Optimization and Operations Research in Mitigation of a Pandemic

Cai-Hua Chen¹ · Yu-Hang Du² · Dong-Dong Ge³ · Lin Lei² · Yin-Yu Ye³

Received: 24 October 2020 / Revised: 22 December 2021 / Accepted: 24 December 2021 / Published online: 11 May 2022
© Operations Research Society of China, Periodicals Agency of Shanghai University, Science Press, and Springer-Verlag GmbH Germany, part of Springer Nature 2022

Abstract
The pandemic of COVID-19 initiated in 2019 and spread all over the world in 2020 has caused significant damages to the human society, making troubles to all aspects of our daily life. Facing the serious outbreak of the virus, we consider possible solutions from the perspectives of both governments and enterprises. Particularly, this paper discusses several applications of supply chain management, public resource allocation, and pandemic prevention using optimization and machine learning methods. Some useful insights in mitigating the pandemic and economy reopening are provided at the end of this paper. These insights might help governments to reduce the severity of the current pandemic and prevent the next round of outbreak. They may also improve companies’ reactions to the increasing uncertainties appearing in the business operations.

The first author was supported by the Natural Science Foundation of Jiangsu Province (No. BK20181259) and the National Natural Science Foundation of China (No. 11871269). The third author was supported by the National Natural Science Foundation of China (Nos. 11831002 and 11471205).

Dong-Dong Ge
dge.dongdong@mail.shufe.edu.cn
Cai-Hua Chen
cchen@nju.edu.cn
Yu-Hang Du
yuhang_du@163.sufe.edu.cn
Lin Lei
linleish@foxmail.com
Yin-Yu Ye
yyye@stanford.edu

¹ School of Management and Engineering, Nanjing University, Nanjing 210008, Jiangsu, China
² School of Information Management and Engineering, Shanghai University of Finance and Economics, Shanghai 200433, China
³ Department of Management Science and Engineering, Stanford University, Stanford, CA 9430, USA
Although the coronavirus imposes challenges to the entire society at the moment, we are confident to develop new techniques to prevent and eradicate the disease.

**Keywords** Pandemic · Operation research · Optimization · Machine learning

**Mathematics Subject Classification** 90B50 · 90C90

1 Introduction

The coronavirus (COVID-19), triggered in December 2019, has spread very rapidly all over the world in 2020. The pandemic causes huge damages to the society as it has led to tens of millions of people been infected and more than one million deaths, as reported by the WTO in their latest weekly epidemiological update. The pandemic also attacks the global economy, for example, the US unemployment rate reached 14.7% for the first time after the Great Depression. Moreover, China’s GDP shrank 6.8% in the first quarter, also for the first time in the recent two decades.

This large-scale infectious public health event imposed enormous pressure on our society. Governments are having trouble with the preparation and allocation of public resources, especially medical equipments and healthcare services. Companies are facing increasing uncertainties in product demand and supplies, causing significant costs in business operations. Both governments and companies have to adjust their policies in response to the pandemic so as to minimize the disruptions in healthcare system and business environment.

The mitigation of the pandemic requires proactive reactions from both sides. From the governments’ perspective, the policy makers must figure out efficient and effective strategies in identification and protection of vulnerable groups, and allocation of public resources. As for companies, managers are suggested to make more agile, flexible, and robust decisions on supply chain coordination, inventory control, and risk management, when facing the fast changing market environment.

In this paper, we consider possible policies for mitigating the pandemic from the perspectives of supply chain management, public resource allocation, and pandemic prevention using optimization and machine learning methods. In the first part, we consider the supply chain management including demand forecasting, inventory control, and risk reduction, within which the ideas of centralization, data-driven decision making, and Monte Carlo simulation have been discussed. In the second part, we concern the problem of public resource allocation and contact tracing, mainly using the discrete and continuous optimization, together with the computational geometry method. In the third part, we stress the issue of pandemic prevention by identifying high-risk groups using statistical models and machine learning. Finally, we provide some policy suggestions for mitigating the pandemic and reopen the economy.

The rest part of this paper is organized as follows. In Sect. 2, we introduce some methods for supply chain management in a pandemic. Some useful solutions of public resource allocation and contact tracing are provided in Sect. 3. In Sect. 4, we describe how statistical and machine learning methods could be used to epidemic prevention. Section 5 makes some policy suggestions. Finally, a brief conclusion for the paper is provided in Sect. 6.
2 Supply Chain Management in Pandemic

As the pandemic progresses, companies are trying to reopen the businesses to the normal state. However, the spread of pandemic in each country is asynchronous, there might be increasing uncertainties in customer demand and product supplies. The supply chain management in a pandemic becomes fragile and several methods have to be taken to solve these problems.

2.1 Supply Chain Coordination through Centralization

Coordination is the central idea in supply chain management. Supply chain coordination shed lights to cost saving and risk reduction via centralization. As an example, consider a regional distribution center (RDC) who needs to order ventilators to meet the potential demand of patients. Suppose the demand is normally distributed, to achieve a 99% guarantee level, the order quantity can be estimated as the 99% quantile. Now consider a decentralized supply network on the top of Fig. 1, where 4 RDCs need to order ventilators individually. The total number of orders is 101 790 as can be seen in the figure. On the contrary, if we consider a centralized network on the bottom of Fig. 1, the centralized distribution center (CDC) can manage the orders for all RDCs. Suppose the demands are independent, the number of ventilators reduces to 67 279. Even

![Image of Decentralized and Centralized Networks]

Fig. 1 Inventory Network Management: Risk Pooling via Centralization
though they may be correlated, the variance can still be reduced due to time delays. This simple example highlights the role of centralized management of supply chain for weakening the competitiveness among participants. In fact, the out-of-stock (OOS) risk reduces after pooling, which is especially important for preparing ventilators in fighting against COVID-19.

2.2 Inventory Control via Data-Driven Optimization

The pandemic causes significant uncertainties to the inventory control, leading to lowered demand and volatility, longer production lead time, and shortage in critical materials. This brings our attention to more robust, flexible, and agile decisions in supply chain management. To this end, great progresses have been made in data-driven approaches [1–3], making innovations happen in various application areas like demand forecasting and optimization algorithmic design, etc. Indeed, the last decade witnesses an explosion in data availability, which introduces both opportunities and challenges to the research of supply chain management.

Considering demand forecasting, data-driven approach is more robust and flexible. As illustrated in Fig. 2, traditional prediction method builds Gaussian model for safety stock calculation, and days of inventory (DOI) is updated monthly or quarterly. The slowly update prediction is problematic in a fast moving market, while the Gaussian assumption causes troubles when demand distribution is skewed. As compared to the traditional prediction method, the quantile-based method estimates demand based on actual sales data rather than the fitted Gaussian model, and DOI is calculated at SKU level and updated daily. In this case, the simulation result shows that quantile-based method often achieves better OOS performance with lower inventory level. Moreover, dynamic DOI can quickly response to the market changes, so it performs especially better in the fluctuating period.

Data-driven approach can make daily updates for demand forecasting, which brings difficulties to the optimization algorithmic design. Considering a real-world optimization problem for production planning illustrated in Table 1, the execution constraints

![Fig. 2 90% Quantile-Based Dynamic DOI Calculation in Pandemic: model-based vs data-based predication](image)
### Table 1 A Real-World Optimization Problem for Production Planning

\[
\begin{align*}
\text{min} & \quad \text{Transportation Cost} + \text{Risk of Out-of-Stock} \\
& + \text{Risk of Overstock} + \text{Violation of DC Special Request Replacement} \\
& + \text{Usage of Hub DC to Transfer} + \text{Volume of Obsolescent Inventory} \\
\text{s.t.} & \quad 1) \text{Factory Constraints (inventory/production plan/push target)} \\
& + 2) \text{DC Constraints (capacity/hub DC)} \\
& + 3) \text{Transportation Capacity} \\
& + 4) \text{Other Special Constraints (half/full/even pallet, co-shipment)} \\
& + 5) \text{Shipping Constraints (SKU and truck type/weight/MOQ)} \\
& + 6) \text{Stakeholders’ Feedback} \\
& \quad \text{(fix/increment/deduction of replacement, request)} \\
& + 7) \text{D-0 Adjustment (urgent request/tail volume)} \\
& \quad \vdots
\end{align*}
\]

Base Constraints
(2 days ahead of plan date)

Truck Arrangement & Feedback
(1 day ahead of plan date)

Execution/Urgent
(Real-time adjustment)

are usually real-time adjusted that has to be solved by more prompt optimization methods. In this case, the traditional integer-linear programming solver can hardly meet the realistic requirement. For this problem, we propose a three-stage optimization framework in Fig. 3.

In the first stage, we solve a smaller relaxed linear programming (LP) problem to find the initial solution. Then, we fix the solution from stage 1 as parameters, and solve a full-scale relaxed LP problem which satisfies all the priority requirement. Finally, the solution is rounded to ensure feasibility in reality. Applying this method to the optimization problem, we can solve a production planning problem with more than $10^7$ decision variables and $10^7$ constraints in less than 3 hours.

Combining the demand forecasting and optimization method for inventory management, a case study shows the average OOS rate for Budweiser Korea in April 2020 is 0.37%, which is 46% improvement from the original performance (0.69%). Additionally, average misallocation unit cost (MUC) is 15.98 kwr per 10L, which reduces 3.32 from 19.3. Moreover, the sensibility analysis suggests that, if production is improved, OOS further reduces to 0.16% (77% improvement), and MUC reduces to 11 kwr per 10L. Finally, if the transportation capacity, the operation of brewery, and the misallocation of resources return normal, MUC can reduce to 1.2 kwr per 10L (85% improvement). This result proves the advantage of the proposed method for robust and flexible response to emergencies.

### 2.3 Risk Management by Monte Carlo Simulation

The COVID-19 also guides us to the study of risk management, particularly stress test methods for drastic and rare scenario analysis. The stress test method was original
introduced for banking system to estimate the distribution of losses incurred by the initial shock and the losses resulting from the contagion process [4]. For healthcare system, stress tests can be conducted using computer-based Monte Carlo simulation methods. Monte Carlo simulation is an important and flexible tool for modeling situations with uncertainties. Simulation allows us to quickly and inexpensively acquire knowledge concerning a problem that is usually gained through experience. Particularly, we can analyze how a healthcare system fails in pandemic based on drastic and rare event simulations.

Besides the healthcare system, stress test has been successfully applied in other business sectors like the dispatching system, etc. In particular, Cardinal Operations conducted a stress test to evaluate and promote the performance of a fully unmanned warehouse of 2 500 m², 10 000 orders/day, and 335 257 pieces of inventory on Double 11 shopping carnival in 2017. Based on a large number of simulated scenarios, they tested the robustness and efficiency of the supply chain network facing supply disruption and extremely large demand in some regions. The stress test suggested that, by adding 14 AGVs, 3 workstations, and adopting an optimized strategy, the outbound quantity for the unmanned warehouse improved from 20 000 to 56 545, meaning the productivity boosted by 283%. This guarantees the stability of the dispatching system on Double 11 shopping carnival.

3 Optimization in New Social Norm

Affected by the COVID-19, effective measures have to be taken to force people keeping social distance and prevent hospitals from being overloaded, thus slowing down the spread of the virus. For this purpose, policy makers must figure out efficient strategies in contract tracing and allocation of public resources such as hospital service and outdoor or indoor spaces, etc.

3.1 Optimization under Social Distance Constraints

Social distancing induces a “new norm” in society. It arises from the problem of accommodating people in finite space with sufficient distance from each other. In this respect, we discuss two scenarios with people accommodated either continuously or discretely. The continuous accommodation problem is known as the kissing problem [5–7], while the discrete accommodation problem is the max-independent set (MIS) problem [8]. Both the kissing problem and MIS problem are quite complicated in theory and practice.

3.1.1 Kissing Problem

The kissing problem considers people accommodated continuously, which often applies to outdoor scenarios like beach and parks. As illustrated in Fig. 4, the kissing problem is the problem of finding the maximal number of people (the kissing number) around a single person with the safe social areas kissing each other. Generally, there
is no closed-form solution for \(d\)-dimensional kissing problem \([9]\), except for some specific dimensions shown in Table 2. Particularly, the mathematical representation of social distancing appears as

\[ \| x_i - x_j \| \geq \delta \]

which is nonconvex in the position variable \( x \in \mathbb{R}^d \), resulting in great difficulties in optimization.

To deal with the nonconvex constraints, the kissing problem can be formulated and relaxed as an SDP feasibility problem for a given number of spheres.

\[
\begin{align*}
\min_Z & \quad 0 \\
\text{s.t.} & \quad (e_i - e_j)(e_i - e_j)^T \cdot Z \geq \delta^2, \quad \forall i \neq j, \\
& \quad e_i e_i^T \cdot Z = \delta^2, \quad \forall i = 1, 2, \cdots, n, \\
& \quad Z \succeq 0,
\end{align*}
\]

where \( Z = X^T X, X = [x_1 \cdots x_n] \in \mathbb{R}^{d \times n} \), and \( e_i \in \mathbb{R}^n \) is the vector with 1 at the \(i\)-th position and 0 elsewhere. Indeed, solving the SDP relaxation (1) provides an upper bound for the kissing number and the SDP problem can be solved using standard SDP algorithms in practice \([10–12]\).

### 3.1.2 Max-Independent Set Problem

The MIS problem considers accommodating people discretely, which applies to indoor situations such as theaters, restaurants, and schools. MIS is the problem of finding a subset of vertices of maximum cardinality such that no two vertices in the subset are directly connected. Generally, MIS is NP-hard, but its approximation is possible on planar graphs. In particular, we consider an undirected graph \( G = (V, E) \) with \( |V| = n \). An integer programming formulation for MIS problem takes the form

\[
\begin{align*}
\max_x & \quad \sum_i x_i \\
\text{s.t.} & \quad x_i + x_j \leq 1, \quad (i, j) \in E, \\
& \quad x_i \in \{0, 1\}, \quad \forall i = 1, 2, \cdots, n,
\end{align*}
\]

### Table 2 The Kissing Number for \(d\)-dimensional Problem

| Dimension\((d)\) | 1  | 2  | 3  | 4  | 8  | 24 |
|------------------|----|----|----|----|----|----|
| \(K(d)\)     | 2  | 6  | 12 | 24 | 240| 196 560 |
where \( x_i = 1, i \in \{1, 2, \cdots, n\} \) decides whether a vertex appears in the set. Then, an 
SDP relaxation of problem (2) due to Lovasz [13] is as follows:

\[
\max_{X \in S^{n \times n}} \quad \text{Tr}(JX)
\]
\[
\text{s.t.} \quad \text{Tr}(X) = 1, \quad X_{i,j} = 0, \quad (i, j) \in E, \quad X \succeq 0,
\]

where \( J \) is an \( n \times n \) matrix of all ones. Further examples can be seen in Chlamtac and 
Singh [14], Wilson [15], etc. Generally, SDP is quite powerful in MIS modeling.

### 3.1.3 New Extension: Humanized Arrangement

The humanized considerations extend the optimization problem with cluster-based 
social distance constraints. Taking the MIS problem as an example, if families or 
friends are allowed to sit together, which makes potentially more people accommodated, 
an MIS problem with clusters can be derived. To this end, the problem can be 
formulated as a 0-1 integer programming problem

\[
\max_x \quad \sum_{i=1}^{m} \sum_{p=1}^{n} x_{ip}
\]
\[
\text{s.t.} \quad \sum_{i=1}^{m} x_{ip} \leq 1, \quad \forall p, \quad \sum_{p=1}^{n} x_{ip} \leq 1, \quad \forall i, \quad x_{ip} + x_{jq} \leq 1, \quad \forall \text{strangers } i, j, \text{ close seats } p, q, \quad x_{ip} \in \{0, 1\}, \quad \forall i, p.
\]

As far as we know, the MIS problem with clusters is rarely explored that no good 
solution method is currently known. To this end, we may expect active studies on new 
approaches for this problem.

### 3.2 Contact Tracing by Sensor Network Localization

COVID-19 is a respiratory infectious disease. It is vital to clarify the transmission 
chain of the virus and isolate the susceptible patients in time. In epidemiological 
research, the transmission chain is often identified by contact tracking among people. 
For this purpose, GPS can achieve high precision positioning for outdoor tracking, 
but it does not work for indoor tracking due to the signal blocking. Nevertheless, 
indoor positioning can be achieved via sensor network localization (SNL). For SNL, 
consider \( m \) anchor points \( a_1, \cdots, a_m \in \mathbb{R}^d \), whose locations are known, and \( n \) sensors 
points \( x_1, \cdots, x_n \in \mathbb{R}^d \), whose locations we wish to determine. Particularly, given 
the Euclidean distance \( \bar{d}_{kj} \) between anchor \( a_k \) and sensor \( x_j \) for some \( k, j \), and \( d_{ij} \)
between sensor $x_i$ and sensor $x_j$ for some $i, j$, the SNL problem can be written as

$$
\begin{align*}
\min_{X, Y} & \quad 0 \\
\text{s.t.} & \quad (e_i - e_j)^T Y (e_i - e_j) = d_{ij}^2, \quad d_{ij} \text{ specified}, \\
& \quad \left( \begin{array}{l}
(ak)^T \\
(-e_j)
\end{array} \right) \left( \begin{array}{l}
I_d \\
X^T Y
\end{array} \right) \left( \begin{array}{l}
(ak)^T \\
(-e_j)
\end{array} \right) = d_{kj}^2, \quad d_{kj} \text{ specified}, \\
Y & = X^T X,
\end{align*}
$$

where $X = (x_1, x_2, \ldots, x_n)$. Generally, the problem is difficult even for $d = 2$. However, by relaxing $Y$ to be $Y \succeq X^T X$ and let $Z = \left( \begin{array}{l}
I_d \\
X^T Y
\end{array} \right) \succeq 0$, Biswas and Ye [16] showed that the problem can be written as an SDP feasibility problem

$$
\begin{align*}
\min_Z & \quad 0 \\
\text{s.t.} & \quad Z_{1:d,1:d} = I_d, \\
& \quad (0; e_i - e_j) (0; e_i - e_j)^T Z = d_{ij}^2, \quad \forall d_{ij} \text{ specified}, \\
& \quad (-ak; e_j) (-ak; e_j)^T Z = d_{kj}^2, \quad \forall d_{kj} \text{ specified}, \\
Z & \succeq 0.
\end{align*}
$$

It is noteworthy that the relaxation is tight for uniquely localizable graph. However, the dimension of $Z$ is so high that the solution of the SDP relaxation can be quite slow which requires accelerations. For this purpose, Wang et al. [17] introduced a further relaxation called edge-based SDP (ESDP) that can be solved efficiently. To illustrate, considering $d = 2$, the ESDP relaxation is

$$
\begin{align*}
\min_Z & \quad 0 \\
\text{s.t.} & \quad Z_{1:2,1:2} = I_2, \\
& \quad (0; e_i - e_j) (0; e_i - e_j)^T Z = d_{ij}^2, \quad \forall d_{ij} \text{ specified}, \\
& \quad (-ak; e_j) (-ak; e_j)^T Z = d_{kj}^2, \quad \forall d_{kj} \text{ specified}, \\
Z_{(1,2,i,j),(1,2,i,j)} & \succeq 0, \quad \forall d_{ij} \text{ specified}.
\end{align*}
$$

Besides the SNL, Wang and Ding [18] considered extracting dynamic information for moving objects to achieve real-time tracking and trajectory prediction. Combining trajectory prediction and SNL, precise contact tracking can be obtained to identify the transmission chain of the virus.

3.3 Dynamic Region Partitioning for Hospital Services

Efficient treatment is essential to patients infected by COVID-19. Hospital services must be divided equitably by considering the location and capacity of hospital, and the potential distribution density of the pandemic. Specifically, it is desired to partition the city into multiple regions such that each region has a hospital nearby, each hospital will not be overrun, and the partition can be easily adjusted as the input data changes.
Mathematically, the region partitioning problem is viewed as a computational geometry problem. To illustrate, consider a set of points $\mathcal{N} = \{1, 2, \cdots, n\}$ scattered inside a 2D convex polygon $P$ with $m$ vertices, then it is desired to find a partition of $P$ into $n$ subregions satisfying 1) each subregion is a convex polygon for traveling convenience, 2) each subregion contains one point as service center, and 3) all subregions have equal areas for load balance. Intuitively, we note the partition in the Voronoi diagram as shown in Fig. 5 satisfies the first two properties that each subregion is convex and contains one point. However, the subregions in the diagram have unequal areas. In practice, the property of equal areas can be achieved by adjusting the boundary.

More specifically, Carlsson et al. [19] showed that the equal partition always exists and it can be found exactly in $O(Nn \log N)$ time or operations, where $N = m + n$. Firstly, it is shown that the partition exists by viewing the problem as a limiting case of a discrete version of the region partition problem. Additionally, to construct the region partition exactly, Carlsson et al. [19] developed a divide-and-conquer strategy to reduce the problem into two or three smaller problems where $\mathcal{N}$ is partitioned into two or three convex polygons, respectively. The algorithm first determines an approximate partition by performing some binary searches on the vertices of $P$ or the points in $\mathcal{N}$. Once the approximate partition is determined and the edge that the partition of $P$ intersects is known, they solve a one-variable quadratic or linear equation to determine the exact location of the partition. Finally, the result is generalized by considering the relative importance of the spaces.

### 3.4 Public Goods Allocation under Tight Capacity Restriction

The pandemic imposes capacity restrictions on public spaces due to social distance constraints. In this case, the ideal outcome is to prevent public spaces from being either over-consumed or underused. Indeed, efficient allocation must be achieved by deciding who takes the privilege to use the capacity constrained public resources at a specific time. Such an allocation can be derived from the equilibrium model known as Fisher market, where consumers spend their budget on goods to maximize the individual utility, and producers sell capacity constrained goods for currency. At the market equilibrium, each agent purchases the most preferred bundle of goods affordable at the equilibrium prices, with all budgets being spent and all goods being sold [20].
Traditionally, Fisher market considers only budget constraint and capacity constraint. This fails to capture additional physical constraints imposed by the availability of substitutes. In this regard, Jalota et al. [21] introduced a modified Fisher market to incorporate the customers’ physical constraints. Particularly, suppose there are \( m \) goods in the market and each public good belongs to exactly one resource type. Denote \( T \) to be the set of all resource types and assume each customer consumes a subset \( T_i \subset T \) of resource types. By normalizing the constraint such that the customer consumes at most one unit of good in each type, the individual optimization problem for customer \( i \) with physical constraint is as below:

\[
\max u_i(x_i) = \sum_j u_{ij} x_{ij}
\]

s.t.
\[
\begin{align*}
    p^T x_i & \leq w_i, \\
    A_{t}^{(i)} x_i & \leq 1, \quad \forall t \in T_i, \\
    x_i & \geq 0,
\end{align*}
\]

where \( x_i \in \mathbb{R}^m \) decides the quantity for \( m \) goods being purchased, \( A^{(i)} \in \mathbb{R}^{m \times |T|} \) and \( A_t^{(i)} \) is the row corresponding to resource type \( t \in T_i \), \( w_i \) is the budget of customer \( i \), \( u_i(x_i) \) is the utility function, and \( p \in \mathbb{R}^{m}_{\geq 0} \) is the vector of prices for the goods. Unfortunately, the existence and the uniqueness of the market equilibrium cannot be guaranteed in this model. For this reason, Jalota et al. [21] further introduced a social optimization problem where the budget is perturbed such that the KKT condition establishes the equilibrium prices. The perturbed social problem takes the form

\[
\max u(x_1, \cdots, x_n) = \sum_i (w_i + \lambda_i) \log \left( \sum_j u_{ij} x_{ij} \right)
\]

s.t.
\[
\begin{align*}
    \sum_i x_{ij} = \bar{s}_j, \quad & \forall j = 1, \cdots, m, \\
    A_t^{(j)} x_i & \leq 1, \quad \forall t \in T_j, \forall i = 1, \cdots, n, \\
    x_{ij} & \geq 0, \quad \forall i, j,
\end{align*}
\]

where \( \bar{s}_j \geq 0 \) is the total capacity for good \( j \). Moreover, the perturbation parameter \( \lambda_i \) can be found by a fixed point iterative scheme. Consequently, we can set prices for different time slot to achieve efficient allocation of the public resources.

### 4 Machine Learning in Pandemic Prevention

With the escalation in the severity of the pandemic, some scientists proposed a method called “flatten the curve” [22], which does not mean to eliminate the virus completely, but to decrease peak infections, delay peak time, and reduce the total number of infections, thereby alleviating daily medical pressure and lowering mortality. To flatten the curve, we analyze and predict the death rate using statistics and machine learning to provide information for protecting vulnerable groups.
4.1 Statistical Methods with Individual Features

To prevent the disease from spreading, an urgent need for the government is to identify high-risk groups for designing protective measures accordingly. Statistical method is a useful tool to differentiate high- and low-risk groups. It has been found from the empirical data in [23] that there is no substantial differences in the infectious rate among people from various age groups. However, the death rate is highly related to age. Using the data from mainland China till February 11, 2020, the percentage of deaths from different age groups can be found in Table 3.

The elder the person is, the higher percentage of mortality. The deaths over the age of 50 account for about 95% of the total deaths. Moreover, underlying health conditions is another feature which is regarded as highly relative to the mortality. From the same data set, the death rates for people with different health conditions can be found in Table 4.

It can be found from the table that a patient suffering from cardiovascular disease has the highest mortality than other diseases, and the patient without any health condition has the lowest mortality rate. In particular, the mortality rate for patients with cardiovascular diseases is about twelve times that of normal infected patients.

Given the empirical data, Bayes formula can be used to estimate the death probabilities for patients who are confirmed affected. More specifically, according to Table 3, given the fatality rate of about 7.7%, the percentage of deaths for people confirmed affected can be calculated as:

| Table 3  | Death rate in different age group |
|---------|----------------------------------|
| Age     | Percentage of confirmed cases /% | Percentage of deaths /% |
| Under 50| ≈50                              | ≈5                      |
| Over 50 | ≈50                              | ≈95                     |

| Table 4  | Death risk under different health conditions |
|---------|-----------------------------------------------|
| Underlying health condition | Percentage of deaths/ % |
| Cardiovascular disease      | 10.5                                        |
| Diabetes                    | 7.3                                         |
| Chronic respiratory disease | 6.3                                         |
| Hypertension                | 6.0                                         |
| Cancer                      | 5.6                                         |
| No health condition         | 0.9                                         |
People Confirmed Affected (100%)

Over 50 (50%)
- Death (7.315%)
- Survive (42.685%)

Under 50 (50%)
- Death (0.385%)
- Survive (49.615%)

where $7.315\% = 0.95 \cdot 7.7\%$ and $0.385\% = 5\% \cdot 7.7\%$, and $42.685\% = 50\% - 7.315\%$, $49.615\% = 50\% - 7.315\%$.

Furthermore, it can be calculated that the mortality rate for people confirmed affected and over 50 is 14.63% as compared to 0.44% for normal people over 50. For people under 50, the mortality rates for people confirmed affected and normal people are 0.77% and 0.02%, respectively, as shown in Table 5.

### 4.2 Machine Learning with Multiple Social Features

Apart from the widely used individual features, other social features may also give insights on predicting death rates. As compared to the individual features, examples of social features include national health expenditure, physicians, hospital beds per 1000 people, etc. These features indicate the healthcare service level of a country, which is directly related to the death rate.

Machine learning techniques can be used to deal with various social features. Setting a binary variable indicating whether the patient will survive or not, logistic regression model and support vector machine (SVM) can be implemented to make the prediction. A case study using logistic regression indicates that patients in countries with more well-developed public healthcare systems are at a lower risk of death.

### 5 Mitigation of a Pandemic and Economy Reopening

The studies of optimization and operation research provide insights for the mitigation of the pandemic and economy reopening. Generally, the aim of our work is not to eradicate the virus but to reduce the ultimate fatality rate by various means such as frequent in-group sample testing, vulnerability identification, improved healthcare protection, and time slot scheduling. For economic reopening, we highlight the idea of centralization and encourage the usage of robust, flexible, and agile decision making,

| Table 5 | Mortality rate for people in different groups |
|---------|---------------------------------------------|
| Age     | Normal people | People confirmed affected |
| Over 50 | 0.44%         | $\frac{7.315}{50} = 14.63\%$ |
| Under 50| 0.02%         | $\frac{0.385}{50} = 0.77\%$ |
in order to cope with the increasing uncertainties in customer demand and product supply.

5.1 Mitigating the Pandemic

Facing the pandemic, governments must manage to identify and track vulnerable groups to guide the policy making and resource allocation. Based on nucleic acid tests, high-risk groups can be differentiated from low-risk groups using statistics and optimization method. Then, protective measures should be imposed to cut-off the “thicker edges” between high- and low-risk groups. As the elderly account for the majority of high-risk groups, specially those with underlying diseases, they are encouraged to work at home and go outdoors only at specific time and areas. Since younger people are less fatal to the virus, college students are encouraged to do social works for public benefits. Furthermore, once a vaccine is available, high-risk groups should be assigned higher priorities for inoculation. When there is more than one vaccine, people may be given the most suitable one based on their personal characteristics.

With in-group sample testing and time slot scheduling, public spaces will reopen more safely. As an example, before schools open, returning students can be divided into groups, and each group is treated as a single sample when testing for possible infections. If the test result is positive, further tests should be done on individuals in that group. When scheduling groups for classes or in-person events, contacts among groups should be strictly avoided. For this purpose, time slots can be created for each group to visit the campus, and the schedule can be arranged by similar method as in Sect. 3.4.

It is noteworthy that some of these strategies have been widely used already. Indeed, frequent sample testing is the key for China to put the pandemic in control, and the group sample testing we proposed provides a way to test large amount of people in relatively short periods. This strategy has been applied successfully in Wuhan, Beijing, Dalian, Qingdao, etc. Moreover, reopening public spaces by time slots guarantees the safety and some efficiency for their operations. These strategies deserve more attentions in real practices.

5.2 Reopen the Economy

To reopen the economy safely, enterprises and governments are encouraged to deploy a centralized inventory system, and adopt algorithm-based planning and dispatching. Managers are suggested to rely on data-driven machine decision rather than vision-driven, and focus on short-term actions instead of long-term planning. Actually, a lean and agile supply chain is often more cost-friendly. Finally, low-risk groups are advised to resume working.
5.3 The Role of Our Research Community

For the scientific community, researchers are encouraged to develop more sensitive technologies such as mathematical optimization, statistics and machine learning, computer-based Monte Carlo simulation, mechanism design, and other high-tech solutions for the usage of vulnerable-group identification and resource allocations. These techniques help governments to reduce the severity of the current pandemic and prevent the next round of outbreaks. Our studies also help enterprises to cope with increasing uncertainties appearing in the business operations.

6 Conclusion

In this paper, we have discussed several applications of supply chain management, optimizations, and machine learning to mitigate the impact of the pandemic. In addition to this existing research, there is still much room for further investigations and development on the scientific methods for epidemic prevention. Researchers should take more efforts to search solutions for current situation. Although the coronavirus imposes challenges to the entire society at the moment, we are confident to defeat it in the near future.

Acknowledgements The authors are grateful to the editors and reviewers for their help in improving the paper.

References

[1] Delage, E., Ye, Y.: Distributionally robust optimization under moment uncertainty with application to data-driven problems. Op. Res. 58(3), 595–612 (2010)
[2] Bertsimas, D., Gupta, V., Kallus, N.: Data-driven robust optimization. Math. Program. 167(2), 235–292 (2017)
[3] Esfahani, P.M.: Data-driven distributionally robust optimization using the Wasserstein metric: performance guarantees and tractable reformulations. Math. Program. 171, 115–166 (2018)
[4] Martínez-Jaramillo, S., Pérez, O.P., Embriz, F.A.D., Lopez, G.: Systemic risk, financial contagion and financial fragility. J. Econ. Dyn. Control 34(11), 2358–2374 (2010)
[5] Musin, O.R.: The kissing number in four dimensions. Annal. Math. 35, 1–32 (2008)
[6] Bachoc, C., Vallentin, F.: New upper bounds for kissing numbers from semidefinite programming. J. Am. Math. Soc. 21(3), 909–924 (2008)
[7] Lee, J., Liberti, L.: On an SDP relaxation for kissing numbers. Optim. Lett. 14(2), 417–422 (2020)
[8] Chiba, N., Nishizeki, T., Saito, N.: An approximation algorithm for the maximum independent set problem on planar graphs. SIAM J. Comput. 11(4), 663–675 (1982)
[9] Kucherenko, S., Belotti, P., Liberti, L., Maculan, N.: New formulations for the kissing number problem. Discr. Appl. Math. 155(14), 1837–1841 (2007)
[10] Nesterov, Y.: Semidefinite relaxation and nonconvex quadratic optimization. Optim. Methods Softw. 9(1–3), 141–160 (1998)
[11] Luo, Z.-Q., Ma, W.-K., So, A.-C.: Ye, Y., Zhang, S: Semidefinite relaxation of quadratic optimization problems. IEEE Signal Process. Magaz. 27(3), 20–34 (2010)
[12] Zheng, X.J., Sun, X., Ling, L.D.: Convex relaxations for nonconvex quadratically constrained quadratic programming: matrix cone decomposition and polyhedral approximation. Math. Program. 129(2), 301–329 (2011)
[13] Lovasz, L.: On the Shannon capacity of a graph. IEEE Trans. Inf. Theory 25(1), 1–7 (1979)
[14] Chlamtac, E., Singh, G.: Improved approximation guarantees through higher levels of SDP hierarchies: A pproximation, randomization and combinatorial optimization. Algorithms and Techniques, pp. 49–62. Springer, Cham (2008)

[15] Wilson, Aaron T.: Applying the boundary point method to an SDP relaxation of the maximum independent set problem for a branch and bound algorithm. PhD thesis, New Mexico Institute of Mining and Technology (2009)

[16] Biswas, P., Ye, Y.: Semidefinite programming for ad hoc wireless sensor network localization. In: Proceedings of the 3rd international symposium on Information processing in sensor networks, pages 46–54 (2004)

[17] Wang, Z., Zheng, S., Ye, Y., Boyd, S.: Further relaxations of the semidefinite programming approach to sensor network localization. SIAM J. Optim. 19(2), 655–673 (2008)

[18] Wang, Z., Ding, Y.: Real-time tracking for sensor networks via SDP and gradient method. In Proceedings of the first ACM international workshop on Mobile entity localization and tracking in GPS-less environments, pages 109–112 (2008)

[19] Carlsson, J.G., Armbruster, B., Ye, Y.: Finding equitable convex partitions of points in a polygon efficiently. ACM Trans. Algorithms 6(4), 1–19 (2010)

[20] Devanur, N.R., Papadimitriou, C.H., Saberi, A., Vazirani, V.V.: Market equilibrium via a primal-dual algorithm for a convex program. J. ACM 55(5), 2541 (2008)

[21] Jalota, D., Pavone, M., Ye Y.: Markets for efficient public good allocation (2020). http://arxiv.org/abs/2005.10765

[22] Feng, Z., Glasser, J.W., Hill, A.N.: On the benefits of flattening the curve: a perspective. Math. Biosci. 364, 108389 (2020)

[23] Jordan, Rachel E., Adab, P., Cheng KK.: Covid-19: risk factors for severe disease and death, BMJ (2020). https://doi.org/10.1136/bmj.m1198