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A dynamic approach to supply chain reconfiguration and ripple effect analysis in an epidemic

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ABSTRACT

The COVID-19 pandemic has illustrated the unprecedented challenges of ensuring the continuity of operations in a supply chain as suppliers' and their suppliers stop producing due the spread of infection, leading to a degradation of downstream customer service levels in a ripple effect. In this paper, we contextualize a dynamic approach and propose an optimal control model for supply chain reconfiguration and ripple effect analysis integrated with an epidemic dynamics model. We provide supply chain managers with the optimal choice over a planning horizon among subsets of interchangeable suppliers and corresponding orders; this will maximize demand satisfaction given their prices, lead times, exposure to infection, and upstream suppliers' risk exposure. Numerical illustrations show that our prescriptive forward-looking model can help reconfigure a supply chain and mitigate the ripple effect due to reduced production because of suppliers' infected workers. A risk aversion factor incorporates a measure of supplier risk exposure at the upstream echelons. We examine three scenarios: (a) infection limits the capacity of suppliers, (b) the pandemic recedes but not at the same pace for all suppliers, and (c) infection waves affect the capacity of some suppliers, while others are in a recovery phase. We illustrate through a case study how our model can be immediately deployed in manufacturing or retail supply chains since the data are readily accessible from suppliers and health authorities. This work opens new avenues for prescriptive models in operations management and the study of viable supply chains by combining optimal control and epidemiological models.

1. Introduction

The COVID-19 pandemic has illustrated the unprecedented challenges of ensuring the continuity of operations in a supply chain as suppliers' and their suppliers stop producing due to the spread of infection, leading to a degradation of downstream customer service levels and the ripple effect (Llaguno et al., 2021). This study was motivated by the practical example of a French subsidiary of a Belgian chemical company which packages some intermediate product in powder form in big bags for delivery to other customers. The big bags are sourced from an international supplier in Turkey. The manufacturing of big bags is highly labor intensive. In April 2020, the plant in Turkey was closed due to the infection of its labor force. Supply had to switch to a plant in Bangladesh. The lead time for delivery to the French company increased from three to 12 weeks. After some months, the Bangladeshi plant in turn had to close. The delivery of such big bags was then entrusted to a Chinese plant for which the lead time was now 14 weeks. The French company was able to handle such dire situation through constant high level communication with suppliers, delaying some deliveries to its customers and fast-tracking a batch of big bags using aerial transport. In this example, a manifestation of both the ripple effect and the supply chain reconfiguration can be observed.

Disruptions at one supplier upstream frequently have a cascading effect that propagates through the whole supply chain network (Sinha et al., 2020; Nuss et al., 2016; Garvey and Carnovale, 2020; Lücker et al., 2020). As shown by the COVID-19 pandemic (which has now been demoted to the status of an epidemic), epidemic outbreaks qualify as a distinctive source of such disruptions, which then ripple down the chain to the final customer (Ivanov, 2020; Sawik, 2022). The ripple effect occurs when a disruptive event triggers a wave of disturbances at different echelons (Kinra et al., 2020; Li and Zobel, 2020; Park et al., 2021; Llaguno et al., 2021; Ivanov et al., 2021) in the supply chain (Dolgui et al., 2018; Li and Zobel, 2020; Sinha et al., 2020;

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Li et al., 2021; Park et al., 2021). Therefore, it becomes crucial for managers to both understand how their supply chain's operations can be affected by the ripple effect, so as to prepare for and mitigate the disruptions by reconfiguring their supply base (Choi, 2021; Paul and Chowdhury, 2021; Paul et al., 2021).

Proactive approaches to supply chain risk management involve taking preventive measures to mitigate risks before they occur, while reactive approaches involve responding to disruptions after they happen. The use of forward-looking prescriptive tools can be applied to both strategies by providing a means to anticipate and plan for potential disruptions proactively.

In the literature, disruptions and associated ripple effects have been usually related to the context of supply chain resilience. During the COVID-19 pandemic, a novel concept of supply chain viability has been developed (Ivanov, 2022; Ivanov and Keskin, 2023; Sawik, 2023). However, the research on the ripple effect in the setting of viability is still in its infancy — our study contributes to this important research area. Viability is an extended resilience perspective related to deep uncertainty and severe crises (Ivanov and Dolgui, 2020; Lowe et al., 2020; Ivanov et al., 2023). In optimization terms, the principal difference between resilience and viability can be explained as follows. Resilience is the ability to recover *after* a disruption (e.g., an earthquake) and return to the initial state. Viability is the ability to operate and keep serving markets with products and services *in the presence* of a long-term disruption or crisis through structural adaptations and reconfigurations. While literature is rich on models related to resilient recovery strategies, our study is among the first papers that consider the viability perspective.

Our study develops a model that can assist a focal company in preventively reconfiguring the supply base to take into account the ripple effect that arises from an epidemic context. The types of supply chains to which this model can be applied includes all those for which there exist alternative suppliers of a substitutable product which requires manpower to be produced. For example, foundries manufacturing wafers for electronic chips are not affected but the plants checking the quality of those chips would (Hille, 2021). Other examples include many food processing industries as well as labor-intensive manufacturing sectors. The model accounts for the impact of infection dynamics on the production capacity at the focal company and suppliers and from the ripple effect that results from the propagation of epidemic disruptions along each supplier's supply network.

The model is prescriptive and proactively offers a focal company the optimal choice over a planning horizon among subsets of interchangeable suppliers, given their prices, lead times, exposure to infection risks, and their upper-level suppliers' risk exposure. It combines two different models: one is an epidemiological model, while the other is an optimal control one. Such a combination allows us to provide a forward-looking risk decision support tool. This departs from the usual operations management methods that propose decision-support models built on extrapolations using data from the past.

Our model and managerial insights represent an innovative contribution to supply chain management, with an immediate and practical application to supply base dynamic reconfiguration in a epidemic context with mediation of the ripple effect. Our contribution also extends the research on disruptions, ripple effect, supply chain reconfiguration and the selection of suppliers.

To conclude, to the best of our knowledge, no studies have combined an epidemiological model with an optimal control one in the context of supply chain viability (as recommended in Ghadge et al., 2012). Our model provides both a risk characterization and decision support framework for selecting suppliers in an epidemic context; in addition, this model does not rely on a subjective Bayesian degree of belief (Paté-Cornell and Dillon, 2006). The main contributions of our study are as follows:

- A dynamic approach to supply chain reconfiguration and ripple effect analysis in an epidemic context contextualized and formalized using continuous optimization and differential equations for both epidemic and supply chain modeling.
- A model for ripple effect analysis and mitigation in the epidemic context within the setting of viability.
- A forward-looking, proactive model for supply chain reconfiguration that integrates disruption dynamic prediction and recovery decisions and considers a multi-echelon supply base.

The remainder of the paper is organized as follows. After reviewing the literature in Section 2, we describe the problem that we aim to solve in Section 3. We then describe the model, which combines a generic epidemic framework in Section 4.1 with an optimal control model in Section 4.2. In Section 5, we show how the proposed model helps a supply network to recover and become viable. We then perform a sensitivity study in Section 6 through three infection scenarios: (a) when the epidemic limits the ability of all suppliers to fulfill the focal firm's orders, (b) when the epidemic recedes but not at the same rate in all suppliers, and (c) when infection waxes and wanes thus affecting suppliers differently. We further illustrate how such a model can be implemented through a case study in Section 7. We conclude in Section 8 by summarizing the major results and outlining future research avenues.

2. Literature review

We build on and contribute to three research streams: supply base reconfiguration under disruptions (including supplier selection), impact of epidemic disruptions in supply chains and the corresponding ripple effect, and epidemic models in supply chains. The corresponding references are listed in Table 1. We organize our literature review accordingly.

2.1. Supplier base reconfiguration under disruptions

Supply network disruption is generally defined as an unplanned and unanticipated event that disrupts the normal flow of goods and materials in a supply network (Garvey et al., 2015; Ivanov and Dolgui, 2020). Few papers propose forward-looking prescriptive tools to help managers in reconfiguring their supplier base. Esmaeili-Najafabadi et al. (2019) investigate supplier selection under two possible attitudes of the decision-maker with respect to risk: risk neutrality and risk aversion. The results flag the impact of the decision maker's attitude on supplier selection and order quantity. Given the increased complexity of disruptions, Kaur and Singh (2021) propose a multistage hybrid model for integrated supplier segmentation, selection, and order allocation.

As noted by Naqvi and Amin (2021), there is an extensive literature on supplier selection; some of these studies focus on resilience and disruption risks (Hamdi et al., 2018; Esmaeili-Najafabadi et al., 2019, 2021; Kaur and Singh, 2021; Govindan et al., 2017, to cite a few of them). We now focus on the relevant ones.

Torabi et al. (2015) propose a forward-looking, mixed possibilistic, two-stage stochastic programming model with recourse for resilient supplier selection. The model requires data about proactive supplier fortification, suppliers' business continuity plans, and prepositioned inventories. This work has been extended in Vahidi et al. (2018), which considers both the sustainability and resilience criteria in supplier selection. The above papers address single occurrence disruptions where mitigation and recovery decisions are separated in time (Aldrighetti et al., 2023), whereas we consider disruptions which extend in time, such as epidemics. However, other factors such as the recovery time and lead time at the different layers of the network are not accounted for, even though they are also critical in practical settings (Li et al., 2023).

Kellner et al. (2019) propose a multi-objective Pareto optimization regarding supplier choice, which is done by using a nonstandard

Table 1
Summary of research works on viability, ripple effect, reconfiguration and supplier selection, and epidemics and optimal control models in supply chain management literature.

References (alphabetical order)	Viability	Ripple effect	Reconfig. supp. selec.	Epidemic & cont. models
Aldrighetti et al. (2023)			x	
Bakare et al. (2014)				x
Bensoussan et al. (2011)				x
Brusset et al. (2022b)				x
Brusset et al. (2022)				x
Brusset et al. (2023)				x
Buonomo et al. (2014)				x
Cavalcante et al. (2019)			x	
Chick et al. (2008)				x
Choi (2021)		x		
Deng et al. (2019)		x		
Dolgui et al. (2018)		x		x
Enayati and Özaltın (2020)				x
Esmaeili-Najafabadi et al. (2019)			x	
Esmaeili-Najafabadi et al. (2021)			x	
Garvey et al. (2015)		x	x	
Garvey and Carnovale (2020)		x		
Govindan et al. (2017)			x	
Govindan et al. (2020)		x		
Gupta et al. (2021)		x		
Hamdi et al. (2018)			x	
Hosseini et al. (2019)			x	
Ivanov et al. (2018)				x
Ivanov and Dolgui (2020)	x	x	x	
Ivanov (2020)		x		
Ivanov et al. (2021)		x		x
Ivanov (2022)	x	x		
Ivanov and Dolgui (2021)		x		
Ivanov et al. (2023)	x	x		
Llaguno et al. (2021)		x		
Kaur and Singh (2021)			x	
Kellner et al. (2019)			x	
Kinra et al. (2020)		x		
Li and Zobel (2020)		x		
Lowe et al. (2020)	x	x		
Lücker et al. (2020)		x		
Mamani et al. (2013)				x
Nagurney (2021)		x		
Naqvi and Amin (2021)			x	
Nuss et al. (2016)		x		
Park et al. (2021)		x		
Paul and Chowdhury (2020)		x		
Paul and Chowdhury (2021)		x	x	
Paul et al. (2021)		x		
Queiroz et al. (2022)		x		
Rothan and Byrareddy (2020)		x		
Sawik (2022)		x		
Sawik (2023)	x			
Ouardighi et al. (2021)		x		x
Shamsi et al. (2018)				x
Sinha et al. (2020)		x		
Torabi et al. (2015)			x	
Torabi et al. (2018)				x
Vahidi et al. (2018)			x	
Li et al. (2023)			x	
Yusuf and Benyah (2012)				x
Our paper	x	x	x	x

portfolio selection problem with past supplier data and four criteria: purchasing cot, logistic service, risk, and sustainability. Hosseini et al. (2019) propose a stochastic multi-objective optimization model for resilient supplier selection and demand allocation using probabilistic graphical model for computing the probability disruption of the supplier. However, none of the above explicitly incorporate disruptions resulting from the ripple effect from suppliers that are further upstream.

Cavalcante et al. (2019) propose a combined simulation machine learning approach for supplier selection; this approach is based on dynamic analysis of supplier performance risk profiles according to on-time delivery. A ranking of suppliers is dynamically established using machine learning techniques on prior records of delivery. However, the use of past data makes it less useful in an epidemic context in which there are new waves of infections with different effects on suppliers. Overall, our review of the literature reveals the paucity of works on resilient supplier selection that consider the particular features of pandemic or epidemic disruptions and their propagation which extend over a period of time.

2.2. Epidemic disruptions in supply chains and the ripple effect

The pandemic context has spawned a relatively large number of studies that have mostly described the pandemic's impact on supply chains and ex-post remedies or mitigating measures, rather than suggesting prescriptive, proactive measures (Rothan and Byrareddy, 2020; Queiroz et al., 2022; Paul and Chowdhury, 2020; Ivanov et al., 2021; Govindan et al., 2020; Sinha et al., 2020; Nagurney, 2021).

Such literature underlines the necessity of considering epidemic dynamics in decision-support models (Paul and Chowdhury, 2021; Ouardighi et al., 2021).

Nagurney (2021) addresses the pandemic context of supply chain disruptions. The proposed model analyzes a supply network through the modeling of competition for a common labor pool under illness-driven constraints. This study does not consider the supply chain manager, who must contend with uncertain or delayed inputs. Nor does it consider the ripple effect as a major supply chain disruption driver (Choi, 2021; Ivanov, 2020; Sawik, 2022).

Regarding specific features of our study, i.e., product substitution and multi-stage network, the research is scarce. Gupta et al. (2021) consider product substitutability from a retailer's perspective in the context of supply disruption. But only the price decisions of the retailer and non-disrupted retailer are studied.

In Deng et al. (2019) the propagation of risk along a food supply chain is countered by countermeasures involving the reorganization of the modules of the supply chain so as to privilege the best-performing ones according to data envelopment analysis. Another approach is presented in Garvey and Carnovale (2020), which uses the conditional probability functions of the inventory ordering decisions and the binary probabilities for risks occurring in a Bayesian network, here deriving the results through numerical simulations.

To summarize, the literature on the COVID-19 pandemic is characterized by several distinct aspects. First, mitigation and recovery decisions happen simultaneously. Second, these decisions are taken in the presence of disruption and prediction of disruption dynamics. Especially the last aspect has not been addressed in literature. We address this gap by proposing a combination of epidemiological and reconfiguration models.

2.3. Epidemic and optimal control models in supply chains

Only a few supply chain or operations management models have integrated epidemic models. The models proposed in Torabi et al. (2018), Chick et al. (2008), and Mamani et al. (2013) consider contract design problem with multiple governments and possibility of intranational transmission of the disease. Yusuf and Benyah (2012) and Buonomo et al. (2014) determine by an optimal control model the equilibrium between infection and the cost of vaccination and treatment strategies. Bakare et al. (2014) finds the optimal treatment and educational campaign strategies in an SIR optimal control model. All such models only consider a macro-economic or social policy framework and implicitly assume that production facilities are not affected by the epidemic. Shamsi et al. (2018) looks into the procurement of vaccines and uses an optimal control model to minimize the procurement and social costs using the SIR epidemic model. Whereas Enayati and Özaltın (2020) addresses the optimal influenza vaccine doses number for distribution.

Because of its ability to address optimization problems by combining several objectives at a time while taking into account dynamic nonlinear feedback effects, optimal control theory has been frequently used in the modeling and analysis of dynamic operational systems (Ivanov et al., 2018) such as, scheduling and planning problems (Dolgui et al., 2018). In particular, Ivanov et al. (2021) illustrates how a production environment can support highly flexible individual jobs when a dynamically reconfigurable process design and operation sequencing system is used. Moreover, optimal control has been extensively used in modeling production–inventory systems (Bensoussan et al., 2011; Ouardighi et al., 2021).

Since most of the known epidemic control models are based on differential equations, optimal control is a convenient method for representing both epidemic dynamics and supply chain dynamics within the unified theory of continuous optimization. For example, Brusset et al. (2022) shows how a production manager can optimize the effort in prophylactic and social distancing measures for a plant or facility workforce to balance the corresponding cost with the demand addressed to the plant. Brusset et al. (2022) evaluate and quantify the ripple effect when an epidemic impacts the production capacity of suppliers. Brusset et al. (2023) present models which describe how, in time, a supply chain manager must deploy prophylactic measures. However, all these papers do not address how a supply chain can be reconfigured in the case of disruptions due to epidemics.

3. Problem context and statement

Our problem and model are motivated by the following practical context: A network today has a tree structure with hundreds, if not thousands, of leaves that can all suffer from disruptions (Nuss et al., 2016). These disruptions ripple down to the trunk at varying speeds, thus affecting the overall output to various degrees over time. The output at the focal company – as well as suppliers and their own suppliers – depend on the presence of workers at the production sites. Workers' presence depends on an epidemic's dynamics: the workforce availability decreases during an infection wave and increases when this wave ebbs. The quarantines imposed by governmental authorities also impact worker presence which can be forecast based on curve fitting of the pandemic dynamics (Nikolopoulos et al., 2021).

To mitigate the effects of such disruptions and so increase the viability of the whole network, managers need to both anticipate the capacity disruptions and proactively modify the network by reconfiguring the supplier base. To do so, early warnings about disruptions are required; this can be obtained using epidemic forecast models. In the case of the COVID-19 pandemic, as in any type of epidemic, dynamic effects have to be considered. Specifically, in the epidemic setting, mitigation and reaction decisions are integrated and based upon prediction of disruption dynamics.

We state our problem as follows: A focal company needs to source a component from different suppliers to produce final products and satisfy demand, which varies over time. We consider a multi-echelon supplier base. The lead time and unit product costs of suppliers at the upstream echelons and to the focal company are known. The focal company output and that of suppliers at different upstream stages depend on the number of workers, which may vary because of the epidemic's dynamics. The latter can be forecast using an epidemiological model ahead of the actual capacity disruptions because of missing workers, allowing for time to reconfigure the supplier base. We assume in this paper that the focal company can turn to a set of alternative (backup) suppliers which can all provide substitute products. The selection of the backup suppliers is based on price, lead time, exposure to infection risks, and their upper-level suppliers' risk exposure. The objective is to minimize the total penalty for not matching supply and demand, the total sourcing costs, and the risk among the selected suppliers through a risk aversion function.

The main purpose of the model is to equip supply chain managers with the optimal choice over a planning horizon among the subsets of interchangeable suppliers and corresponding orders. Doing this will maximize the demand satisfaction level of the focal firm given its exposure to infection, and upstream suppliers' risk exposure and so preserve the viability of the whole network. As the epidemic waxes and wanes, a manager will run the model again for a new set of suppliers and orders over a new planning horizon. The main assumptions in this problem are as follows:

- A focal company has a choice of substitutable products that can be purchased from N suppliers exposed to epidemic-induced disruption risk.
- The inventory is empty at the beginning of the planning horizon $[0, T]$, and all products have a shelf life largely superior to the planning horizon.
- Suppliers have different delivery lead times, production capacities, risk exposure to capacity loss, and prices.
- The supply structure of the N first-tier suppliers is known.
- Demand for focal company products varies over time.
- Production at any supplier is directly proportional to the productivity of the healthy workers (Brusset et al., 2022b).

4. Combination of an epidemiological and optimal control model

In the next two subsections, we present the combined epidemiological and optimal control models.

4.1. An epidemic framework

There is a growing interest in understanding the mutual relation between epidemics and economics, and several studies have determined the optimal policy measures to control the epidemic spread and limit the negative effects on the economic system (see, e.g., Capasso et al., 2013; Goldman and Lightwood, 2002; La Torre et al., 2020, 2021a,b; Ma, 2020; Nikolopoulos et al., 2021).

To model the epidemic spread, any susceptible–infected (SI) framework in which the individuals can be either infectives or susceptibles (as they are named in the epidemiological literature) to the disease but cannot acquire permanent immunity are suitable. The SI epidemiological models represent a general framework that can analyze disease dynamics and, depending on the particular structure of the model, capture complex behavior. They are best suited for discussing the implications of infectious diseases that do not confer immunity, including sexually transmitted diseases or diseases caused by bacteria, seasonal influenza, and other diseases characterized by seasonal patterns.

Note that several epidemiological models can be included into the general SI framework used in this work. The aim is to be able to model the spread of infection over time in a limited, homogeneous population that is sharing the same location. This framework allows for modeling how, over time, the workers in a facility become unable to work because, since they are not isolated and have contacts with people outside, they become infected. In this framework, both infected and quarantined workers are taken into account because they impact production capability, as can be observed in the COVID-19 pandemic and in the later epidemic infection waves (Cookson and Barnes, 2022).

If we denote by $I(t)$ the number of infected people at time t, by $S(t)$ the number of susceptible people at time t, and by M the size of the total population, we have $S(t) = M - I(t)$. The model takes the general form (Capasso, 2008):

$$\begin{cases} \dot{I}(t) = f(I(t)), \\ I(0) = I_0, \end{cases} \tag{4.1}$$

with $\dot{I}(t) > 0$ implying a local growth of the epidemic and decrease if $\dot{I}(t) < 0$. Different factors influence $\dot{I}(t)$: infection rate, effort for implementing prophylactic measures, recovery rate, or vaccination campaign efforts. From a practical perspective, it is always possible to approximate f at the first order using Taylor's formula and, following local linear approximation over a generic interval $[T_I, T_F]$, get $\dot{I}(t) = \alpha_{[T_I,T_F]} I(t)$ with $I(T_I) = I_{T_I}$ where $\alpha_{[T_I,T_F]}$ is the growth rate of infection, with the closed-form solution

$$I(t) = I_{T_I} e^{\alpha_{[T_I,T_F]}(t-T_I)}. \tag{4.2}$$

Note that in the absence of any intervention to curb the spread of the infection (such as a vaccination campaign), $\alpha_{[T_I,T_F]} = \beta_{[T_I,T_F]} - \delta_{[T_I,T_F]}$, where $\beta_{[T_I,T_F]}$ and $\delta_{[T_I,T_F]}$ are the infection and the recovery rate during the interval $[T_I, T_F]$, respectively. This approach is sufficiently general to capture any epidemiological model described by the function f, as well as to capture the different waves of an epidemic in time.

4.2. The optimal control model

Consider N suppliers that a focal company has identified to source a set of substitutable products. The demand of the focal company can be fulfilled by any of the considered substitutable products indifferently. Usually, a product is sourced from a principal supplier, and the others represent backup sources (as defined in Torabi et al., 2015; Vahidi et al., 2018). Therefore, for the sake of simplification, they will not be distinguished in the model.

The notation used in our model is presented in Table 2. Note that $u_i(t) = 0$ means that at time t, no product is ordered and departing from the ith supplier. Furthermore, we suppose that $u_i(t) = 0$ for any $t < 0$ and $t > T - T_i$. To maximize the viability of the supply chain, we define an objective function (4.3) to minimize the following: (a) the supply at risk of the selected suppliers through the risk aversion functions $R_i(.)$; (b) the penalty for not matching the supply with the demand; (c) the fixed cost of managing the selected suppliers; (d) the purchasing cost; (e) and the holding inventory cost. Note that $R_i(.)$ is used by the focal company to assess the supply at risk of the ith supplier and, when combined with the second term, enhance the viability of the supply chain over the whole planning horizon T. This function will be detailed in Section 4.4. Moreover, as can be noted from (b) and (c), the supply of the focal company depends on the number of available workers in its plant at time t, $S(t) = M - I(t)$. We emphasize that this number is a function over time of the number of infected at the beginning of the planning horizon and of the infection and recovery rates (β and δ) at the facility of the focal company.

$$\begin{aligned}\min_{\substack{u_i(t),y_i,\\ i=1,\dots,N}} J(u_i(t), y_i) := &\sum_{i=1}^{N} \int_0^T R_i(u_i(t), t)\, dt \\ &+ \xi \int_0^T \left(\theta \frac{M - I(t)}{M} K(t) - D(t)\right)^2 dt + \sum_{i=1}^{N} \gamma_i y_i \\ &+ \sum_{i=1}^{N} p_i \int_{T_i}^{T} u_i(t - T_i)\, dt \\ &+ h \int_0^T \left[\theta \frac{M - I(t)}{M} K(t) - D(t)\right]^+ dt,\end{aligned} \tag{4.3}$$

subject to

$$K(t) = \sum_{i=1}^{N} u_i(t - T_i), \qquad t \in [0, T] \tag{4.4}$$

$$u_i(t) \le \theta_i (M_i - I_i(t)) y_i, \qquad i = 1, \dots, N, \quad t \in [0, T - T_i], \tag{4.5}$$

$$u_i(t) = 0, \qquad i = 1, \dots, N, \quad t \in [T - T_i, T], \tag{4.6}$$

$$\dot{I}_i(t) = f_i(I_i(t)), \qquad i = 1, \dots, N, \quad t \in [0, T], \tag{4.7}$$

$$\dot{I}(t) = f(I(t)), \qquad t \in [0, T], \tag{4.8}$$

$$u_i(t) \ge 0, \qquad i = 1, \dots, N, \quad t \in [0, T], \tag{4.9}$$

$$K(t) \ge 0, \qquad t \in [0, T], \tag{4.10}$$

Table 2
Notations.

Time-independent parameters	
N	Number of suppliers considered by the focal company
T	Length of the planning horizon
M	Total number of workers at the facility of the focal company
β	Infection rate at the facility of the focal company
δ	Recovery rate from infection at the facility of the focal company
M_i	Total number of workers at the facility of the ith supplier, $i = 1 \dots N$
β_i	Infection rate in supplier i's location, $i = 1 \dots N$
δ_i	Recovery rate from infection in supplier i's location, $i = 1 \dots N$
T_i	Lead time of the ith supplier, $i = 1 \dots N$. For simplicity, $T_1 \le T_2 \le \dots T_N$
θ_i	Productivity rate per worker at the facility of the ith supplier, $i = 1 \dots N$
ξ	Penalty for not matching supply with demand at the focal company, $i = 1 \dots N$
θ	Number of units produced from each input unit supplied to the focal company
p_i	Unit product price purchased from supplier i, $i = 1 \dots N$
γ_i	Fixed cost of managing the ith supplier, $i = 1 \dots N$
Time-dependent parameters	
$D(t)$	Demand of the focal company at time t, $t \in [0, T]$
$I(t)$	Number of infected workers at the focal company at time t, $t \in [0, T]$
$S(t)$	Number of healthy workers at the focal company at time t, $t \in [0, T]$ ($S(t) = M - I(t)$)
$I_i(t)$	Number of infected workers at the facility of the ith supplier, $i = 1 \dots N$, at time t, $t \in [0, T]$
$S_i(t)$	Number of healthy workers at the ith supplier at time t, $t \in [0, T]$ ($S_i(t) = M_i - I_i(t)$)
Decision variables	
y_i	$= 1$ if the ith supplier, $i = 1 \dots N$, is selected; 0, otherwise
$u_i(t)$	Quantity of product leaving the ith supplier of the focal company, $i = 1 \dots N$, at time t, $t \in [0, T]$
$K(t)$	Total quantity of product received by the focal company at time t, $t \in [0, T]$

$$y_i \in \{0, 1\}, \qquad i = 1, \dots, N. \tag{4.11}$$

This is an optimal control problem with mixed variables and delays. Constraint (4.4) determines the total supply of the focal company. Constraint (4.5) caps the quantity sent by each supplier i at time t to the quantity the latter can produce given the number of available workers at its facility, $S_i(t) = M - I_i(t)$. As such, for each supplier i, this quantity is a function over time of the number of infected at the beginning of the planning horizon and of the infection and recovery rates, (β_i and δ_i) at its facility location. Constraint (4.6) considers only the quantities delivered to the focal company during the planning horizon. Constraints (4.7) and (4.8) express the dynamics in the number of infected workers in each supplier's facility and in the focal company facility respectively. They are based on the functions f and f_i that describe the epidemiological model at the facility of the focal company and each supplier i's location, respectively. Constraints (4.9)–(4.11) are domain constraints.

Having defined what happens at the focal firm, we now turn to understanding how the epidemic impacts upstream suppliers. Consider one of the first upstream suppliers of the focal firm. As decision maker in his own right, this supply firm receives inputs and components from upstream suppliers. This firm is also at risk of not receiving goods from an upper level of suppliers and so suffer from disruption at its own production facility because of infected workers.

Hence, without loss of generality, we can state that an upstream supplier, as decision maker, can also use our model, here represented by (4.3), subject to the constraints in (4.4)–(4.11). Obviously, this applies to any supplier of any layer j of a given supply network. Indeed, any supplier should pursue an objective similar to the one at the focal company.

4.3. Accounting for the upper layers of the supply chain

Let us consider a supplier i at the layer j of the focal company's upstream supply chain. We denote by K_{ip}^{j} the set of suppliers k of supplier i providing a part p and C_i^j the set of parts needed by supplier i to satisfy the demand. If u_k^{j+1}(t) is the quantity of part p leaving the facility of supplier k at the layer $j+1$ at time t and T_k is the lead time of supplier k then the quantity u_i^j(t) of the product that can be obtained from supplier i verifies the following inequality:

$$u_i^j(t) \leq Min_{p\in C_i^j} \sum_{k\in K_{ip}^j} u_k^{j+1}(t-T_k) \tag{4.12}$$

Note that u_i^j and u_k^{j+1} should both verify inequality (4.5) because the produced quantity in any supplier facility is restricted by the number of healthy workers. For example, for $j=1$, u_i^1 and u_k^2 represent for supplier i the quantity that this supplier can deliver to the focal company and the quantity that can be received from its supplier k, respectively. Hence, u_i^1 is not only capped by the loss in production capacity of supplier i in layer 1 of the focal company upstream supply chain, but it can also be limited by the loss of capacity of the suppliers in layer 2. This applies to all suppliers at the different layers of the focal company upstream supply chain. More importantly, this allows us to capture the ripple effect because of the loss of capacity resulting from the infection of workers at the various upper nodes of the supply chain over time. So if, for example, the supplier k of a supplier i of the focal company is unable to provide the full quantity of a particular part (or service), supplier i can still consider other supply options. However, the possible different lead times ripple down to the focal company, which can no longer be delivered the needed quantity on time.

What we show here is that for a focal firm to place an order for a product needed at time t, the focal firm must be aware, at time t - T_i, not only of the number of infected at the facility of each tier 1 supplier i (next level up node in the supply chain), but also of the availability of the parts needed for its production which, in turn, depends on the number of infected at the suppliers' facilities. The focal firm must be made aware of the same availability at the tier 2 suppliers (two levels up) and with the corresponding lead time. By repeating this exercise, we can easily see that for a product that has 3 or 4 levels of suppliers, as in Nuss et al. (2016), the system requires constant and updated information about the number of infected workers at each level, not only in time t, but also in prior periods, given the lead times for any correct orders and deliveries to take place. Casual empirical evidence from managers and the motivating example in introduction show that managers have been engaging in intense and continuous requests for extra information about lead times, recovery times, and availabilities from the upper levels in the supply chain. It is arguably extremely unlikely that a decision maker at a focal firm will have the needed information to accurately assess the ripple effect risk exposure due to the propagation of loss of capacity faced by suppliers at different levels of the supply chain.

This is clearly a tall order for a supply chain with four to six levels, as evidenced in Nuss et al. (2016). Thus, we propose to incorporate this information "short-sightedness" in the selection of suppliers through a risk aversion function.

4.4. Definition of the risk aversion factor

The risk aversion function introduced in the objective function is expressed as the sum of the quantity of product received from each supplier times the associated risk aversion factor (RAF). The latter represents a proxy for evaluating the disruption risk that a specific first-tier supplier might cause to the focal company. It takes into account the risk of a first-tier supplier as assessed through the possible maximum loss of capacity to deliver on time a needed quantity. Therefore, it is based on the maximum loss of capacity stemming from the propagation of disruption across the supply chain including the first-tier supplier of the focal company and its upper-level suppliers, and hence it embeds an assessment of the ripple effect exposure (REE). At this level, it is worth noting that the RAF associated with a first-tier supplier i does not distinguish the risk among its upper-level suppliers but aggregates it into a single time-independent factor that is hereafter denoted by a_i.

As such, a_i is a proxy of the REE of the upstream supply chain of the first-tier supplier i based on the exposure of its upper-level suppliers to epidemic risk. It is determined following the scheme proposed in Kinra et al. (2020) but based on the possible maximum loss of capacity, not of profit.

As mentioned above,

$$R_i(u_i(t),t) = u_i(t)\Omega_i(t), \tag{4.13}$$

where

$$\Omega_i(t) = e^{-\phi\frac{(1-\beta_i)S_i(t)}{a_iM_i}} \tag{4.14}$$

is the RAF, with a_i as a proxy for the risk exposure of supplier i from its upper-level suppliers and ϕ, a scaling parameter. We consider that supplier i assembles various subcomponents or parts, as in Kinra et al. (2020), is exposed to epidemic risk, and its suppliers are also exposed to the same type of risk and so are subject to a potential loss of capacity.

These suppliers to supplier i generate a risk that evolves over time based on their respective recovery time. Showing how such a factor evolves is left for further study.

Note that at the supplier level, we do not consider substitutable products: if one of the parts needed by supplier i is not available, then supplier i cannot complete the product that should be sold to the focal firm. If supplier i adopts a single sourcing strategy, then the wider the variety of parts needed by supplier i, the higher the risk of supplier i failing and the higher a_i must be. Markedly, this risk is reduced whenever a multi-sourcing strategy is adopted by supplier i. In addition, a_i captures the structure of the supply network. For example, if two suppliers of the focal company, i and i', source parts from the same pool of suppliers then a_i and $a_{i'}$ are equal. Oppositely, if these two suppliers source from different suppliers, then a_i and $a_{i'}$ are independent and each relies on the deployed sourcing strategy, the variety of purchased parts, and the location of the upper-level suppliers.

The RAF $\Omega_i(t)$ evolves between 1 when $S_i(t)=0$ or when $\beta_i=1$ and $e^{-\frac{(1-\beta_i)}{a_i}}$ when all workers are working in the supplier's production facility. If the infection rate is $\beta_i=0$ and all workers are producing, $\Omega_i(t)=e^{-\frac{1}{a_i}}$ for all t. Note that $e^{-(1-\beta_i)\frac{S_i(t)}{a_iM_i}} \leq 1$ for all $0<S_i(t)/M_i\leq 1$, $\beta_i>0$ and $a_i>0$. By easy computation, we get the following:

- $\frac{\partial\Omega_i}{\partial\beta_i}>0$, if β_i increases , then the RAF increases;
- $\frac{\partial\Omega_i}{\partial a_i}>0$, if a_i increases, then the RAF increases;
- $\frac{\partial\Omega_i}{\partial S_i}<0$, if the number of susceptibles at the ith supplier increases, then the RAF decreases.

The RAF is a forward-looking factor that can help the decision maker choose the suppliers (while considering their upper-level suppliers) with consideration of their risk exposure in terms of maximum capacity loss.

5. Recovery process of a viable supply chain

Having modeled how a supply chain can suffer from the ripple effect, we now explain how it recovers to full operation and provide some indications as to how to make such a supply chain viable (Ivanov and Dolgui, 2020; Ivanov, 2022). We first observe that in this model, available information about β_i, δ_i, M_i, the initial number of infected and estimated risk exposure a_i of supplier i are mandatory and must be updated as new information becomes available. For instance, when

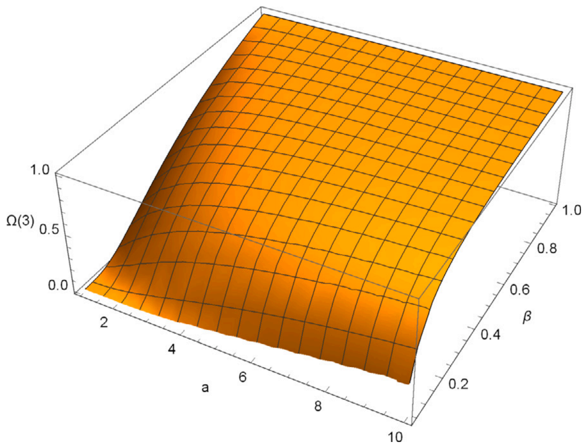


Fig. 1. Evolution of $\Omega_i(t)$ in terms of β_i and of a_i when $\phi = 100$.

β_i decreases, the model would suggest ordering larger quantities of the product from supplier i in t because the workforce is expected to turn up for work in upcoming periods. In this way, our model shows how a supply chain can meet demand in a degraded mode while still trying to minimize the costs for a period of time and then progressively come back to optimal operation (see Section 6.3 for the numerical illustration). If all suppliers apply the same criteria and the same model for selecting suppliers, the overall supply chain should progressively see its demand-satisfying capability come back to a higher level. Ensuring that over successive planning horizons allows the viability of the supply chain.

Contrary to most models in supply chain risk quantification, our model is a forward-looking one thanks to its ability to combine both the information available to a supply chain manager and epidemiological information relative to the evolution of the epidemic. Ours extends the quantitative model presented in Kinra et al. (2020) by assessing the supplier risk exposure based on the possible maximum loss of capacity in epidemic context.

To obtain insights into the behavior of the RAF Ω_i for a supplier i, its evolution in terms of a_i and of the infection rate β_i is presented in Fig. 1. Note how the RAF is increasingly sensitive as β_i increases.

In the next section, we illustrate numerically this mechanism for a focal firm with five suppliers of substitutable products through three infection scenarios and a baseline one where no infection limits the supplier selection.

Table 3
Supplier parameters under increasing, recovering, and mixed infection trend scenarios. The five suppliers are listed in the first column.

Supp.	p_i	θ_i	T_i	a_i	I_0	Scenarios					
						β_i			δ_i		
						increas.	recover.	mixed	increas.	recover.	mixed
0	0.1	1.7	1	1	.010	0.3	0.1	0.3	0.0	0.2	0.2
1	0.2	1.4	2	2	.015	0.5	0.1	0.1	0.2	0.4	0.4
2	0.1	1.5	2	1	.035	0.4	0.0	0.4	0.1	0.3	0.1
3	0.2	1.6	1	1	.200	0.8	0.4	0.4	0.5	0.7	0.7
4	0.1	1.7	2	2	.100	0.7	0.3	0.3	0.4	0.6	0.6

Table 4
Table of supplier sets (the best are in bold with an asterisk).

Supplier sets	Scenarios					
	Infection				Mixed infection	
	None	Increasing	Increasing	Recovering	Profiles	
	($T = 10$)	($T = 10$)	($T = 20$)	($T = 10$)	$a_0 = 10$	$a_2 = 10$
(0, 0, 0, 0, 1)	14.79	18.77	35.01	15.33	15.33	14.43
(0, 0, 0, 1, 0)	12.01	18.74	35.14	13.22	13.22	18.98
(0, 0, 0, 1, 1)	13.37	11.35	18.49	12.68	12.68	14.27
(0, 0, 1, 0, 0)	15.04	17.90	39.31	15.28	17.90	19.18
(0, 0, 1, 0, 1)	14.65	13.33	21.90	14.06	13.81	14.19
(0, 0, 1, 1, 0)	10.30	10.25	18.81	10.14	10.08	14.12
(0, 0, 1, 1, 1)	37.88	21.20	29.03	34.53	31.67	31.53
(0, 1, 0, 0, 0)	17.15	18.57	36.54	17.24	17.24	16.38
(0, 1, 0, 0, 1)	14.99	13.96	21.57	14.53	14.53	12.76
(0, 1, 0, 1, 0)	10.75	10.92	18.48	10.72	10.72	12.72
(0, 1, 0, 1, 1)	36.61	21.87	31.26	33.66	33.66	31.47
(0, 1, 1, 0, 0)	12.32	12.83	22.48	12.21	12.43	12.84
(0, 1, 1, 0, 1)	36.46	26.58	34.40	34.49	31.91	31.42
(0, 1, 1, 1, 0)	30.70	20.50	28.08	28.92	26.52	26.78
(0, 1, 1, 1, 1)	82.36	49.35	67.45	76.33	71.13	67.26
(1, 0, 0, 0, 0)	9.99	11.70	29.14	10.06	11.70	13.74
(1, 0, 0, 0, 1)	13.12	11.09	18.54	12.49	12.59	13.73
(1, 0, 0, 1, 0)	11.58	**9.73***	**17.06***	10.69	10.88	12.81
(1, 0, 0, 1, 1)	42.60	24.62	34.18	38.64	37.33	35.09
(1, 0, 1, 0, 0)	**9.85***	9.90	19.57	**9.70***	**9.90***	13.21
(1, 0, 1, 0, 1)	39.15	27.56	35.81	36.99	32.88	35.30
(1, 0, 1, 1, 0)	36.09	23.20	31.15	33.43	29.60	29.81
(1, 0, 1, 1, 1)	92.90	55.94	74.74	85.85	77.72	73.80
(1, 1, 0, 0, 0)	10.19	10.60	19.02	10.12	10.46	**11.64***
(1, 1, 0, 0, 1)	37.77	28.24	37.77	35.96	34.80	35.07
(1, 1, 0, 1, 0)	34.81	23.91	33.11	32.51	31.44	29.59
(1, 1, 0, 1, 1)	89.90	56.64	79.20	83.48	80.90	74.93
(1, 1, 1, 0, 0)	31.66	26.79	35.35	30.97	27.57	30.02
(1, 1, 1, 0, 1)	85.04	62.28	80.53	81.28	73.57	75.12
(1, 1, 1, 1, 0)	80.56	54.95	72.71	76.07	68.64	65.11
(1, 1, 1, 1, 1)	161.44	105.52	145.11	151.52	139.78	132.12

6. Numerical illustration for three infection scenarios

We start by the infection-free baseline scenario where the suppliers can operate at full capacity (Section 6.1). In Section 6.2 infection limits the ability of all suppliers to satisfy the focal firm's ability to serve demand; in Section 6.3 the epidemic recedes but not at the same pace for all suppliers, we evaluate the results with an extended planning horizon of 20 periods; and in Section 6.4 infection waves affect some suppliers while others are in a recovery phase. In Section 6.5, as in our baseline infection-free scenario, suppliers 0 and 2 are optimally selected, but this time both suppliers suffer from a relatively high risk exposure compared with the other three.

We proceed by enumeration and determine the optimal solution by exploring all possible supplier configurations. Without loss of generality and for the sake of a numerical simulation, we propose using the susceptible–infected–susceptible (SIS) model to determine the number of infected at both the focal company facility and at the suppliers' facility locations. In this epidemiological model, individuals can move from the susceptible to the infected group when a susceptible person comes in contact with an infected person. This is modeled, for the focal company, by means of the system of coupled differential equations (6.1).

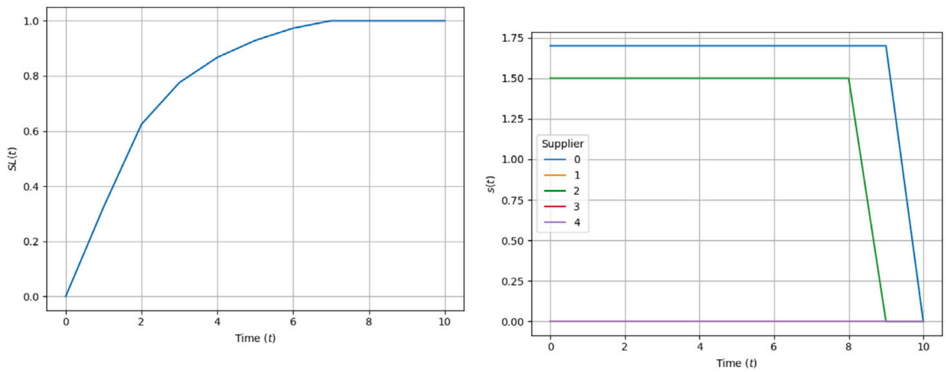
$$\begin{cases} \dot{I}(t) = \beta S(t)I(t) - \delta I(t), \\ \dot{S}(t) = -\beta S(t)I(t) + \delta I(t), \\ I(0) = I_0, S(0) = S_0, \end{cases} \tag{6.1}$$

By substituting $S(t) = M - I(t)$, the model (6.1) becomes a Bernoulli-type equation in $I(t)$ whose solution is:

$$I(t) = \frac{I_0(\beta M - \delta)}{\beta I_0 + e^{-(\beta M - \delta)t}\left((\beta M - \delta) - I_0 \delta\right)}. \tag{6.2}$$

The fraction β/δ is defined as the reproduction number and denoted by R_0. Obviously, the same model is considered and solved for the suppliers.

In all the numerical experiments, demand is fixed $D(t) = 2.5$, $\xi = 0.6$, $M_i = 1$, and $\phi = 0.3$. The results are listed in Table 4. The lowest objective function value is marked in bold and with an asterisk marking the corresponding optimal configuration.



(a) Service level of the focal company given deliveries expected from suppliers 0 and 2.

(b) Level of u_i for chosen suppliers, here 0 and 2.

Fig. 2. Baseline scenario.

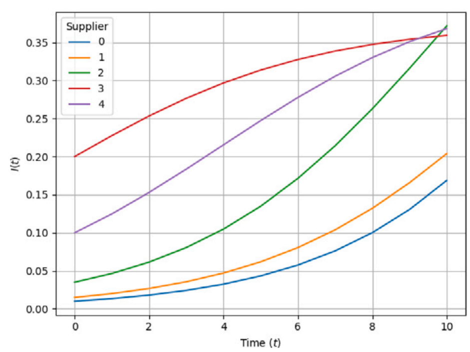


Fig. 3. Increasing infection profile scenario: level of infected I_i.

6.1. Supplier selection with no infection

This baseline scenario considers a world where a select group of five suppliers labeled from 0 to 4 work under normal circumstances and are all able to supply a precise product or component (see Fig. 2). Such suppliers in an infection-free environment operate as characterized by the productivity, price, and lead time parameters in the first three columns in Table 3. The best choice of suppliers are 0 and 2 (see Fig. 2(b)) yielding a cost of 9.85 (see second column in Table 4).

6.2. Supplier selection under infection dynamics

In this scenario, we model the evolution in the choice of supplier under increasing infection using the parameters defined in Table 3 and present in Fig. 3 how the suppliers' workforce becomes increasingly infected over time, with suppliers 0 and 1 doing slightly better. Even though any of these five suppliers can produce the required product for the focal firm, the best solution is now to drop supplier 2 and pick supplier 3 (see the third column in Table 4) because the infection progresses faster for supplier 2, implying that this supplier would not be able to deliver the expected quantities (Fig. 4(b)).

Our model enables the decision maker to estimate *ex ante* the cost of this switch. This can be seen in Table 4 by subtracting the reported values of the objective function $J(.)$ in column 3 from the ones in column 2. The objective function value for the choice of suppliers 0 and 3 under an increasing infection scenario is 9.73, as opposed to 9.85 in the baseline scenario: there is basically no impact when considered over T time periods. In addition, when comparing the service level (SL) per period in both scenarios from Figs. 2(a) and 4(a), we see that the SL is better in the first periods in the infection scenario and is only superseded from periods 8 to 10. This is because of the low lead time for supplier 3, even though p_i, I_0, β_i are higher.

The overall SL almost reaches 100% by period 10 (Fig. 4(a)), implying that this choice of suppliers does not satisfy demand but cannot be complemented by a third as this would exceed demand and increase the inventory holding cost. Incidentally, when the planning horizon period T is augmented to 20, the optimal configuration does not change, even as, obviously, the objective function value has increased (see the fourth column of Table 4).

6.3. Supplier selection in a recovery phase

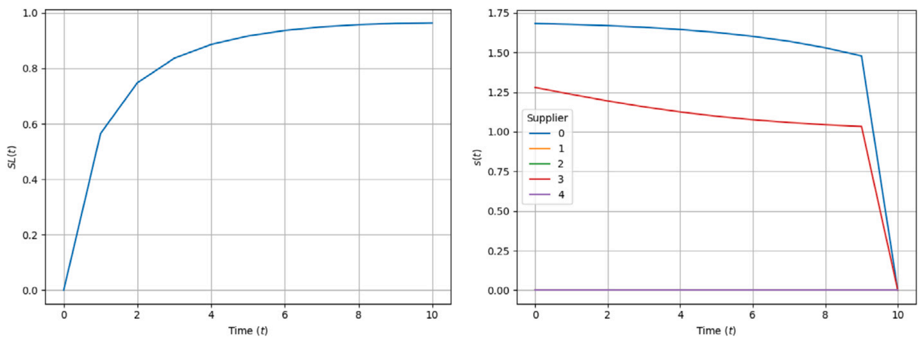
In this scenario, the infection becomes endemic: the disease still exists but the recovery rate δ_i is higher than the infection rate β_i for all suppliers i, as characterized in Table 3. In Fig. 5, suppliers 0 and 1 are the least infected and consistently have the highest proportion of their workers back to work. Given this pattern of recovery in the suppliers' workforce, the eligible set of suppliers that achieves the lowest objective function $J(.)$ is back to $\{0, 2\}$, as in the baseline scenario (see the fifth column in Table 4). Note in figure Fig. 6(a) that much like the base case, a 100% SL can be achieved toward the end of the planning horizon period (even as orders are lower, as can be seen in Fig. 6(b)). More importantly, this result indicates that in the endemic phase, a focal company would select the suppliers it once sourced from before the epidemic.

6.4. Supplier selection during mixed infection dynamics

In this scenario, we suppose that the suppliers are in different regions of the world: in some areas (suppliers 0 and 2), the infection rate is increasing, while in others (suppliers 1, 3, and 4), the peak has passed and they are in a recovery phase (see Table 3 and Fig. 7). Once again, the best choice consists in selecting suppliers 0 and 2 (see the sixth column in Table 4).

6.5. Supplier selection under risk variation

To see the impact of a_i on supplier selection, we consider a scenario in which suppliers 0 and 2, given their respective upstream supply chain, have high risk exposure in terms of capacity loss. For this scenario, we keep all parameters as in Table 3, except for a_0 and a_2, which are both set to 10. Now, even if supplier 0 is retained as the best in terms of lead time and low starting point for infection, supplier 2 is discarded and replaced by supplier 1, as can be seen from the last two columns in Table 4. The orders addressed to both are presented in Fig. 9 and the corresponding SLs in Fig. 8. This scenario shows how our model enables the decision maker to navigate around the dangers of a



(a) Service level of the focal company given the deliveries expected from suppliers 0 and 3.

(b) Level of u_i for the chosen suppliers, here 0 and 3.

Fig. 4. Increasing infection scenario.

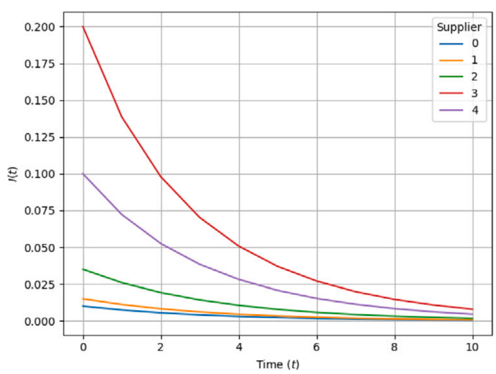


Fig. 5. Recovery scenario: level of infected I_i.

reappearing infection. The necessary information for the model to work are: infection and recovery rates available at each supplier location, available suppliers (costs, lead time, capacity), and upstream supply chain (upper-level suppliers, supplier importance, supplier location). Some of this information needs to be updated often (infection per location, capacity), others less so (costs, lead times, importance of upper-level suppliers).

To get a sense of how this scenario might develop in practice, consider the case in the introduction of the French subsidiary selling an intermediate product and in need of big bags. Upon first knowledge of infection in the Turkish plant, a simulation is made using the available big bag suppliers worldwide, so as to select a set valid throughout the increasing infection planning period. Whenever COVID-19 turns into an endemic disease, the decision maker updates the supplier set over a new planning horizon by using our model. This illustrates our statements in Section 5: the prescriptive model helps the decision maker in meeting demand in a degraded mode while still trying to minimize costs. The reader will note that our method extends and completes the one exposed in Kinra et al. (2020) in that it is a prescriptive and anticipatory managerial tool.

7. A case study: the role of the RAF

This section is devoted to the illustration of our model in a specific real life case and is distinct from the previous theoretical example. We solicited one of the most important automotive manufacturers located in Germany for information about its brake suppliers. Its top

Table 5
Lead times, country of origin, RAF, and regional infection rates for brake suppliers.

Brake suppliers	Origin	Lead time	RAF	Regional infection rates
Beringer SAS	France	74	0.29	0.006
Brembo	Italy	86	0.48	0.011
Continental	USA	362	0.91	0.012
EBC Brakes	UK	98	0.72	0.005
Stoptech	Australia	1154	0.41	0.078

five automotive high-performance brake system market vendors are[1]: Beringer SAS, Brembo, Continental, EBC Brakes, StopTech. Table 5 shows the lead times (in days) of each of the above brake suppliers. The infection rates have been calculated using the data available from a public database with updated real data about COVID infection in various countries (see the fifth column in Table 5).[2]

All the suppliers have been endowed with a specific risk factor, evaluated using the RAF formula exposed in Appendix A.3, ranging from Continental with the highest risk factor of approximately 0.91 to the lowest risk factor of 0.29 scored by Beringer (see fourth column in Table 5). Recall that the RAF Ω_i is determined using a_i, the risk exposure of each brake supplier i from its own suppliers. To estimate the RAF, we have taken into account the information provided by the automotive manufacturer about the location of the brake system suppliers, and public information about health protection policies and infection figures in each of the countries where the suppliers are located. In particular, the Australian government has put in place one of the most restrictive strategy against COVID.

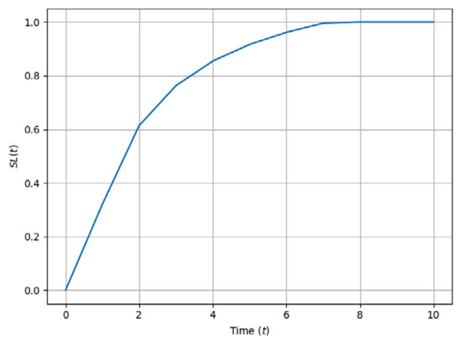
For lack of the necessary information about cost, reliability, or other supplier quality criteria, we selected three random suppliers in the initial combination: Brembo, Continental, and EBC Brakes. As we consider that the suppliers provide substitutable brake systems, to find the optimal combination of suppliers we ran the numerical algorithm in Appendix A.3 10 times to obtain a new set of suppliers with only Brembo in common with the initial combination. The two newly added suppliers were Beringer and Stoptech, with a RAF of 0.29 and 0.41, respectively.

The number of infected workers at each supplier is portrayed in Fig. 10(a), while the orders placed with each of the three suppliers selected are presented in Fig. 10(b).

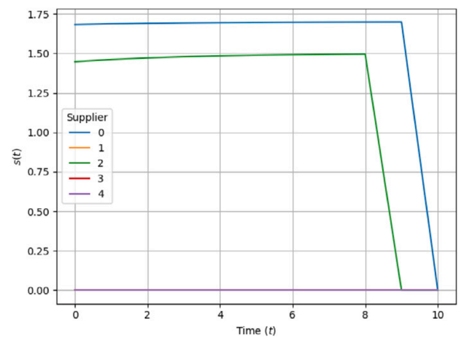
The choice of Stoptech instead of Continental is counter-intuitive as the latter's lead time and infection rate are lower (see Fig. 10(a)).

1 https://www.businesswire.com/news/home/20170315005492/en/Top-5-Vendors-in-the-Automotive-High-Performance-Brake-System-Market-from-2017-to-2021-Technavio.

2 At https://www.worldometers.info/coronavirus/.



(a) Service level



(b) Level of u_i for the chosen suppliers

Fig. 6. Recovery scenario.

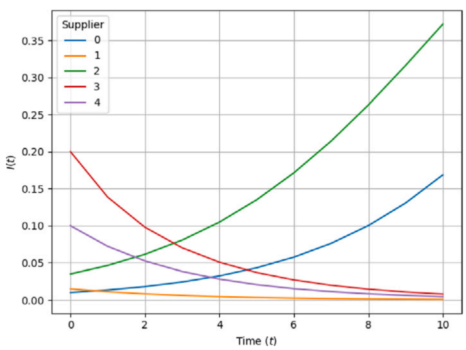


Fig. 7. Level of infected I_i in a mixed scenario.

We attribute this to the much lower RAF of Stoptech as opposed to Continental. In other words, the RAF term is playing a major role in the selection process. This result confirms our sensitivity assessment made in Section 6.5 where we modified the RAF and observed that the selected suppliers were different.

The optimal supplier selection is superior in terms of cost. It indeed allows for a supply by the focal company that is closer to the demand. In addition, it allows the selection of suppliers which are exposing the focal company to lower risk in terms of loss of supply.

8. Conclusion

In this paper, we contextualized and formalized a dynamic approach to supply chain reconfiguration and ripple effect mitigation during a pandemic or an epidemic.

Whereas the first theoretical contribution of the present paper is related to the decision support literature on supply base reconfiguration under disruptions, this paper also contributes to the literature on ripple effect in supply chains. By extending this through the epidemic context, the present paper also contributes to the literature on pandemic-induced disruption modeling (and in particular to the predictive forward-looking model in Nikolopoulos et al., 2021) and supply chain reconfiguration with supplier selection, here following Queiroz et al. (2022) and Li and Zobel (2020). It also contributes to the viability in supply chains stream (Ivanov and Dolgui, 2020; Ivanov, 2022), as well as to the upstream risk modeling one (Adhikari et al., 2020).

On the managerial level, we show how to model the reconfiguration and ripple effect in a supply chain that is subject to disruptions at one or various levels in any pandemic or epidemic context by considering the associated epidemic propagation dynamics. The decision-support model presented is a prescriptive forward-looking one that mitigates the ripple effect by reconfiguring the supply chain.

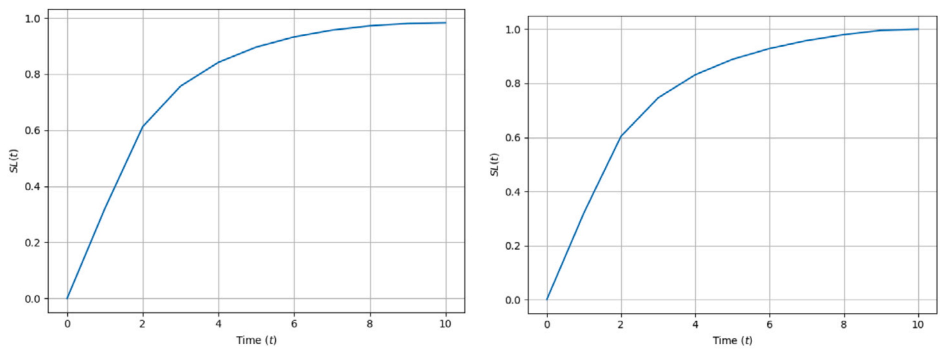
Our academic contribution is a combination of epidemiological and optimal control models that presents the supply chain manager with the optimal choice over a planning horizon among subsets of interchangeable suppliers. In this way, demand satisfaction is maximized given the suppliers' prices, lead times, exposure to infection risks and the risk stemming from their upper-level suppliers. The model can be re-run whenever the parameters change beyond what was anticipated initially. Doing that for successive planning horizons fosters the viability of the supply chain through reconfiguration. The model builds on the increasingly available epidemiological data about reinfection and recovery at the regional or country level. This strengthens the decision maker's ability to plan changes between suppliers when a disease turns from an endemic to epidemic state and when it varies across regions.

As noted in Nuss et al. (2016), managers sometimes do not understand the complexity of their upstream supply chain. In our model, to ensure tractability and feasibility, only the first echelon of suppliers is taken into account, and a proxy is used to replace information about disruption risk in the upper-level echelon of suppliers. As the manager of the focal company becomes aware of risks in the upper echelons of the supply chain, a new plan can be worked out. The practical contribution is that, in this way, our model can be implemented quickly and efficiently in any industrial or retailing sector where suppliers may be located in regions sufficiently far apart as to have distinct infection and recovery patterns. Further, if all suppliers of the focal firm also use the present model, the ripple effect could be overcome.

Finally, the proposed model can be extended to other infection outbreaks in supply chains that are more frequent, such as e-coli or norovirus, bird flu outbreak that may affect supplier's outputs. The model can be adapted by changing the parameters associated with the epidemic propagation dynamics and the risk exposure of the suppliers, and by considering the specific characteristics of the new outbreak. By doing so, the decision-support model can help mitigate the ripple effect and optimize the supply chain configuration by selecting suppliers with appropriate lead times, prices, and risk exposure.

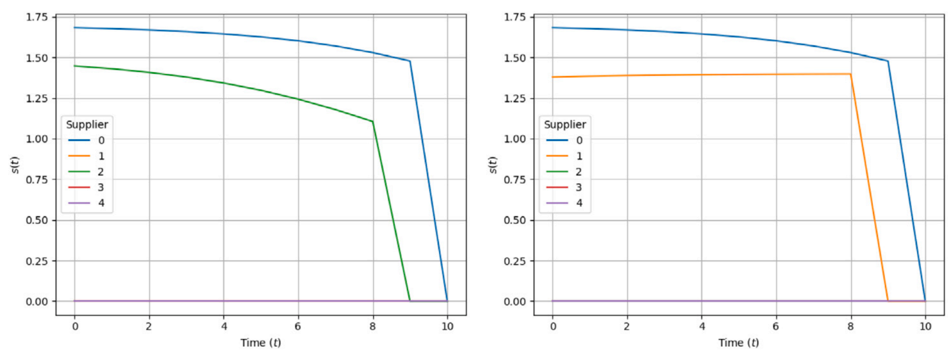
Our paper still has some limitations. The RAF is very basically described and should be discussed further in future work: it should better take into account the risk exposure of each supplier's supplier maximum loss of capacity and the possibility that it varies over time. Our model does not distinguish between main, preferred, or principal supplier from the backup ones. The assumption is that a supply chain manager or procurement manager at each echelon in the chain will have previously built a list of alternative suppliers.[3] A third limitation is in the required data needed not just from the first-tier suppliers of the focal company but also from their upper-level suppliers. As mentioned, such data include information about those infected, remaining

[3] We refer here the reader to Lisa Ellram's research: Ellram (1990) and Weber and Ellram (1993).



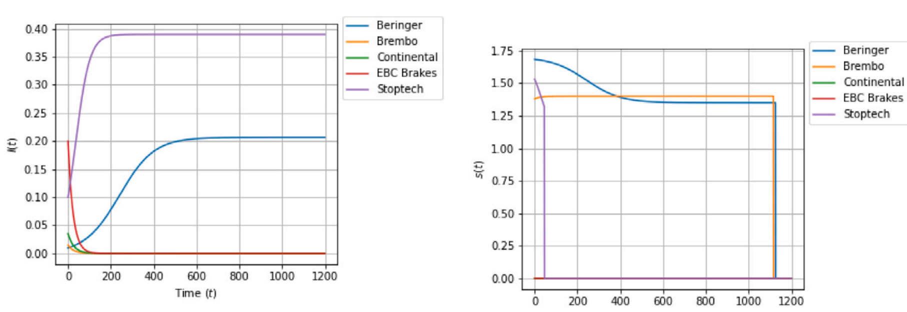
(a) $a_0 = 1$ and $a_2 = 1$ (b) $a_0 = 10$ and $a_2 = 10$.

Fig. 8. Mixed infection scenario: service level of demand in the mixed infection scenario under two hypotheses of risk.



(a) Suppliers 0 and 2 selected, $a_0 = 1$ and $a_2 = 1$ (b) Suppliers 0 and 1 selected, $a_0 = 10$ and $a_2 = 10$.

Fig. 9. Mixed infection scenario: level of u_i in the mixed infection scenario.



(a) Case study: level of infected I_i for each brake supplier i.

(b) Level of u_i for the selected suppliers.

Fig. 10. Case study of a German automotive firm for the selection of brake suppliers.

available production capacity, and the lead times at each level. This access requires intense communications such as those mentioned in the motivating example.

Data availability

Data will be made available on request.

Appendix

A.1. Model implementation

For tractability purposes and without loss of generality, we use a discretized version of the time-continuous model described in (4.3)–(4.11) in Section 4.

A.2. Model discretization

Let us suppose that the interval time $[0, T]$ is split into integer time units. The discretized model becomes

$$\min_{\substack{u_i(t), y_i,\\ i=1,\dots,N}} J(u_i(t), y_i) := \sum_{i=1}^{N} \int_0^T R_i(u_i(t), t)\, dt + \xi \int_0^T \left(\theta \frac{M - I(t)}{M} K(t) - D(t) \right)^2 dt + \sum_{i=1}^{N} \gamma_i y_i + \sum_{i=1}^{N} p_i \int_{T_i}^{T} u_i(t - T_i)\, dt + h \int_0^T \left[\theta \frac{M - I(t)}{M} K(t) - D(t) \right]^+ dt, \tag{A.1}$$

subject to

$$\begin{aligned}
K(t) &= \sum_{i=1}^{N} u_i(t - T_i), && t = 0 \dots T \\
u_i(t) &\le \theta_i (M_i - I_i(t)) y_i, && i = 1 \dots N \quad t = 0 \dots T - T_i \\
u_i(t) &= 0, && i = 1 \dots N \quad t = T - T_i \dots T \\
I_i(t+1) - I_i(t) &= f_i(I_i(t)), && i = 1 \dots N \quad t = 0 \dots T - 1 \\
I(t+1) - I(t) &= f(I(t)), && t = 0 \dots T - 1 \\
u_i(t) &\ge 0, && i = 1 \dots N \quad t = 0 \dots T \\
K(t) &\ge 0, && t = 0 \dots T \\
y_i &\in \{0, 1\}, && i = 1 \dots N
\end{aligned}$$

This is a convex static model with Boolean and real variables. By construction, the model is NP-hard (Bertsekas, 2016). The next subsection describes a numerical sorting algorithm that provides a sequence of suboptimal solutions.

A.3. Algorithm implementation

The complexity of the optimization model is NP-hard and therefore, whenever a large number of suppliers is considered, computationally challenging. To determine an approximate solution, we propose implementing a heuristic that generates a sequence of suboptimal solutions.

Let us consider each supplier's corresponding risk aversion function $R_i(u_i(t), t) = u_i(t)\Omega_i(t)$ and calculate the following *average* risk over the interval $[0, T]$: $\bar{R}_i = \int_0^T R_i(1, t) dt = \int_0^T \Omega_i(t) dt$. The value of $\bar{R}_i$ is used to sort the suppliers by risk and Algorithm 1 ranks the optimal solutions.

Algorithm 1 Numerical solution algorithm

Require: Determine a statistical estimation of the infection parameters for each supplier as well as the corresponding risk level;

Require: Sort all suppliers from the lowest to the highest risk and randomly generate an initial set of suppliers once a given level of risk has been defined.

Require: Define J_c to be the objective function value of the current configuration.

STEP 1: Pick the supplier with the lowest level of risk and add it to the current suppliers' configuration;

STEP 2: Compute the following quantities:

$$\begin{aligned}
K(t) &= \sum_{i=0}^{N} u_i(t - T_i) \\
u_i(t) &= \theta_i y_i \left(M_i - I_i(t) \right), && t = 0 \dots T - T_i \\
u_i(t) &= 0, && t = T - T_i \dots T \\
I_i(t+1) &= I_i(t) + f_i(I_i(t)), && i = 1 \dots N \quad t = 0 \dots T - 1 \\
I(t+1) &= I(t) + f(I(t)), && t = 0 \dots T - 1 \\
K(0) &\ge 0
\end{aligned}$$

that is, we choose to ship from the i-th supplier the maximum amount produced instead of only what is needed to complete the demand occurring $D(t)$, $u_i(t) = \theta_i(t)(M_i - I_i(t))$. This simplification does not affect the overall demonstration.

STEP 3: Calculate the functional value $J(u_i(t), y_i)$ and compare $J(u_i(t), y_i)$ with J_c. If $J(u_i(t), y_i) < J_c$, then $J_c = J(u_i(t), y_i)$ and go to STEP 1. Otherwise, stop.

References

Adhikari, A., Bisi, A., Avittathur, B., 2020. Coordination mechanism, risk sharing, and risk aversion in a five-level textile supply chain under demand and supply uncertainty. European J. Oper. Res. 282 (1), 93–107.

Aldrighetti, R., Battini, D., Ivanov, D., 2023. Efficient resilience portfolio design in the supply chain with consideration of preparedness and recovery investments. Omega 117, 102841.

Bakare, E.A., Nwagwo, A., Danso-Addo, E., 2014. Optimal control analysis of an SIR epidemic model with constant recruitment. Int. J. Appl. Math. Res. 3 (3).

Bensoussan, A., Cakanyildirim, M., Sethi, S.P., Wang, M., Zhang, H., 2011. Average cost optimality in inventory models with dynamic information delays. IEEE Trans. Autom. Control 56 (12), 2869–2882.

Bertsekas, D., 2016. Nonlinear Programming. In: Athena scientific optimization and computation series, Athena Scientific.

Brusset, Xavier, Davari, Morteza, Kinra, Aseem, Torre, Davide La, 2022. Modelling ripple effect propagation and global supply chain workforce productivity impacts in pandemic disruptions. Int. J. Prod. Res. 61 (8), 2493–2512. http://dx.doi.org/10.1080/00207543.2022.2126021.

Brusset, X., Jebali, A., Torre, D.L., 2022b. Production optimization in a pandemic context. Int. J. Prod. Res. 61 (5), 1642–1663.

Brusset, X., Jebali, A., Torre, D.L., Liuzzi, D., 2023. Production optimization in the time of pandemic: an SIS-based optimal control model with protection effort and cost minimization. Ann. Oper. Res..

Buonomo, B., Lacitignola, D., Vargas-De-León, C., 2014. Qualitative analysis and optimal control of an epidemic model with vaccination and treatment. Math. Comput. Simulation 100, 88–102.

Capasso, V., 2008. Mathematical Structures of Epidemic Systems. Springer Science & Business Media, Google-Books-ID: 2_ZFpIMgEQgC.

Capasso, V., Kunze, H., La Torre, D., Vrscay, E.R., 2013. Solving inverse problems for biological models using the collage method for differential equations. J. Math. Biol. 67, 25–38.

Cavalcante, I.M., Frazzon, E.M., Forcellini, F.A., Ivanov, D., 2019. A supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing. Int. J. Inf. Manage. 49, 86–97.

Chick, S.E., Mamani, H., Simchi-Levi, D., 2008. Supply chain coordination and influenza vaccination. Oper. Res. 56 (6), 1493–1506.

Choi, T.-M., 2021. Fighting against covid-19: What operations research can help and the sense-and-respond framework. Ann. Oper. Res..

Cookson, C., Barnes, O., 2022. Omicron Surge Raises Covid Reinfection Concern. Financial Times.

Deng, X., Yang, X., Zhang, Y., Li, Y., Lu, Z., 2019. Risk propagation mechanisms and risk management strategies for a sustainable perishable products supply chain. Comput. Ind. Eng. 135, 1175–1187.

Dolgui, A., Ivanov, D., Sokolov, B., 2018. Ripple effect in the supply chain: an analysis and recent literature. Int. J. Prod. Res. 56 (1–2), 414–430.

Ellram, L.M., 1990. The supplier selection decision in strategic partnerships. J. Purch. Mater. Manag. 26 (4), 8–14.

Enayati, S., Özaltın, O.Y., 2020. Optimal influenza vaccine distribution with equity. European J. Oper. Res. 283 (2), 714–725.

Esmaeili-Najafabadi, E., Azad, N., Nezhad, M.S.F., 2021. Risk-averse supplier selection and order allocation in the centralized supply chains under disruption risks. Expert Syst. Appl. 175, 114691.

Esmaeili-Najafabadi, E., Nezhad, M.S.F., Pourmohammadi, H., Honarvar, M., Vahdatzad, M.A., 2019. A joint supplier selection and order allocation model with disruption risks in centralized supply chain. Comput. Ind. Eng. 127, 734–748.

Garvey, M.D., Carnovale, S., 2020. The rippled newsvendor: A new inventory framework for modeling supply chain risk severity in the presence of risk propagation. Int. J. Prod. Econ. 228, 107752.

Garvey, M.D., Carnovale, S., Yeniyurt, S., 2015. An analytical framework for supply network risk propagation: A bayesian network approach. European J. Oper. Res. 243 (2), 618–627.

Ghadge, A., Dani, S., Kalawsky, R., 2012. Supply chain risk management: present and future scope. Int. J. Logist. Manage. 23 (3), 313–339.
Goldman, S., Lightwood, J., 2002. Cost optimization in the sis model of infectious disease with treatment. Top. Econ. Anal. Policy 2 (1), 1007–1007+, Copyright - Copyright Berkeley Electronic Press Apr 24, 2002; Document feature - references; equations; Last updated - 2021-09-12.
Govindan, K., Fattahi, M., Keyvanshokooh, E., 2017. Supply chain network design under uncertainty: A comprehensive review and future research directions. European J. Oper. Res. 263 (1), 108–141.
Govindan, K., Mina, H., Alavi, B., 2020. A decision support system for demand management in healthcare supply chains considering the epidemic outbreaks: A case study of coronavirus disease 2019 (COVID-19). Transp. Res. E 138, 101967.
Gupta, V., Ivanov, D., Choi, T.-M., 2021. Competitive pricing of substitute products under supply disruption. Omega 101, 102279.
Hamdi, F., Ghorbel, A., Masmoudi, F., Dupont, L., 2018. Optimization of a supply portfolio in the context of supply chain risk management: literature review. J. Intell. Manuf. 29 (4), 763–788.
Hille, K., 2021. Taiwan's Covid-19 Outbreak Spreads To Chip Companies. Financial Times.
Hosseini, S., Morshedlou, N., Ivanov, D., Sarder, M., Barker, K., Al Khaled, A., 2019. Resilient supplier selection and optimal order allocation under disruption risks. Int. J. Prod. Econ. 213, 124–137.
Ivanov, D., 2020. Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. Transp. Res. E 136, 101922.
Ivanov, D., 2022. Viable supply chain model: integrating agility, resilience and sustainability perspectives—lessons from and thinking beyond the COVID-19 pandemic, covid; pandemic. Ann. Oper. Res. 319, 411–431.
Ivanov, D., Dolgui, A., 2020. Viability of intertwined supply networks: extending the supply chain resilience angles towards survivability. a position paper motivated by COVID-19 outbreak. Int. J. Prod. Res. 58 (10), 2904–2915.
Ivanov, D., Dolgui, A., 2021. OR-methods for coping with the ripple effect in supply chains during COVID-19 pandemic: Managerial insights and research implications, covid; pandemic. Int. J. Prod. Econ. 232, 107921.
Ivanov, D., Dolgui, A., Blackhurst, J., Choi, T.-M., 2023. Toward supply chain viability theory: From lessons learned through COVID-19 pandemic to viable ecosystems. Int. J. Prod. Res..
Ivanov, D., Keskin, B., 2023. Post-pandemic adaptation and development of supply chain viability theory. Omega 116, 102806.
Ivanov, D., Sethi, S., Dolgui, A., Sokolov, B., 2018. A survey on control theory applications to operational systems, supply chain management, and industry 4.0. Annu. Rev. Control 46, 134–147.
Ivanov, D., Sokolov, B., Chen, W., Dolgui, A., Werner, F., Potryasaev, S., 2021. A control approach to scheduling flexibly configurable jobs with dynamic structural-logical constraints. IISE Trans. 53 (1), 21–38.
Kaur, H., Singh, S.P., 2021. Multi-stage hybrid model for supplier selection and order allocation considering disruption risks and disruptive technologies. Int. J. Prod. Econ. 231, 107830.
Kellner, F., Lienland, B., Utz, S., 2019. An a posteriori decision support methodology for solving the multi-criteria supplier selection problem. European J. Oper. Res. 272 (2), 505–522.
Kinra, A., Ivanov, D., Das, A., Dolgui, A., 2020. Ripple effect quantification by supplier risk exposure assessment. Int. J. Prod. Res. 58 (18), 5559–5578.
La Torre, D., Liuzzi, D., Marsiglio, S., 2021a. Epidemics and macroeconomic outcomes: Social distancing intensity and duration. J. Math. Econom. 93, 102473.
La Torre, D., Liuzzi, D., Marsiglio, S., 2021b. Mobility choices and strategic interactions in a two-group macroeconomic–epidemiological model. Dyn. Games Appl. 58 (in press), 2904–2915.
La Torre, D., Malik, T., Marsiglio, S., 2020. Optimal control of prevention and treatment in a basic macroeconomic–epidemiological model. Math. Social Sci. 108, 100–108.
Li, Y., Chen, K., Collignon, S., Ivanov, D., 2021. Ripple effect in the supply chain network: Forward and backward disruption propagation, network health and firm vulnerability. European J. Oper. Res. 291 (3), 1117–1131.
Li, S., He, Y., Huang, H., Lin, J., Ivanov, D., 2023. Supply chain hoarding and contingent sourcing strategies in anticipation of price hikes and product shortages. IISE Trans..
Li, Y., Zobel, C.W., 2020. Exploring supply chain network resilience in the presence of the ripple effect. Int. J. Prod. Econ. 228, 107693.
Llaguno, A., Mula, J., Campuzano-Bolarin, F., 2021. State of the art, conceptual framework and simulation analysis of the ripple effect on supply chains. Int. J. Prod. Res..
Lowe, D., Espinosa, A., Yearworth, M., 2020. Constitutive rules for guiding the use of the viable system model: Reflections on practice. European J. Oper. Res. 287 (3), 1014–1035.
Lücker, F., Chopra, S., Seifert, R.W., 2020. Mitigating product shortage due to disruptions in multi-stage supply chains. Prod. Oper. Manage. 30 (4), 941–964.
Ma, J., 2020. Estimating epidemic exponential growth rate and basic reproduction number. Infect. Dis. Model. 5, 129–141.
Mamani, H., Chick, S.E., Simchi-Levi, D., 2013. A game-theoretic model of international influenza vaccination coordination. Manage. Sci. 59 (7), 1650–1670.
Nagurney, A., 2021. Supply chain game theory network modeling under labor constraints: Applications to the Covid-19 pandemic. European J. Oper. Res. 293 (3), 880–891.
Naqvi, M.A., Amin, S.H., 2021. Supplier selection and order allocation: a literature review. J. Data Inf. Manage. 1–15.
Nikolopoulos, K., Punia, S., Schäfers, A., Tsinopoulos, C., Vasilakis, C., 2021. Forecasting and planning during a pandemic: COVID-19 growth rates, supply chain disruptions, and governmental decisions. European J. Oper. Res. 290 (1), 99–115.
Nuss, P., Graedel, T., Alonso, E., Carroll, A., 2016. Mapping supply chain risk by network analysis of product platforms. Sustain. Mater. Technol. 10, 14–22.
Ouardighi, F.E., Khmelnitsky, E., Sethi, S.P., 2021. Epidemic control with endogenous treatment capability under popular discontent and social fatigue. Prod. Oper. Manage..
Park, Y.W., Blackhurst, J., Paul, C., Scheibe, K.P., 2021. An analysis of the ripple effect for disruptions occurring in circular flows of a supply chain network. Int. J. Prod. Res..
Paté-Cornell, M.E., Dillon, R.L., 2006. The respective roles of risk and decision analyses in decision support. Decis. Anal. 3 (4), 220–232.
Paul, S.K., Chowdhury, P., 2020. Strategies for managing the impacts of disruptions during COVID-19: an example of toilet paper. Glob. J. Flex. Syst. Manag. 21 (3), 283–293.
Paul, S.K., Chowdhury, P., 2021. A production recovery plan in manufacturing supply chains for a high-demand item during COVID-19. Int. J. Phys. Distrib. Logist. Manage. 51 (2), 104–125.
Paul, S.K., Moktadir, M.A., Sallam, K., Choi, T.-M., Chakrabortty, R.K., 2021. A recovery planning model for online business operations under the COVID-19 outbreak. Int. J. Prod. Res. 1–23.
Queiroz, M.M., Ivanov, D., Dolgui, A., Wamba, S.F., 2022. Impacts of epidemic outbreaks on supply chains: mapping a research agenda amid the COVID-19 pandemic through a structured literature review, covid; pandemic. Ann. Oper. Res. 319, 1159–1196.
Rothan, H.A., Byrareddy, S.N., 2020. The epidemiology and pathogenesis of coronavirus disease (covid-19) outbreak. J. Autoimmun. 109, 102433.
Sawik, T., 2022. Stochastic optimization of supply chain resilience under ripple effect: A COVID-19 pandemic related study. Omega 102596.
Sawik, T., 2023. A stochastic optimization approach to maintain supply chain viability under the ripple effect. Int. J. Prod. Res..
Shamsi, G.N., Ali Torabi, S., Shakouri, G.H., 2018. An option contract for vaccine procurement using the SIR epidemic model. European J. Oper. Res. 267 (3), 1122–1140.
Sinha, P., Kumar, S., Prakash, S., 2020. Measuring and mitigating the effects of cost disturbance propagation in multi-echelon apparel supply chains. European J. Oper. Res. 282 (1), 148–160.
Torabi, S., Baghersad, M., Mansouri, S., 2015. Resilient supplier selection and order allocation under operational and disruption risks. Transp. Res. E 79, 22–48.
Torabi, S.A., et al., 2018. An option contract for vaccine procurement using the sir epidemic model. European J. Oper. Res. 267 (3), 1122–1140.
Vahidi, F., Torabi, S.A., Ramezankhani, M., 2018. Sustainable supplier selection and order allocation under operational and disruption risks. J. Clean. Prod. 174, 1351–1365.
Weber, C.A., Ellram, L.M., 1993. Supplier selection using multi-objective programming: A decision support system approach. Int. J. Phys. Distrib. Logist. Manage. 23 (2), 3–14.
Yusuf, T.T., Benyah, F., 2012. Optimal control of vaccination and treatment for an SIR epidemiological model. World J. Model. Simul. 8 (3), 194–204.