens of thousands and multiple million inhabitants. In general, Canadian provincial health authorities responded to the COVID-19 pandemic with agility and resilience, thus presenting insightful case studies for research. The long-term duration and magnitude of supplier shortages and price and demand volatility during the COVID-19 pandemic was unprecedented thus lacking comparable pre-COVID-19 baselines.

The case study presented below demonstrates how SC managers can enhance SC resilience. It is inspired by the largest healthcare provider in Canada’s PPE SC. The NSHA Supply Operations Department procures medical equipment and distributes it to hospitals located throughout Nova Scotia using numerous warehouses. The purpose is to develop mathematical models that can support decision-making prior to and during long-term SC disruptions with the specific aim of discovering generally applicable managerial insights and demonstrating the process by which any healthcare provider can implement the presented models to improve SC resilience during pandemics.

The remaining sections in this paper are ordered as follows. Section 2 discusses relevant literature on SC resilience, while Section 3 contextualizes and defines the framework of the SC network used in this article based on the NSHA case study. Section 4 presents the deterministic and DRO models developed. Numerical experiments are conducted in Section 5. Managerial insights are presented in Section 6. Finally, conclusions and a discussion of future extensions are presented in Section 7.

2. Literature review

This literature review concentrates on the disruptive nature of pandemics and supply chain optimization under uncertainty. This research falls under SC network design (SCND) under uncertainty (Govindan, Fattahi, & Keyvanshokooh, 2017), SC risk management (SCRM) (Barzegar, Validi, Dani, & Antoniou, 2019; Bohez & Minner, 2017; Heckmann, Comes, & Nickel, 2015; Ivanov, Dolgui, Sokolov, & Ivanova, 2017), SC resilience (Chaffey, Hayya, & Cook, 2013; Dolgui, Ivanov, & Sokolov, 2018; Golan et al., 2020; Hosseini, Ivanov, et al., 2019; Kamalahmadi & Parast, 2016), and SC disruptions during COVID-19 (Chowdhury, Paul, Kaisar, & Moktadir, 2021; Ivanov, 2020; Mehrrota, Rahimian, Barah, Luo, & Schantz, 2020).

SC disruptions are defined as events with low probabilities of occurrence and severe negative consequences on SC performance (Torabi, Bagheriad, & Mansouri, 2015). Previous research on SCND under disruption risk generally studies localized disruptions such as building fires, natural disasters, or political unrest (Gharib, Fatemi Ghomi, & Jolali, 2020; Rottkemper, Fischer, & Blecken, 2012; Sun, Wang, & Xue, 2021). Disruptions caused by pandemics differ from localized disruptions due to the potentially longer duration and unforeseeable propagation of pandemics (Ivanov, 2020). Modelling changes in pandemic severity over a potentially multi-year time span requires multi-period optimization. Another difference between pandemics and localized disruptions is that while the latter impedes sections of a SC, pandemics can simultaneously affect multiple geographic regions and echelons of the SC (Sheffi, 2015). Pandemics can also generate panic in the general public resulting in unstable pricing and demand (Sheffi, 2015).

Further complicating the predictability of pandemic disruptions is the variation in epidemiological and pathological features among viruses. Despite the shared ancestry of SARS-CoV, MERS-CoV, and COVID-19 (Hu et al., 2020), COVID-19 has higher infectivity (Goh, Dunker, Foster, & Uversky, 2020) resulting in a significantly higher number of cases. These different disease characteristics have caused worldwide SC disruptions of a larger scale than seen during other disease outbreaks, further motivating the need for research on SCND under large-scale or global disruption risk.

Ivanov and Dolgui (2021) state that the pandemic setting is different from previous disruption types studied in the literature. First, pandemics are characterized by long-term disruption and unpredictable scale. After their review, Ivanov and Dolgui (2021) affirm that SC resilience theory has not studied such settings. Secondly, the authors also report simultaneous disruption and epidemic outbreak propagation which is a novel timing setting with simultaneous and/or sequential openings and closings of suppliers, facilities and markets. Thirdly, they report that the pandemic setting specifically sees simultaneous severe disruptions in supply, demand, and logistics infrastructure leading to a novel complex setting with both forward and backward disruption propagation (i.e., forward and reverse ripple effects). For healthcare PPE there is no reverse logistics, therefore our study will focus on the first two characteristics: long-term disruption with uncertain severity factors, and stochastic supply capacity.

In the following subsections, we review the extant literature on supply chain planning under uncertainty according to two classification schemes: objectives & settings, and methodologies used.

2.1. Objectives and settings for supply chain planning under uncertainty

Monetary objective functions that minimize cost or maximize profit are commonly used in SC optimization models (Hosseini, Ivanov, et al., 2019). Jeong, Hong, and Xie (2013) design emergency logistics networks using a multi-objective mixed-integer linear program (MILP) that minimizes operating cost and penalty costs incurred during disruptions. Hosseini, Marshed, Hashemi, et al. (2019) select suppliers with a multi-objective MILP that minimizes total costs and maximizes the sum of geographic distances between suppliers. SC models can also optimize performance level objective functions. In a COVID-19 case study, Mehrrota et al. (2020) allocate ventilators to hospitals so that the maximum shortage in any time period is minimized. Shahed, Azeem, Ali, and Moktadir (2021) use renewal reward theory to design an inventory policy for a SC with a single supplier, manufacturer, and retailer during
the COVID-19 pandemic. Uncertain parameters include randomness in supplier and retailer capacities and the reliability of the supplier and manufacturer’s production systems. Sahebjamnia, Torabi, and Mansouri (2018) use a multi-objective MILP that minimizes time to recover to full capacity as well as operating level loss following disruptions to a manufacturing company. Multi-objective optimization models can combine monetary and performance level objective functions. Rottkemper et al. (2012) minimize both cost and the amount of unsatisfied demand when solving a transshipment model for humanitarian relief supply chains. Gharib et al. (2020) propose a deterministic bi-objective optimization model to allocate emergency vehicles to casualty transportation following an earthquake. They minimize both waiting time and total cost using the ε-constraint method. Also in the context of earthquake relief, Sun et al. (2021) minimize weighted sum of injuries by severity and the total cost using RO to consider uncertainty in the number of casualties requiring transport and the demand for medical supplies. The cost objective contains penalty costs for transportation and medical supply shortages. Most papers discussed above, do not consider the context of pandemics. The few ones dealing with a pandemic context do not consider its severity. In contrast, the proposed models in our paper consider pandemic severity and two objective functions.

Li, Ghadami, Drake, Bohani, and Eparvaran (2021) analyze the interactive effects of SC disruption and infectious disease dynamics using a methodology that couples production and disease networks. They find that time-sensitive containment strategies, lean resource allocation strategy, cross-sectoral coordination and region-wise collaboration can help reduce the negative effects of the pandemic. The authors also report the snowballing effect of supply disruption that slows down governments’ ability to respond, but also allows the disease to spread by limiting resources, which in turn increases demand. Hence, creating a self-sustained crisis mode and deepens the severity of the pandemic. In our model, the severity of the pandemic is modeled at three levels (Low, Medium, and High) for each time period of the planning horizon. Combining varying levels of severity over several time periods allows to model different pandemic evolution scenarios and investigate the best responses.

Ivanov (2021) reviews the recent literature and identify some of the general characteristics of adaptation strategies during the COVID-19 pandemic. They conclude by proposing some open research questions and outline several future research directions, among which they list contractual mechanisms for SC adaptation in pandemic settings. Our paper proposes to study the interactions between contractual, open-market supply capacities and emergency stockpiles.

The majority of SCND under uncertainty literature studies operational risk rather than long-term disruptions as this study does (Govindan et al., 2017). Furthermore, the papers reviewed above, except Mehrotra et al. (2020), dealt with SC decision making in non-pandemic situations. Contextual parameters and decision makers’ objectives are different in this study, as it investigates the critically important PPE-provisioning problem during the recent COVID-19 pandemic.

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Friday et al. (2021) use insights from the pre-pandemic literature to demonstrate that current inventory optimization objectives are inappropriate for healthcare supply chains (HCSCs) under pandemic conditions. They propose collaborative practices in planning, forecasting and replenishment. They propose two qualitative models. This paper contributes new quantitative models and includes uncertainties in demand and pricing while parametrizing a decision maker’s risk preference.

Lin, Fan, Shi, and Fu (2021) investigate the effects of supply chain diversification amid the COVID-19 pandemic. They sampled 1434 Chinese manufacturing firms during the crisis and used regression analyses to show that firms with diversified supply base are associated with enhanced supply stream and profitability. Our model extends their empirical study by considering multiple suppliers (both local and overseas) and emergency stockpiles.

Hajiagha, Mahdiraji, Behnam, Nekoughadirli, and Joshi (2021) propose a scenario-based robust optimization model investigate time, cost, and risk trade-off problems on the management of projects in supply chains during the COVID-19. Their focus is on project management in the supply chains but not on the actual flow of goods.

Hosseini and Ivanov (2021) build a multi-layer Bayesian network model to identify SC disruption triggers and risk events amid the COVID-19 pandemic and quantify their consequences. As the authors recognized, their study is limited because the triggers and risk factors that they considered is specific to the meat industry and not applicable directly to healthcare. This study is specific to the healthcare supply chain and his guided by the guidance of a Health Authority.

Inpired by conditions under the COVID-19 pandemic, Kenan and Diabat (2022) formulate a two-stage stochastic programming model of the SC of blood products during such a pandemic to capture the uncertainty in both supply and demand. Their model decides on the location of permanent facilities and temporary facilities, the assignment of donors to these facilities, the delivery of the products to the hospitals, and inventory decisions at hospitals. The inherent characteristics of blood products and PPE make their study different from ours. Blood products are perishable unlike most PPE that have longer shelf-life. PPE can be stockpiled, provisioned locally or over great distances unlike most blood products. Furthermore, our model assumes that pandemics are typically sudden therefore decision-makers do not have the time or luxury to alter existing facilities and must make their provisioning decisions within the limitations of the existing supply network.

In a recent review dedicated to COVID-19 pandemic related supply chain issues, Chowdhury et al. (2021) find that there is a lack of empirically designed and theoretically grounded studies. Our study aims to be one such theoretical model anchored in actual practices by a healthcare provider.

2.2. Methodologies for supply chain planning under uncertainty

Distributionally robust optimization (DRO) is a technique that unifies the robust and stochastic optimization frameworks, making it less prone to the weaknesses of each individual approach (Jia, Liu, & Bai, 2020; Liu, Wu, Ji, Qu, & Raza, 2021; Shang & You, 2018). It is therefore the appropriate framework in the context of a pandemic where there is no prior historical data for SC managers to rely on to make risk-benefit decisions. While RO optimizes the worst-case outcome and SP optimizes the expected outcome, DRO optimizes the worst-case expected outcome among a set of possible probability distributions called the ambiguity set. DRO offers less conservative solutions than RO while still performing risk-averse decision making, and it counteracts the tendency to over-fit SP models by considering a family of probability distributions rather than just one. The strength of a DRO approach stems
from utilizing available data to estimate the probability distribution without assuming the expected value’s absolute correctness as SP does (Shang & You, 2018).

Zhang, Liu, Yang, and Zhang (2020) propose a bi-objective DRO model that minimizes transportation time and maximizes patient safety to deliver post-earthquake medical relief under uncertainty in the demand, transport times, and safety factors. Yang, Liu, and Yang (2021) pre-position emergency supplies throughout a geographic region in preparation for future earthquakes. The inventory size and facility locations are determined by a pre-disaster DRO model with demand uncertainties, while unmet demand penalty costs and transportation costs are minimized by a separate multi-stage post-disaster model.

Wang, Chen, and Liu (2020) compare the out-of-sample performance of DRO, RO, and SP on facility location problems with uncertain demand and shipping costs. In their experiments, optimal solutions obtained from nominal data and out-of-sample data were closer in DRO models than SP models. They also found lower expected values, values-at-risk, and conditional-values-at-risk in DRO models compared to RO models.

These results demonstrate the potentially superior performance of DRO to RO or SP when unexpectedly optimizing with out-of-sample data. Encountering out-of-sample data on pandemics is a likely occurrence, as pandemic severity can vary by geographic region and throughout its own progression due to virus mutation. The adjustable conservatism of DRO models and their protection against out-of-sample data makes them flexible for use by multiple different healthcare providers.

Model conservatism can protect decision makers’ against common human biases. Jain, Hazra, and Cheng (2018) found that an over-confidence bias during sourcing causes buyers and suppliers to underestimate demand variability resulting in less reserve capacity and fewer suppliers in the supply base. Similarly, Tang (2006) found that ignoring probabilities of occurrence, as in RO, protects decision makers from underestimating disruption risks and being ill-prepared for them.

Uncertainty regarding SC disruptions is typically modeled using stochastic programming (SP) which requires historical data to estimate scenario probabilities (Govindan et al., 2017). This data does not necessarily exist given the infrequency with which pandemics occur and unique characteristics of the COVID-19 pandemic. SP can produce poor results if probability distributions are estimated from out-of-sample or limited amounts of data (Smith & Winkler, 2006).

RO is another technique used in SC research that can be performed without estimated probabilities of occurrence, but it often produces overly conservative solutions. RO facilitates health authorities’ risk aversion regarding demand satisfaction by minimizing the maximum PPE shortage in any time period and scenario. Ultimately, the poor expected performance of RO did not seem to justify its proposed benefits, which can also be realized using DRO. RO performs better on average than RO, but it was decided against due to the lack of data at the onset of the pandemic. DRO was selected as the best modeling approach, as it incorporates available data while simultaneously safeguarding against the data’s incorrectness. DRO allows decision makers to easily adjust model conservatism based on the organization’s risk tolerance. This research is positioned in the small subset of SC research that optimizes multiple objective functions rather than just one. This paper’s combination of multi-objective optimization and DRO further separates its approach from more common approaches used in existing literature.

Implementing optimization models in real systems is often complicated by uncertainty about the future and multiple decision-making criteria (Ije & Schobel, 2016). The multi-objective DRO approach used in this study incorporates both future uncertainties and multiple goals. It allows decision makers to select a solution and the trade-off between cost and service level that best serves their organizational strategy.

Another benefit of multi-objective optimization is its independence of shortage penalty costs which have the undesirable traits of impacting optimal decisions and being difficult to accurately estimate. Using DRO, the study aims to uncover managerial insights and policies to help guide SC decisions during pandemics under uncertainty.

3. Problem definition

Health authorities consider various decision criteria when procuring medical supplies. Two common performance measures are: (i) to maximize the portion of PPE demand that is satisfied and, (ii) to minimize operating cost. The healthcare provider involved in this study needed to simultaneously maximize service level and minimize total provisioning cost.

The models in this paper select suppliers and allocate forecast demand to multiple sources (hospitals, home care and long-term care facilities) over multiple time periods. These are consistent with key decisions in SC disruption management identified by Hosseini, Morshedlou, et al. (2019). Furthermore, our models incorporate multiple sourcing and emergency inventory stockpiles, as these strategies were identified to be promising risk mitigation strategies for risk-averse organizations in Tomlin (2006).

The three types of PPE sources modeled in this study are long-term contracts, one-time purchases on the open-market, and federal emergency stockpiles. Canada maintains a national emergency stockpile and allocates PPE to the provinces upon request (Government of Canada, 2021). This is modeled by parameterizing the total supply of emergency stock PPE available to the healthcare provider, while its consumption in each time period is a decision variable. The modeled SC contains some unique features compared to traditional SC networks such as an externally-managed emergency stockpile and differences in supplier prices and reliability depending on foreign or domestic location. Given that structural changes are difficult to make in the middle of a pandemic, the primary focus of this research is to use existing SC structures to better defend against disruptions.

To reduce SC complexity, warehouses are represented by individual decision variables representing the net inventory and the net shipment quantities of each product in each time period. Similarly, the demand at all destinations is aggregated into a single parameter for each product and time period. The flow of PPE in the modeled SC is depicted in Fig. 1. As recommended by Ivanov and Dolgui (2021), the proposed system includes three echelons (sources, warehouses, and destinations) to better track the effects of the SC disturbances.

During a pandemic, the PPE SC is fraught with complications as global demand sky rockets due to increased PPE usage, panic purchasing, and hoarding. This pressure on the SC can lead to contracts being unfulfilled, volatile market prices, and other foreseen and unforeseen consequences. This model is based on the experiences of our healthcare provider partner and has the following characteristics/assumptions which are all fully integrated in the proposed mathematical models.

1. Undelivered units are not paid for and there is no recourse if suppliers cannot produce the contracted amount. This is reasonable in the context of pandemics. No SC manager will be spending valuable time pursuing redress for undelivered PPE.

2. Only PPE that passes quality inspection when it arrives at delivery warehouses is stored in inventory. The cost of defective products is not refunded. This is reasonable in the context of pandemics. Storage capacity is limited due to high demand from end-users. Thus, only non-defective batches are stored and no redress is pursued for any reasonable number of defectives as SC managers have many other important issues to deal with.
3. Suppliers can offer all-unit quantity-based price discounts on contracts but not on open-market purchases. This is commonly done and accepted practice.

4. PPE demand must be satisfied in its respective time period. Back-ordering is not an option in early pandemic settings.

### 4. Optimization framework

The deterministic multi-objective model is first formulated in this section followed by its distributionally robust counterpart. The following notation is used for model formulation.

**Sets**
- \( s \) : Suppliers
- \( P \) : Products
- \( T \) : Time periods \( t \in [1 \ldots T] \)
- \( S \) : Suppliers \( s \)
- \( I \) : Parameters \( i \)
- \( K \) : Portion of net demand for product \( i \) in period \( t \)
- \( J \) : Quantity-based price breaks \( j \)
- \( K \) : Warehouse capacities (sq.ft.) \( k \)
- \( J \) : Portion of supplier \( s \) nominal-open market capacity for sale in period \( t \)

**Parameters**
- \( A_{ij}^s \) : Portion of contractual obligations supplier \( s \) can satisfy in period \( t \)
- \( A_{ij}^k \) : Portion of supplier \( s \) nominal-open market capacity for sale in period \( t \)
- \( c_{ij}^s \) : Unit cost to transport product \( i \) from supplier \( s \) to warehouse
- \( c_{ij}^k \) : Unit cost to transport product \( i \) from emergency stockpile to warehouse
- \( c_{ij}^w \) : Unit cost to transport product \( i \) from warehouse to destination
- \( c_{ij}^p \) : Cost of net warehouse capacity \( k \)
- \( c_{ij}^e \) : Product \( i \) holding cost per unit per period at warehouse
- \( c_{ij}^a \) : Administrative cost to contract each supplier
- \( D_n \) : Net demand for product \( i \) in period \( t \)
- \( d_{isj} \) : Fraction of product \( i \) from supplier \( s \) that is non-defective
- \( d_{isj}^s \) : Fraction of nominal product \( i \) price given by discount \( j \) from supplier \( s \)
- \( k_i \) : Net warehouse capacity (sq.ft.)
- \( k_i^s \) : Footprint of one unit of product \( i \) (sq.ft.)
- \( p_{ij}^s \) : Nominal contract price per unit of product \( i \) from supplier \( s \)
- \( p_{ij}^k \) : Open-market price per unit of product \( i \) from supplier \( s \) in period \( t \)
- \( p_{ij}^e \) : Emergency stockpile price per unit of product \( i \)
- \( q_{ij}^s \) : Price break quantity for all-unit discount \( j \) on supplier \( s \) contracts
- \( q_{ij}^m \) : Maximum contract quantity for product \( i \) and supplier \( s \)
- \( q_{ij}^e \) : Minimum contract quantity for product \( i \) and supplier \( s \)
- \( q_{ij}^w \) : Nominal amount of product \( i \) that supplier \( s \) sells on open-market
- \( q_{ij}^p \) : Net supply of product \( i \) in emergency stockpile allocated to healthcare provider
- \( v_i \) : Amount of product \( i \) in inventory at start of disruption
- \( M \) : Arbitrarily large number
- \( c \) : Parameter of the c-constraint approach

**Decision variables**
- \( q_{ij}^s \) : Quantity of product \( i \) contracted per period to supplier \( s \) at discount \( j \)
- \( q_{ij}^m \) : Quantity of product \( i \) procured from open-market supplier \( s \) in period \( t \)
- \( q_{ij}^e \) : Quantity of product \( i \) procured from emergency stockpile in period \( t \)
- \( q_{ij}^w \) : Quantity of product \( i \) sent from warehouses to destinations in period \( t \)
- \( k_i \) : Portion of net demand for product \( i \) that is unsatisfied in period \( t \)
- \( v_i \) : Inventory level of product \( i \) at start of period \( t \)
- \( w_o \) : 1 if net warehouse capacity is option \( k \); 0 otherwise
- \( y_{ij} \) : 1 if product \( i \) is contracted from supplier \( s \) at discount \( j \); 0 otherwise

**Objective functions**

**Z1** is expressed using a minimax objective: minimizing the maximum percent of demand that is unmet for any product \( i \) and period \( t \) in objective function \( Z_2 \).

\[
Z_1 = \min \left[ \sum_{i \in I} \sum_{j \in J} \sum_{s \in S} \sum_{t \in T} \left( \sum_{k \in K} A_{ij}^s \sum_{s \in S} q_{ij}^m + \sum_{s \in S} \sum_{t \in T} p_{ij}^s q_{ij}^w + \sum_{s \in S} \sum_{t \in T} p_{ij}^e q_{ij}^e \right) \right]
\]

\[
Z_2 = \min \max_{i \in I, s \in S, t \in T} k_i
\]

The first objective function \( Z_1 \) in Eq. (1) has 10 terms which account for costs associated with procurement, shipping, warehousing, inventory, and administration. Specifically, they are the long-term contract procurement costs, open-market procurement costs, emergency stockpile procurement costs, shipping costs from contracted suppliers to warehouses, shipping costs from open-market suppliers to warehouses, shipping costs from the emergency stockpile to warehouses, shipping costs from warehouses to destinations, overhead cost of having net warehouse capacity \( k \), inventory holding costs, and administration costs incurred by each long-term contract including the cost of negotiating with, documenting, and inspecting suppliers. Assumption 1 is covered under Eq. (1) because the total purchase cost is calculated on the total purchased quantity including the defective items delivered.

The second objective function is the service level \( Z_2 \) in Eq. (2) which is optimized using a minimax approach: minimizing the maximum percent of demand that is unmet for any product and time period. Minimax terms are more likely to spread unmet demand evenly across all products and time periods than an objective function that optimizes the sum of all shortages (Mak & Shen, 2012; Mehrotra et al., 2020). Most health providers would prefer smaller shortages in several time periods over one large shortage.

Multi-objective optimization is used to optimize the trade-off between these two competing objective functions. A strength of this approach is the ability of multi-objective optimization to analyze cost and service level trade-offs without a defined penalty cost for shorted/ unmet demand. Unmet demand can have long-lasting performance impacts making its cost to an organization unclear and tough to accurately estimate (Simchi-Levi, Wang, & Wei, 2018).

Demand points in the modeled SC include hospitals, home care facilities, and long-term care facilities. Demand quantities can vary significantly between these different types of facilities and even within the same type of facility depending on the size of the serviced population. It is therefore important to minimize the portion of demands shorted rather than absolute numbers to prevent larger disruptions at facilities with lower demands.

The deterministic model is bound by constraints (3)–(20).
than the product of the supplier \( q_i \) count price is used for each product-supplier combination. Constraints (14) ensure that at most one dis

\[
\sum_j q_i^j \leq Q^j \quad \forall i \in I, s \in S, j \in J
\]  

(4)

\[
q_i^j \leq Q^j \quad \forall i \in I, s \in S, j \in J
\]  

(5)

\[
q_i^j \geq Q^j \quad \forall i \in I, s \in S, j \in J
\]  

(6)

\[
q_i^j \leq Q^j \quad \forall i \in I, s \in S, j \in J
\]  

(7)

\[
\sum_j K^j v_s \leq \sum_i K^j w_i \quad \forall t \in T
\]  

(8)

\[
\sum_j \sum_s A^i_j F^j s q^j + \sum_i F^i h q^i_s + q^i_s - d^i_s + \nu_i = v_{i+1} \quad \forall i \in I, t \in T
\]  

(9)

\[
v_i = V^i \quad \forall i \in I
\]  

(10)

\[
v_{i+1} \geq V^i \quad \forall i \in I
\]  

(11)

\[
q^j_i - (1 - s^j_k) D^j = 0 \quad \forall i \in I, h \in H, t \in T
\]  

(12)

\[
\sum_i w_i = 1
\]  

(13)

\[
\sum_i \lambda_i v_s \leq 1 \quad \forall i \in I, s \in S
\]  

(14)

\[
\sum_i q^j_i \leq Q^j \quad \forall i \in I
\]  

(15)

\[
q^j_i \geq 0 \quad \forall i \in I, s \in S, j \in J
\]  

(16)

\[
q^j_i \leq 0 \quad \forall i \in I, s \in S, t \in T
\]  

(17)

\[
q^j_i, s^j_k, v^j_s, d^j_s \geq 0 \quad \forall i \in I, t \in T
\]  

(18)

\[
w_i \in \{0,1\} \quad \forall k \in K
\]  

(19)

\[
y^j_s \in \{0,1\} \quad \forall i \in I, s \in S, j \in J
\]  

(20)

Constraint (3) ensures that open-market order quantities are less than the product of the supplier’s nominal capacity \( Q^j \) and their availability factoring in disruption from the pandemic \( A^i_j \). Constraints (4) and (5) enforce maximum and minimum contract sizes. The price discount binary variables are set by constraints (6) and (7) so that contract quantities are within their quantity-based discount bracket (Assumption 3). Constraints (8) limit inventory space to the net warehouse capacity in each time period. Constraints (9) equate net inventory in the following time period to its current value plus or minus PPE shipments during the current period for each product. The left-hand side of the constraints has five terms. The first term is the total quantity of non-defective PPE received from contractual suppliers (Assumption 2). The second term is the total quantity of non-defective PPE received from open-market suppliers (also Assumption 2). The third term is the quantity received from the Emergency stockpile, the fourth term is the quantity sent to healthcare facilities (destinations). The fifth term is the inventory at the beginning of the current period. Constraints (10) set the initial inventory level for each product. Inventory levels in the final time period \((T + 1)\) must be equal to or greater than their starting inventory levels, which is enforced by constraints (11). The purpose of this constraint is to prevent the model from using all of the internal inventory which is required to respond quickly to sudden variations in demand. Constraints (12) ensure that PPE quantities shipped to destinations exceed the service level for each product \( i \) and period \( t \) (Assumption 4). Constraint (13) ensures that only one warehouse net capacity is selected. Selecting the smallest warehouse capacity has zero cost, as the smallest option is the current pre-pandemic capacity. Constraints (14) ensure that at most one discount price is used for each product-supplier combination. Constraints (15) guarantee that the sum of shipments from the federal emergency stockpile over all periods does not exceed the emergency stockpile fraction allocated to the Health Provider. Constraints (16)–(20) are non-negativity and binary constraints.

Methods for solving multi-objective mathematical programming problems can be classified into three categories according to the phase in which the decision makers express their preferences: the a priori methods, the interactive methods and the a posteriori or generation methods. The most common a priori methods are the weighted-sum and the \( \epsilon \)-constraint methods (Gayebloo, Tarokh, Venkatadri, & Diao, 2015; Hwang & Masud, 2012). With the weighted-sum method, the objective functions are combined by assigning appropriate weights to each function. The weights are determined by the stakeholders. When the stakeholders are unable or not sure about the weights to assign to each objective but can nonetheless specify which objective function takes precedence other the other(s), then the \( \epsilon \)-constraint method is preferred. In the \( \epsilon \)-constraint method, the multi-objective optimization problem is transformed into a single objective optimization problem with additional constraints. The objective function with the highest priority is retained as the sole objective function and the other objectives are written as constraints with right-side values set to required values \( \epsilon \) for these lesser objectives as identified by the stakeholders (Ehrgott, 2005; Gayebloo et al., 2015; Hwang & Masud, 2012). Our healthcare partner identified total cost as the primary objective and the service level as the lesser objective with \( \epsilon \) being set at the maximum fraction of unmet demand.

The robust \( \epsilon \)-constraint approach (Ehrgott, 2005) was chosen to solve the multi-objective models in this study. The proposed model has two objectives, so it only requires one additional \( \epsilon \)-constraint. Efficient solutions, also referred to as Pareto-optimal solutions, in multi-objective programming cannot enhance the value of any objective function without degrading the value of another objective (Ehrgott, Ide, & Schöbel, 2014). Efficient solutions are realized by optimizing (21) and then setting the value of \( \epsilon \) to its objective value and optimizing (22). A set of efficient solutions obtained from different values of \( \epsilon \) are typically referred to as a Pareto-front.

\[
\begin{align*}
\text{min} \quad & Z_t \\
\text{s.t} \quad & \text{Eqs. (3)–(20)} \quad \forall i \in I, t \in T
\end{align*}
\]  

(21)

\[
\begin{align*}
\text{min} \quad & \theta \\
\text{s.t} \quad & s^i_t \leq \theta \quad \forall i \in I, t \in T \\
& \text{Eqs. (3)–(20)}
\end{align*}
\]  

(22)

4.2. Distributionally robust formulation

In this subsection, the deterministic model is modified to incorporate scenario-based uncertainty in PPE supply, price, and demand. This necessitates an additional notation set \( H \) for uncertainty scenarios \((H = 1 \ldots H)\). Parameters \( A^i_s A^i_h D^i_t \) and \( P^i_s \) and decision variables \( q^i_s, q^i_h, s^i_s, v^i_s \) require an additional index to denote their value in scenario \( h \) (i.e., \( A'^i_{s,h} A^i_{s,h} D^i_{s,h} P^i_{s,h} \)). Constraints (3), (8), (9), (10), (11), (12), (15), (17), (18) and the \( \epsilon \)-constraint now exist \( \forall h \in H \), as they contain at least one uncertain parameters or decision variables. The new set of constraints is given below and numbered from (23a)–(23r).

\[
q^i_s \leq Q^i_s \quad \forall i \in I, s \in S, t \in T, h \in H
\]  

(23a)

\[
q^i_s \leq Q^i_s \quad \forall i \in I, s \in S, j \in J
\]  

(23b)

\[
q^i_s \geq Q^i_s \quad \forall i \in I, s \in S, j \in J
\]  

(23c)
The obtained DRO model can be classified as a multi-stage recourse model, as there are multiple time periods in which decisions must be made under uncertainty of future outcomes. In our data set, there are three potential values for each uncertain parameter in each time period. Scenarios with the same uncertain parameter realizations in the current and preceding time periods must have identical decision variable values. This is accomplished by introducing constraints (24)–(28) to the DRO model. As a result of the three potential outcomes in each time period, these constraints equate decision variables in scenarios 1 to 3, 4 to 6, ... 3\(^2\)–2 to 3\(^3\) in the second last time period, scenarios 1 to 9, 10 to 18, ... 3\(^3\)–8 to 3\(^3\) in the third last time period, etc. Each additional time period multiplies the number of distinct disruption paths by a factor of 3, so constraints (24)–(28) do not exist for the scenario numbers that are multiple of 3\(^r\).

DRO problems can be formally represented as inf\(\sum f(x, \xi)\) \(\in\) \(\mathbb{R}^n\) subject to \(f(x, \xi) \leq 0\) for all \(\xi \in \Xi\) and \(x \in \mathbb{X}\), where \(\Xi\) is the space of feasible probability distributions, \(f\) is the probability distribution that results in the worst-case expected value of objective function \(g\) which depends on known parameters \(x\) and uncertain parameters \(\xi\).

The obtained DRO model can be classified as a multi-stage recourse model, as there are multiple time periods in which decisions must be made under uncertainty of future outcomes. In our data set, there are three potential values for each uncertain parameter in each time period. Scenarios with the same uncertain parameter realizations in the current and preceding time periods must have identical decision variable values. This is accomplished by introducing constraints (24)–(28) to the DRO model. As a result of the three potential outcomes in each time period, these constraints equate decision variables in scenarios 1 to 3, 4 to 6, ... 3\(^2\)–2 to 3\(^3\) in the second last time period, scenarios 1 to 9, 10 to 18, ... 3\(^3\)–8 to 3\(^3\) in the third last time period, etc. Each additional time period multiplies the number of distinct disruption paths by a factor of 3, so constraints (24)–(28) do not exist for the scenario numbers that are multiple of 3\(^r\).
problem which consists of the first two terms of objective function (31), constraints (23a)–(23r), (24)–(28). The inner and outer problems can be rectified using primal-duality theory. The standard formulation of a primal LP problem is:

\[
\text{(Primal)} \quad \max \{ \langle c, x \rangle : Ax = b, x \geq 0 \}
\]

where \( A \in \mathbb{R}^{n \times m} \), \( \text{rank}(A) = m \), \( b \in \mathbb{R}^n \), and \( c \in \mathbb{R}^m \). The corresponding dual problem is:

\[
\text{(Dual)} \quad \min \{ \langle b, y \rangle : A^T y + s = c, s \geq 0 \}
\]

Dualizing the inner problem converts it from a maximization problem to a minimization problem and eliminates decision variables \( f_i \) and \( d_i \) in the process. \( \gamma, \pi, \psi \), and \( \psi^* \) are the dual variables attached to constraints (32)–(35) respectively. The dualized inner problem is formulated in Eqs. (37)–(42).

\[
\begin{align*}
\min_{\gamma, \pi, \psi, \psi^*} & \quad \gamma + \pi x - \sum_i \hat{f}_i \psi^*_i - \sum_j \hat{f}_j \psi^*_j \\
\pi - \psi^*_i - \psi^*_j & \geq 0 \quad \forall h \in H \\
\gamma - \psi^*_i + \psi^*_j & \geq \sum_j \sum_{j'} \sum_{i'} A_{i'j'} f_{i'j'} + \sum_j \sum_{i'} A_{i'j} f_{i'j} + \sum_{i'} \sum_{j'} A_{i'j'} f_{i'j'} \quad (37) \\
\gamma - \psi^*_i + \psi^*_j & \geq \sum_j \sum_{j'} \sum_{i'} A_{i'j'} f_{i'j'} + \sum_j \sum_{i'} A_{i'j} f_{i'j} + \sum_{i'} \sum_{j'} A_{i'j'} f_{i'j'} \quad (38) \\
\gamma - \psi^*_i + \psi^*_j & \geq \sum_j \sum_{j'} \sum_{i'} A_{i'j'} f_{i'j'} + \sum_j \sum_{i'} A_{i'j} f_{i'j} + \sum_{i'} \sum_{j'} A_{i'j'} f_{i'j'} \quad (39) \\
\sum_{j} \sum_{j'} \sum_{i'} A_{i'j'} f_{i'j'} & + \sum_{j} \sum_{i'} A_{i'j} f_{i'j} + \sum_{i'} \sum_{j'} A_{i'j'} f_{i'j'} \quad \forall h \in H \\
\gamma & \geq 0 \quad (40) \\
\psi^*_i, \psi^*_j & \geq 0 \quad \forall h \in H \quad (41) \\
\end{align*}
\]

The dual of the inner problem is then reintroduced to the outer problem, and the DRO objective function becomes Eq. (43).

\[
\text{min} Z_{\lambda} = \sum_{k} c_k w_k + \sum_{j} \sum_{j'} c_{j'k} y_{j',k} + \gamma + \rho \pi - \sum_{k} \hat{f}_k \psi^*_k + \sum_{k} \hat{f}_k \psi^*_k \quad (42)
\]

Efficient DRO solutions are found by solving formulation (44), then setting the value of \( \epsilon \) to its objective value and optimizing formulation (45). This follows the approach proposed by Kuroiwa and Lee (2012), where minimax robustness is applied to multi-objective models by optimizing objective functions’ worst-case values across all scenarios. This formulates the multi-objective model as a deterministic problem to which the \( \epsilon \)-constraint method can be applied.

\[
\begin{align*}
\min_{\lambda, \pi} & \quad Z_{\lambda} \\
\text{s.t} & \quad \text{Eqs. (23a)–(23r)} \quad (\text{Nominal Constraints}) \\
& \quad \text{Eqs. (24)–(28)} \quad (\text{Multi-Stage Recourse Constraints}) \\
& \quad \text{Eqs. (38)–(42)} \quad (\text{DRO Constraints}) \\
& \quad \forall i \in \mathbb{H}, t \in \mathbb{T}, h \in H \\
\end{align*}
\]

\[
\begin{align*}
\min_{\theta} & \quad Z_{\theta} \\
\text{s.t} & \quad \text{Eqs. (23a)–(23r)} \quad (\text{Nominal Constraints}) \\
& \quad \text{Eqs. (24)–(28)} \quad (\text{Multi-Stage Recourse Constraints}) \\
& \quad \text{Eqs. (38)–(42)} \quad (\text{DRO Constraints}) \\
& \quad \forall i \in \mathbb{E}, t \in \mathbb{T}, h \in H \\
\end{align*}
\]

\[
\begin{align*}
\text{5. Numerical experiments} \\
\end{align*}
\]

When the availability of pandemic related data is limited, the focus naturally becomes to optimize SCs under uncertainty which this study does considering uncertainty in both parameter values and probability distributions. Experiments inspired by the NSHA case were run with the DRO model using realistic, although mostly generated, data. One source of actual data reported by the Society for Healthcare Organization Procurement Professionals (2020) was open market PPE prices prior to and during the COVID-19 pandemic.

Pandemic scenarios were generated based on plausible and actual pandemic trajectories seen around the world during the COVID-19 pandemic including single-wave, two-wave, and exponential growth. Each time period has three possible pandemic severity factor values: Low (L), Medium (M), and High (H), which are plotted in Fig. 2. There are four four-month time periods in the data set resulting in \( 3^4 = 81 \) disruption scenarios: (1) LLLL, (2) LLLM, (3) LLLH, (4) LLML, (5) LLMM, (6) LLMH, … (79) HHHL, (80) HHHH, (81) HHHH. These scenarios mimic how the pandemic would evolve during the course of the planning horizon.

The severity of the pandemic, which is denoted by a numerical factor, sets the values of the four uncertain parameters: demand \( D_{it} \), open market price \( p_{it} \), open market supply \( A_{it} \), and contract fulfillment \( A_{it}^{*} \). PPE prices and demands have a positive correlation to pandemic severity, while open market and contract supply have a negative correlation to it. Open market prices \( p_{it} \), contract fulfillment \( A_{it}^{*} \), and open market supplier availability \( A_{it} \) have a linear relationship with pandemic severity factors, so an X% change in the pandemic severity factor value corresponds with an X% change in these parameter values. Total hospital demand increases by a factor of \((1 + \text{pandemic severity factor})\), so increases in the pandemic severity factor correspond with less than proportional increases in demand for PPE. Changing the values of pandemic severity factors would only change the values of the four uncertain parameters \( A_{it}^{*}, A_{it}, D_{it}, p_{it} \).

There are seven potential suppliers. The single domestic supplier has higher prices and lower magnitude disruptions than the six foreign suppliers. Further, PPE contracts experience lower magnitude disruptions than open-market availability, as the model assumes that suppliers satisfy their contractual obligations before accepting open-market orders. The average availability of contracted suppliers \( A_{it}^{*} \) is 71%, while the average availability of open-market suppliers \( A_{it} \) is 63%. The net supply of each product allocated from the emergency stockpile can cover between 21% and 24% of total demand for that product depending on the scenario.

The cost of the three PPE sources relative to one another changes depending on the time period and scenario. Emergency stockpile PPE is the cheapest source in some time periods and scenarios and the most expensive source in other time periods and scenarios.

The minimum and maximum value of each parameter is presented in Table 1. The remaining data given its large size is available upon request.

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**Fig. 2.** Plot of potential pandemic severity factor values.
Fig. 3 plots the Pareto fronts of the DRO model at a 99% service level sampled by varying parameter $\rho$ as a supplementary document. Parameter value ranges. 

All models were programmed in MATLAB with the Optimization Toolbox and solved using Gurobi 9.0.0 (Academic License) on a Dual-Core Intel® i5 CPU running at 1.6 GHz with 8.00 GB RAM.

### 5.1. Cost and service level trade-off

Pareto fronts are sets of efficient solutions from a multi-objective model. In this first experiment, Pareto fronts with net cost as a function of the portion of demand satisfied is plotted. Efficient solutions were sampled by varying parameter $\epsilon$ between 0% and 20% at step sizes of 1%. Fig. 3 plots the Pareto fronts of the DRO model at a 99% service level with $\rho$ set to 0 (SP), 0.8 (DRO), and $\infty$ (RO). As expected, the DRO model with $\rho$ equal to 0.8 is more conservative (costs more) than SP but less conservative (costs less) than RO.

### 5.2. DRO model conservatism

Increasing the value of $\rho$ increases the size of the ambiguity set, which makes the DRO model more conservative (more costly). The worst-case expected cost values of the DRO model at a 99% service level are plotted for various values of $\rho$ in Fig. 4. The worst-case expected cost increases along with the value of $\rho$. The cost objective at $\rho = 0$ is equivalent to the optimal solution of a SP model with scenario probabilities of $f_i$. The objective function value of the DRO model converges on the objective value of the RO model as $\rho$ increases and equals the robust solution for all instances of $\rho \geq 2$. The curve is concave (the rate of increase of worst-case expected cost decreases) meaning that midpoint values of $\rho$ provide good trade-offs between conservatism and worst-expected cost. Low, moderate, or high DRO conservatism ranges are defined by setting the value of $\rho$ within the intervals $[0,1]$, $(1, 1.6)$, or $[1.6, \infty)$ and are shaded in Figs. 4–7.

Increased conservatism reduces the risk of high expected costs associated with incorrect probability estimates, but it can increase expected costs when probability estimates are correct. Fig. 5 plots the expected cost of the DRO model at a 99% service level given that the probability estimates are correct against the value of $\rho$. Fig. 5 confirms that increasing model conservatism generally decreases performance under the estimated probability distribution. Here again, the increase rate of expected cost is linearly and slow for low to midpoint values of $\rho$. The increase is steep for values higher than 1.6. This means that good expected cost and risk trade-offs can be achieved for midpoint values of $\rho$.

### 5.3. Relative standard deviation in cost

The relative standard deviation (RSD), which is the standard deviation divided by the mean, of scenario cost was calculated for the DRO model for various values of $\rho$. Fig. 6 shows that the DRO model with a 99% service level experiences a decrease in cost variance as the value of $\rho$ increases. Interestingly, RSD in cost increases again as $\rho$ approaches 2, which is the point at which the DRO model is equivalent to a pure RO model. One potential explanation of this behavior is that as the size of the ambiguity set increases, the DRO model optimizes fewer scenarios as the probability of many scenarios approaches 0. Sub-optimal solutions for scenarios with extremely low probabilities of occurrence causes the RSD in scenario cost to increase again when $\rho$ is greater than or equal to 2.

The DRO model with the value of $\rho$ set between 1 and 1.8 is recommended for decision makers that prioritize low variance in cost. Decision makers in favour of average cost performance can still benefit from the lower cost variance of DRO models with small values of $\rho$, such as $\rho = 0.6$ which reduces RSD by 20% compared to $\rho = 0$. Overall, $0.6 \leq \rho \leq 1.8$ provide sufficiently low variance in cost to be appealing to decision-makers in the context of a pandemic where every other factor is varying widely from period to period.

### 5.4. Utilization of PPE sources

Long-term contract selection is a crucial strategic decision. Fig. 7 plots the percent of available contract units selected by the model at a 99% service level for various values of $\rho$. Contract prices can be higher or lower than open-market prices depending on the scenario and time period, so it was anticipated that less conservative models would suggest signing fewer long-term contracts than more conservative models. Contract utilization increases from 82% to 90% as the value of $\rho$ increases, while open market purchases and emergency stockpile utilization decreases. As the value of $\rho$ exceeds 1.8, utilization of the emergency stockpile increases from 20% to 36% and open market purchase volumes decrease further. The overall behavior regardless of the value of $\rho$ shows that emergency stockpiles play a crucial hedging role.

![Pareto Fronts](image_url)

Fig. 3. Pareto fronts of SP ($\rho = 0$), DRO ($\rho = 0.8$), and RO ($\rho = \infty$).
Indeed, Fig. 7 shows that when open-market utilization drops, contracts are first used to compensate for the decrease in supply capacity. When the contracts reach their capacity, the emergency stockpile becomes the last resort to make-up the difference. This means that in the Canadian context, the federal government has a crucial role to play by proactively maintaining the centralized stockpile and providing supplies to provincial jurisdictions as safety stocks to compensate their own purchased from contractual suppliers and from the open-market. This is important as the federal government has more negotiating and buying-power and more resources (civil servants and the military) to help transport and distribute the items to lower jurisdictions.

6. Managerial insights

The case study presented in this paper investigates 81 different scenarios accounting for a range of three severity levels over four consecutive four-month periods. In face of this uncertainty, decision maker’s actions can take on a range of risks. In our approach, this risk is modeled by $\rho$. A larger $\rho$ represents a more conservative decision maker who chooses less risky and higher cost decisions. Likewise, a smaller $\rho$ represents a less conservative decision maker who chooses higher risk and less costly decisions. Using data representative of actual operations, this study finds a reasonable range of the decision conservatism that yield good cost-service level trade-offs. Furthermore, given its flexibility in modelling risk-tolerance under uncertainty, DRO is a preferred optimization approach when decision makers want to explore several ranges of conservatism under uncertain supply chain conditions.

The model signs more contracts as the value of $\rho$ and by extension the size of the ambiguity set increases. These results confirm that signing more long-term contracts is beneficial in worst-case scenarios where open-market PPE is limited and expensive, but it can be a hindrance in less-severe scenarios where cheaper PPE is available on the open-market. Cost-conservative SC managers will source less PPE through one-off open market purchases as these prices are extremely elevated during worst-case scenarios. Emergency stockpile utilization drops as contract utilization increases but the most cost-conservative SC man-

**Fig. 4.** Plot of worst-case expected cost against values of $\rho$.

**Fig. 5.** Plot of expected cost under estimated probability distribution against $\rho$. 
agers will rely more on emergency stockpiles to reduce the use of open market purchases in worst-case scenarios.

Another important factor in model selection is the decision makers’ prioritization of average cost performance, cost variance, or worst-case cost performance. This study recommends three intervals of $\rho$ values to achieve each preference. DRO with $\rho$ less than 1 is recommended for decision makers with higher confidence in scenario probability estimates and a preference for average cost performance. Even when decision makers are confident in the accuracy of their scenario probability estimates, the DRO model with small values of $\rho$ offers some advantages over SP models by decreasing cost variance and the risk of out-of-sample predictions. For example, the solution when $\rho = 0$ has an expected cost with estimated probabilities of $1,868,000$ and an RSD of 0.057 which corresponds with a standard deviation (SD) of $106,000$. Meanwhile, the solution when $\rho = 0.6$ has an expected cost with estimated probabilities of $1,885,000$, an RSD of 0.046, and an SD of $106,000$. This small increase in the value of $\rho$ reduces SD by 18.3% and increases expected cost by only 1.0%.

DRO with $\rho$ greater than 1.6 should be used when decision makers prioritize worst-case cost performance over expected cost performance or have limited data with which to estimate the scenario probability distribution. Values of $\rho$ between 1 and 1.6 will be ideal when decision makers prefer to minimize cost-variance or suspect that some historical data could be out-of-sample data. Increasing the value of $\rho$ from 1.2 to $\rho = 1.8$ causes the expected cost with estimated probabilities to increase from $1,894,000$ to $1,937,000$ (7.3%) and the SD to decrease from $84,000$ to $76,000$ (9.5%). The moderate conservatism of $\rho$ between 1 and 1.6 will best suit health authorities that have strict budget constraints. Requesting additional funds can be an arduous process, so minimizing cost variance and thus the chance of exceeding the planned budget is desirable. It was recommended to our healthcare partner to use the moderate conservatism of $1 \leq \rho \leq 1.6$ given that it provided good trade-offs while minimizing the risk of exceeding budget.

The values of $\rho$ that define these three intervals may vary for other data sets, so the DRO model should first be tested with all values of $\rho$ between 0 and 2. The proposed DRO approach can be applied prior to disruption in the supply chain design phase. It can also be applied during a pandemic by constraining the decision variables $q_{ij}$ that represent

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![Relative Standard Deviation in Scenario Cost vs. $\rho$](image1)

**Fig. 6.** RSD in scenario cost for different values of $\rho$.

![Utilization of PPE Sources vs. $\rho$](image2)

**Fig. 7.** Utilization of PPE sources as $\rho$ increases.
responsive strategic decisions, such as warehouse location, would crucial role to play by proactively maintaining the centralized stockpile hedging role. In the Canadian context, the federal government has remain constant in normal as well as disrupted time periods. 

develop systems that detect pandemics as soon as possible, perhaps through an internal business intelligence unit or frequent communica-
tion with the World Health Organization. Early warning notifications regarding a potential pandemic should result in immediate action to scale-up certain resilience strategies like contracting more suppliers. This is supported by results from other researchers such as Li et al. (2021), who recommend cross-sectoral coordination and information transparency between suppliers across the world. Conversely, less responsive strategic decisions, such as warehouse location, would remain constant in normal as well as disrupted time periods.

It was also revealed that the emergency stockpiles play an important hedging role. In the Canadian context, the federal government has a crucial role to play by proactively maintaining the centralized stockpile and providing supplies to provincial jurisdictions as safety stocks to compensate their own purchased from contractual suppliers and from the open-market. The federal government can use its buying-power and access to more resources such as civil servants and the military to help transport and distribute the items to lower jurisdictions. Other regions or countries can also benefit from similar arrangements by pooling re-
source for purchasing and distributing PPE. This is supported by the recommendations in Friday et al. (2021). Our healthcare partner pri-
arily relied on their traditional suppliers to provision the bulk of the PPE needs and used the transfers from the federal stockpile as a safety stock.

This paper contributes to SC resilience literature through its focus on the rarely studied topic of pandemics as disruptions. A survey by Govindan et al. (2017) on SCND under uncertainty literature from 2000 to 2015 finds that less than 20% of studies focus on disruption risks while the rest focus on operational risk. The authors suggest further research on multi-period models where disruptions impact the SC over multiple periods such as the one developed in this study. Additionally, the use of DRO, non-monetary objective functions, and multi-period models with long-term disruptions are not common in the fields of SC resilience and SCRM (Baryannis et al., 2019; Govindan et al., 2017; Heckmann et al., 2015; Hosseini, Ivanov, et al., 2019). The results of this study confirm that DRO can achieve lower relative variance in the objective function than RO and SP. Lastly, this paper demonstrates the potential of applying optimization to real-world problems through its own application of DRO to the Canadian health care sector in a COVID-19 context.

7. Conclusion

Four research questions set out at the start of this manuscript have been answered. First, this paper presented a multi-period multi-objec-
tive DRO framework for enhancing the resilience of PPE supply chains against disruptions caused by pandemics. The proposed model is solved using the \( \alpha \)-constraint method which generates multiple Pareto-optimal solutions along the trade-off between cost minimization and service level maximization. The model’s multi-objective nature also allows healthcare providers to assume different risk attitudes regarding cost and service level. Secondly, to account for the uncertainty in pandemic evolution during the planning horizon when making healthcare SC dec-
disions, scenarios based on a combination of severity levels were developed and used to run the proposed mathematical models. The uniqueness of pandemics and infrequency with which they occur can result in a lack of historical data. DRO overcomes this challenge by assuming that the true probability distribution is contained within an ambiguity set whose size can be adjusted by the decision maker. Thirdly, three intervals for the value of \( \rho \) are recommended in this paper depending on the decision makers preference for average cost perfor-
ance, worst-case cost performance, or cost variance. This is important in the healthcare context, as many regional differences exist thus creating the need to model different risk-tolerances and budget re-
strictions. Fourthly, it is shown that emergency stockpiles can be effective to protect against variability in deliveries from contract and open-market suppliers. Indeed, numerical experiments confirm that increasing the portion of fixed contracts in the PPE supply-base im-
proves worst-case costs but increases expected cost performance. Healthcare providers can similarly assess the impact of new procure-
ment policies using the optimization framework outlined in this study. The presented DRO model can enhance SC resilience to pandemic dis-
ruptions by minimizing risks prior to disruption and re-optimizing the supply base during a disruption as new information becomes available.

There are several topics that future research could explore. Multi-
stage modeling under uncertainty requires significant computational resources. Large scale optimization would offer researchers the oppor-
tunity to improve model precision through using a greater number of shorter duration time periods. Another potential avenue of research is having multiple strategic decision periods and allowing the model to change warehouse capacities or contracted suppliers partway through the pandemic. Future work could also consider other types of sourcing, such as contracts that guarantee the price but have a variable order quantity. Lastly, stronger approaches to SCND under uncertainty could include hybrids of the presented DRO model with simulation or data analytics. Pandemic spread and severity could be simulated while the DRO model determines the optimal course of action. Data analytics could be applied to scenario generation and parameter estimation to increase the quality of optimization model inputs.

This study contains limitations including its disregard for lead times on open market purchases. PPE is ordered and delivered in the same per-
iod, which may be unrealistic for some open-market suppliers. Another limitation is that the cost of strategic decisions are not evalu-
ated on a long-term horizon. The cost to maintain additional warehouse capacity or source through premium-priced contracts in the disruption-
free periods between pandemics may be sizeable. This study could be expanded by allowing the emergency stockpile supply to increase during longer pandemics to reflect the federal government’s continual efforts to purchase and allocate PPE to provinces.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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