



An optimization model to assign seats in long distance trains to minimize SARS-CoV-2 diffusion

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ABOUT

The unprecedented spread of SARS-CoV-2 has pushed governmental bodies to undertake stringent actions like travel regulations, localized curfews, curb activity participation, etc. These restrictions assisted in controlling the proliferation of the virus; however, they severely affected major economies. This compels policymakers and planners to devise strategies that restrain virus spread as well as operationalize economic activities. In this context, we discuss some of the potential implications of seat inventory management in long-distance passenger trains and create a balance between operators' operational efficiency and passengers' safety. The paper introduces a novel seat assignment policy that aims to mitigate virus diffusion risk among passengers by reducing interaction among them. A mixed-integer linear programming problem has been formulated that concomitantly maximizes the operator's revenue and minimizes virus diffusion. The validity of the model has been tested using real-life data obtained from Indian Railways. The computational results show that a mere 50% capacity utilization may distress operators' economics and prove ineffectual in controlling SARS-CoV-2 transmission. The proposed model produces encouraging results in restricting virus diffusion and improving revenue even under 100% capacity utilization.

1. Introduction

The SARS-CoV-2 epidemic in early 2020 saw a considerable shift in travel volume and commuter behavior due to varying levels of restrictions imposed in several countries. Infusion of numerous strategies like sealing containment zones, imposing curfews, etc., to mitigate the outburst of SARS-CoV-2 led to a total collapse of economic activities and lifestyles. Chinazzi et al. (2020) suggest that these regulations help in delaying infection proliferation; however, they affect industrial operations and countries' economic growth. The transport sector, which generally witnesses large passenger movements in urban transit systems and regional travels, has been one of the worst-hit businesses. Initial reports suggest that commercial air travel volume has reduced by almost 75% during mid-April 2020 (OECD, 2020; ICAO, 2020). In the case of long-distance passenger rail travel volume, data exhibits a reduction of about 50% compared to pre-SARS-CoV-2 numbers in India (Nag, 2020). Further, we notice a significant drop in land transport activity (around 20%–40% of its baseline) across the globe (Tirachini and Cats, 2020). Fig. 1(a), (b) illustrate a reduction in passenger travel volume across various European countries in the last quarter of 2020 compared to 2019 (Eurostat, 2021).

Travel patterns in big economic countries are triggered mainly due to cultural diversity, job opportunities, and educational facilities. Obviously, policies like work from home and online classes have reduced community movement. However, the phased ease in local restrictions, reopening of business centers, transport services, and tourist activities necessitate close compliance as any modest magnitude of community interaction can catalyze infection rates. Nouvellet et al. (2021) report a significant drop in

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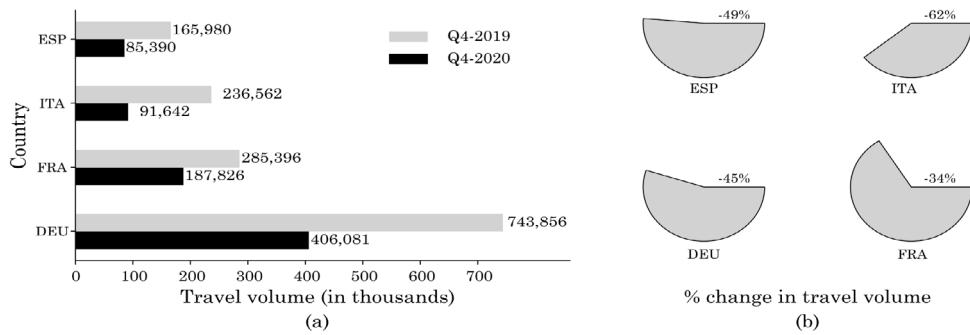


Fig. 1. Rail commuters travel volume across different European countries - (a) actual number (b) % change.

SARS-CoV-2 transmission due to initial reduction in mobility but underlines strong evidence for an uprise in infections with increased mobility and contact rates due to relaxation and unsafe behaviors. [UITP \(2020\)](#) highlights some intrinsic settings associated with public transport that qualifies it as high-risk activity: (i) high occupant density, (ii) large common contact places, and (iii) difficult to track a potentially infected person. Thus, travel operators and governmental bodies must endeavor to develop a new set of operative guidelines that assist in economic revival as well as limit congestion and crowding during travel.

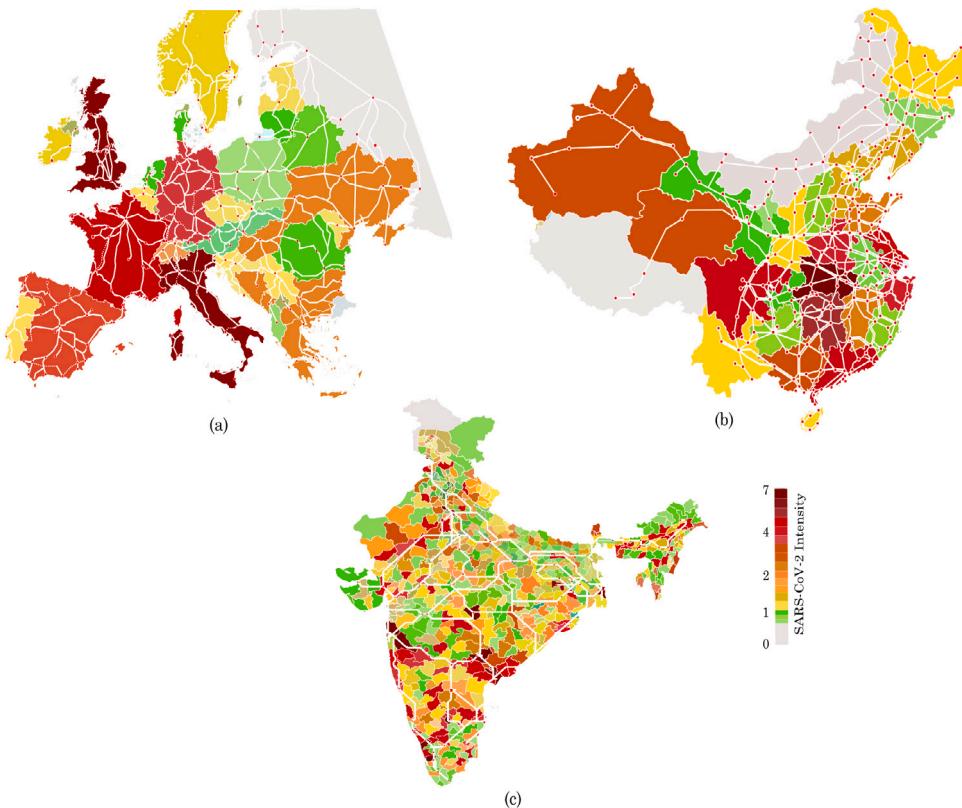


Fig. 2. SARS-CoV-2 intensity in different countries and their major train lines - (a) European countries; (b) China; (c) India.

[Kartal et al. \(2021\)](#) perform an econometric causality analysis between people's mobility and pandemic measures, and show their long-term effects. The authors assert that applying localized restrictions may revive economic activities and control virus outbreaks. The vulnerability of virus also depends on population density, built-up area, and floor area ratio of buildings ([Choerunnisa et al., 2020](#)). The SARS-CoV-2 data also suggest a considerable variation in the virus intensity (number of infections as a percentage of the total population) across geographical regions in different countries, see [Fig. 2](#). Since long-distance trains travel across various cities

and passengers board from stations with varying levels of virus intensity, modest interaction among fellow passengers can ramify virus diffusion. EURNEX (2020) and Love (2020) suggest current pandemic might accelerate a shift in commuter movements from air to rail transport due to:

- (i) ease in adapting new carriage layout that guarantees safe passenger seating;
- (ii) provision of independent cabins or compartments for a relatively small group of commuters to minimize contacts;
- (iii) extensive connection with micro-mobility services;
- (iv) less susceptible to disruptions than road transport and thwart virus dissemination.
- (v) increase in airfares due to crisis and long transit times might supercharge rail competitiveness.

The above assertions motivate the present work, where authors attempt to minimize virus diffusion during travel in a long-distance train by reducing the interaction between passengers from high and low-intensity regions. Schraer (2020) suggests that an occupancy level of 50% may aid in controlling virus diffusion during a train journey; however, these figures turn out to be uneconomical and impracticable due to higher break-even. Thus, train operating companies (TOC) require an effective tool to create equilibrium between service effectiveness and robustness in terms of SARS-CoV-2 diffusion. Considering these factors as stepping-stones to the planning process, we develop a new framework for railway revenue management (RM), where passengers' safety is an integral part of RM (discussed in Section 2). The paper embraces RM by developing an integrated model that simultaneously maximizes revenue and minimizes SARS-CoV-2 diffusion, since performing seat assignment solely on the basis of minimizing virus spread may not be practical for a TOC. Here, virus spread is controlled by reducing interaction among passengers boarding from stations having varying infection levels.

The rest of the paper is organized as follows. In the next section, we briefly review the literature on revenue management for railways and some of the recent operational measures adopted by public transport systems to curb passengers' exposure to SARS-CoV-2. Section 3 describes the problem considered in the study. Further, Section 4 presents the mixed-integer linear programming (MILP) formulation of the problem. Section 5 highlights the results of the computational study on real-life data set to validate our model. Finally, the paper ends with conclusions and directions for future research in Section 6.

2. Related work

Revenue management is considered a structured idea that enhances a firm's revenue using multiple strategies like demand forecast, product availability, price elasticity, etc. Typically RM problems are grouped under *quantity-based* (inventory control decisions) and *price-based* (pricing decisions) strategies. The quantity-based models perform capacity management, whereas pricing models perform time and quantity-based product valuation. The airline industry saw a phenomenal use of RM models in strategy formation and operations planning after the deregulation in the US during the 1970s. However, railways acknowledge similar business policy prospects in the early 2000s only. Fig. 3(a) exhibits a classical framework of RM where each element is studied either individually or as integrated model. However, we believe that the current pandemic and post predicaments will compel operators to adopt a newer RM framework where passengers' safety is accorded high relevance and masks every other constituent, see Fig. 3(b). The importance of passengers' safety in recent times can also be observed by inspecting operators' operational functioning where they seek to create a safe travel environment via seat blockage, distribution of safety gears, reforms in ticket booking and boarding systems (Warpinski, 2020; EASA, 2021; Indigo, 2020; Frost, 2020).

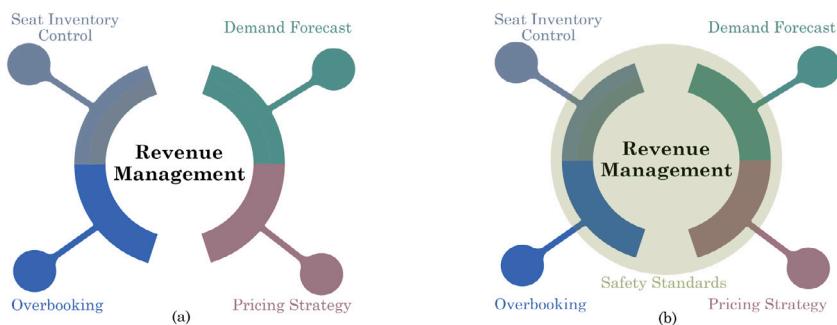


Fig. 3. Dimensions of revenue management - (a) classical; (b) latest.

A brief review of the classical RM concept is as follows. Seat inventory management, having a central theme of optimizing resource (seats) utilization, is a useful tool for revenue maximization. It involves the distribution of seats among different OD pairs along the train route and the actual assignment of seats to passengers in different coaches and cabins. Ciancimino et al. (1999) present a mathematical approach to obtain optimal reservation limits for a multi-segment network under demand uncertainty and non-nested seat allocation. Gopalakrishnan and Rangaraj (2010) consider train capacity management for long-distance passenger

services. Recent studies on quantity-based RM system evaluate the effect of passengers' choice behavior, arrival process, stochastic demand and control strategy on the revenue (Wang et al., 2016; Yuan and Nie, 2020). Further, Yan et al. (2020) introduce capacity elasticity at high-speed rail (HSR) operations through a flexible train composition.

Authors also assess the role of different pricing-based strategies on passengers' rail revenue. The pricing-based strategies are predominantly used at HSR operations and premium services of Indian Railways (Sibdari et al., 2008; Sato and Sawaki, 2012; Xiaoqiang et al., 2017; Qin et al., 2019). Bharill and Rangaraj (2008) evaluate the effect of differential and dynamic pricing (varying ticket price relative to reservation horizon and demand) on passenger rail service revenue. Lin et al. (2019) employ roadway congestion pricing to control demand without increasing supply. The authors exhibit that variation in ticket rates influences passengers' preferences.

Quite a few studies considered seat allocation and pricing strategy as interrelated and complementary to each other. Yuan et al. (2018) investigate seat inventory control to maximize railway profit under dynamic ticket pricing. The authors make use of customers' activity patterns to identify demand, i.e., whether travel is for business intent or leisure. Wen and Zhang (2019) exploit passengers' demand pattern and differential pricing at HSR and examine the efficacy of seat allocation. Pratikto (2020) utilize price variation and capacity management for revenue maximization where customers' willingness-to-pay method is used for demand estimation. Hu et al. (2020b) present an integrated model where pricing policy and seat allocation are studied jointly. The authors assess the effect of dynamic and discriminatory pricing strategies on total revenue where discriminatory pricing involves variation in the ticket price of two trains with similar OD pairs. For a more detailed study on classical railway RM system, the readers may refer to Armstrong and Meissner (2010) and Gorman (2015). Further, details on the contemporary issues in both pricing and quantity-based RM methods can be found at Gönsch (2017), Strauss et al. (2018) and Klein et al. (2020).

Other essential element of the seat assignment process is the ticket booking system, as it provides a mechanism to control seat availability. Two basic types of control systems utilized in rail services include (i) booking limits and (ii) protection levels (Talluri et al., 2004, 2008). The former ration the amount of capacity that can be sold to any particular class at a given time, while the latter defines the number of seats reserved or protected for each class. Both the control systems can be partitioned or nested. The partitioned approach splits available seats into distinct groups or blocks. In contrast, the nested method defines seat availability based on class hierarchy, i.e., higher class subsumes lower class seats. Further, based on the type of control, the actual seat assignment is done at the time of ticket booking (Yuan and Nie, 2020; Yan et al., 2020) or before entering the station, i.e., in real-time (Yazdani et al., 2019).

Apart from inventory control mechanism the seat assignment process may investigate factors like convenience, comfort, and safety (Milan, 1993; Carpenter, 1994; Hensher, 1998). Chang and Yeh (2004) present a multi-objective seat assignment model that addresses passengers' comfort standards along with revenue maximization. The authors define two main discomforts during travel: (i) inconvenience during boarding and alighting of trains and (ii) over-occupancy in non-reserved coaches. Lam et al. (1998) suggest that exorbitant passenger movements at a station induce congestion and train delays. Hulse (2013) and Hunter-Zaworski (2017) exhibit that seat assignment may control platform-train interface accidents that happen while boarding/alighting a train. Yazdani et al. (2019) introduce a real-time seat assignment model that minimizes passenger flow during the boarding/alighting process via uniform distribution of loads across coaches. Above studies ponder passenger safety with an objective of minimizing accidents at the platform-train interface.

The prevailing SARS-CoV-2 pandemic situation worldwide conglomeration researchers to look at safety issues from a different perspective. Here researchers attempt to study community well-being concerning virus diffusion during transit in public transport. Stelzer-Braids et al. (2009) conclude that the likelihood of transmission of respiratory diseases in a confined space is high due to exhaled aerosols circulation. Recently few articles have examined factors that might affect virus transmission during airline travel and suggested preventive measures. Schultz and Fuchte (2020) assess the effect of new boarding-deboarding sequences and reduced hand luggage in airlines on virus transmission. Similarly, Milne et al. (2020a,b) evaluate the effectiveness of variants of reverse pyramid boarding strategy in airlines using various performance indicators related to the risk of virus spread and boarding time. Strategies like "Free COVID insurance" by airline operators, in a sense, provide assurance of safety to boost passenger demand (Newswire, 2020). Hu et al. (2020a) assess the risk of SARS-CoV-2 transmission on passengers of HSR and observes that virus diffusion risk is highly dependent on co-travel time and seat location.

We can clearly observe a dearth of studies on railway operations that give prominence to safety in the post-SARS-CoV-2 world. Since rail transfer plays a vital role in the transport industry, with millions of daily commuters using train services, it demands a careful assessment of passengers movements to contain the spread of virus. The present study proposes a new framework for rail RM where passengers' safety in terms of exposure to the virus is considered paramount. The passengers' safety is rendered by reducing their interaction and maintaining adequate gaps in the seating space. Further, it aims to maximize operators' revenue through efficient seat inventory management. Some of the specific contributions of our paper to the existing literature are as follows:

- (i) The literature so far addresses RM as a part of pricing strategy or capacity management. This is the first attempt to incorporate the revenue model under the umbrella of passengers' safety.
- (ii) Studies so far tackle passengers' safety during seat assignment to avoid accidents at the platform-train interface. However, the present work considers passengers' safety as exposure to the virus due to interaction with fellow passengers during the journey.
- (iii) The paper proposes an integrated optimization model that minimizes passengers' interaction and boosts TOCs revenue via a novel seat assignment policy. It contemplates multi-level safety measures and efficient seat inventory control, respectively. This may help rail operators identify a balance between economy and safety and deduce an effective policy.

3. Problem description

We address a quantity-based railway RM problem, i.e., seat inventory management where passengers' safety is accorded high significance. The safety concerns the exposure to the virus through asymptomatic commuters during travel. The study aims to develop an optimization model that maximizes TOCs revenue by discharging an efficient seat inventory control and ensuring passengers' safety by minimizing interaction between passengers from highly infected cities and low infectious regions during the trip, i.e., maintaining adequate gap between commuters in seating space.

Given the demand requests and ticket price for the OD pairs of a train service, see Fig. 4, the seat inventory management attempts to identify an optimal allocation of seats to OD pairs and assignment of seats to passengers. This study utilizes a partitioned protection level control (PPLC) that groups seats into tickets before the booking period to administer seat availability. Further, PPLC also defines the protection level for each class. Each group is characterized by the number of seats and ticket information (boarding and alighting stations). Fig. 5, adapted from Yuan and Nie (2020), illustrates a simple example of partitioned booking limit control (PBLC) trivially equivalent to PPLC for six seats and five different stations (A, B, C, D, E) along a train route. Based on passenger demand and ticket pricing, a total of eight groups (dotted squares) are formed that maximize revenue and eventually generate 11 different tickets (booking IDs).

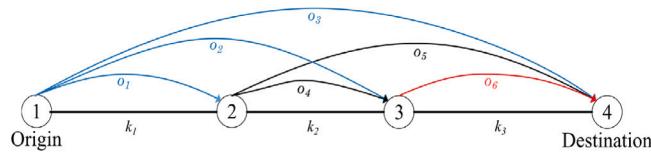


Fig. 4. A train service with sections $\{k_1, k_2, k_3\}$ and OD pairs $\{o_1, o_2, o_3, o_4, o_5, o_6\}$.

Ticket Pool										
Location:	A	B	C	D	E	Booking ID	Group	Seat No.	Start Stn.	End Stn.
						1	1	1	A	E
						2	1	2	A	E
						3	2	3	A	D
						4	3	3	D	E
						5	4	4	A	C
						6	4	5	A	C
						7	5	4	C	E
						8	5	5	C	E
						9	6	6	A	B
						10	7	6	B	D
						11	8	6	D	E

Figure 5 shows a sequence of six seats (1-6) at locations A-E. Seats 1-4 are at A, 5 at B, 6 at C, 7 at D, and 8 at E. Dotted rectangles group seats into tickets: ticket 1 covers seats 1-3 at A; ticket 2 covers seat 4 at A; ticket 3 covers seats 1-3 at A and seat 4 at B; ticket 4 covers seats 4-5 at A and seat 5 at B; ticket 5 covers seats 4-5 at A and seat 6 at C; ticket 6 covers seat 6 at C and seat 7 at D; ticket 7 covers seat 7 at D and seat 8 at E; ticket 8 covers seat 8 at E.

Fig. 5. Illustration of partitioned limit control.

Fig. 6 illustrates the process of ticket booking exploiting PPLC to administer seat availability. The booking mechanism assigns seats to passengers when ticket request information is received. A passenger ticket request for OD pair o is either accepted, provided a waitlisted ticket, or rejected based on the seat availability in the ticket pool and waitlist limit for OD pair o . Further, seat availability in the ticket pool and customer seat assignment is updated based on the reservation and cancellation requests. Thus, in case of high demand for an OD pair against the prescribed quota, a customer is provided with a waitlisted ticket and confirmed accordingly. A major drawback of PPLC is that it produces competent results under deterministic demand only. The travel demand is assumed to be deterministic and easily estimated by aggregating the previous year's data on final seat allocations and waitlisted passengers. On the other hand, the operational requirement of joint seat regulation in railways is easily assured by PPLC provided capacity constraints are met (Ciancimino et al., 1999; Yuan and Nie, 2020). Since a train runs through multiple sections along the route, the joint seat regulation ensures that passengers must be provided with the same seat at all sections of the itinerary.

To make the proposed optimization model sensitive to virus diffusion potential among fellow passengers, we utilize two criteria: (i) virus intensity at each city/station and (ii) interaction characteristics of passengers, i.e., cabin occupancy and interaction hours between fellow passengers. The passengers' seat assignment subsumes these criteria to form four levels of *virus diffusion risk*.

- (i) High: commuters with substantial difference in infection intensity of their origin cities are seated in different coaches. Since the air circulation system of coaches is independent, the coaches are treated as "bio-bubble". Fig. 7(a) depicts a high-risk situation where two passengers are assigned seats in different coaches.

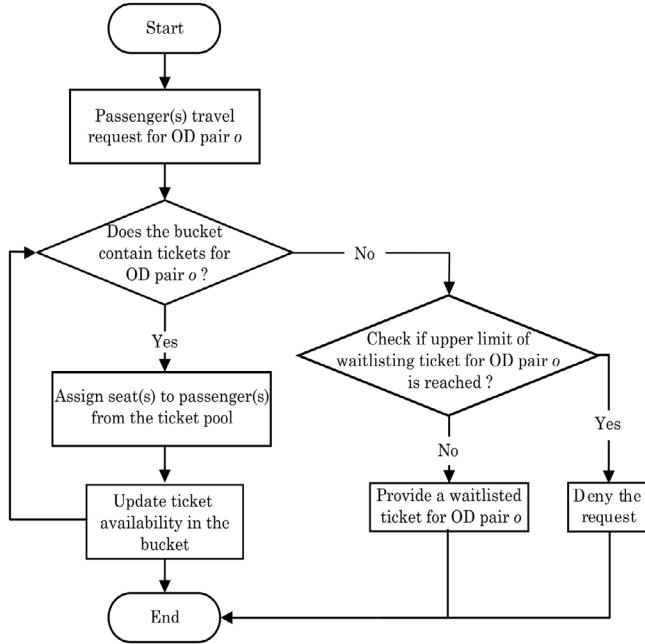


Fig. 6. PPLC ticket booking mechanism.

- (ii) Medium-High: under moderate variation in virus intensity of passengers' boarding city and interaction hours, passengers are allowed to travel in the same coach; however, they must maintain an adequate gap. Fig. 7(b) portrays a medium-high risk case where two passengers' seating is distanced by cabins within a coach.
- (iii) Medium-Low: passengers with minimal variation in infection intensity of their origin cities take seats in proximity. It may be considered as homogenization of cabin and coaches. A medium-low level situation is shown in Fig. 7(c), where passengers from comparable infection intensity cities are seated in proximity.
- (iv) Low: The above three approaches aim to homogenize the coaches based on virus intensity. This approach further minimizes the diffusion probability by uniformly distributing passengers across cabins at each section. Fig. 7(d) represents a low-risk scenario where passengers boarding from the same station are distributed uniformly within a coach.

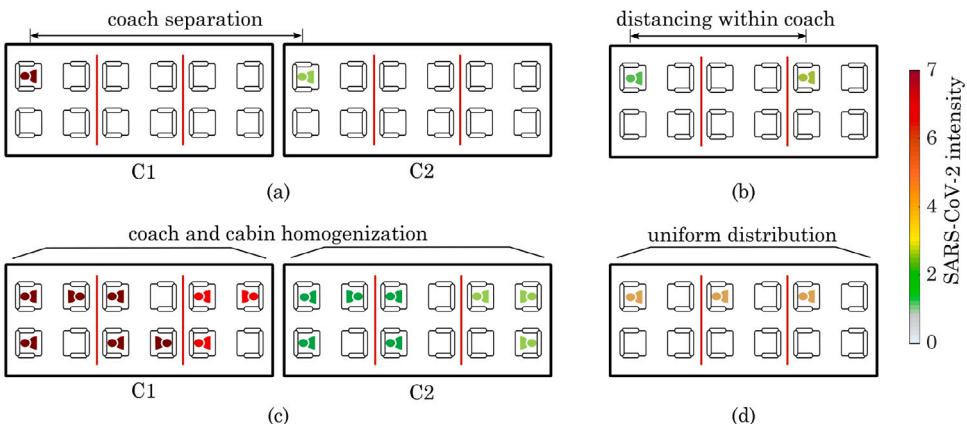


Fig. 7. Seat assignment under different levels of virus diffusion risk - (a) high; (b) medium-high; (c) medium-low; (d) low.

Some of the salient assumptions considered in this study are:

- (i) each train is considered independently — this implies that demand for the OD pairs of a train is independent of other trains;

- (ii) demand is assumed to be deterministic and is estimated as the sum of the actual number of passengers traveled and the number of waitlisted passengers on a similar day in the past for the given train. Thus, estimated demand does not include no-shows, and overall demand = total bookings + waitlists – cancellation requests;
- (iii) the ticket fare follows non-linear pricing, and fare per kilometer is generally higher for short distance OD pairs;
- (iv) higher the infection intensity variation between co-passengers, higher the chance of SARS-CoV-2 diffusion;
- (v) virus intensity variation among passengers boarding from the same station is negligible;
- (vi) the virus diffusion risk within a cabin is irrespective of the passengers' position inside the cabin. This is because the enclosed seating space of a cabin is too small for any distancing measure within the cabin to bring a substantial reduction in virus diffusion risk.

4. Model formulation

The primary decisions involve assigning seats to passengers of different OD pairs based on the susceptibility of SARS-CoV-2 diffusion, demand estimation, and ticket pricing. Since virus diffusion is controlled by distancing passengers boarding from different stations, we utilize decision variables and parameters that define the actual location of passenger's seats and obligatory gap requirements between them. Further, to incorporate a varying level of safety standards (discussed in Section 3), multiple sets and indicator variables are introduced. Tables 1 and 2 describe various notations and decision variables employed in the MILP model, respectively.

Table 1
Sets and parameters used in model formulation.

Notation	Description
N	Set of stations on the train route, $\{1, 2, \dots, n\}$, indexed by i and j
K	Set of sections between stations, $\{(i, j) i, j \in N, j = i + 1\}$, indexed by k
Q	Set of seating classes, indexed by q
O	Set of all OD pairs denoted by $\{(i, j) i, j \in N, i < j\}$, indexed by o and o'
O_k	Set of OD pairs o that overlap with section k
S_k	Set of OD pairs o having k as its starting section
F_o	Set of sections k in OD pair o except its first section
Ω^q	Set of OD pairs couple (o, o') that cannot occupy seats in the same coach of class q
Θ^q	Set of OD pairs couple (o, o') that may occupy seats in the same coach of class q
Φ^q	Set of OD pairs couple (o, o') that may occupy seats in the same cabin of a coach of class q
Ψ_r^q	Set of OD pairs couple (o, o') whose passengers' seat assignment require a minimum gap of r cabins in a coach of class q
C^q	Set of coaches of class q , $\{1, 2, \dots, m^q\}$, indexed by c
B^q	Set of cabins in a coach of class q , $\{1, 2, \dots, m^q\}$, indexed by b
l^q	Lower limit on the number of coaches of class q attached to train
v^q	Cabin capacity of class q
t^q	Seat capacity in a coach of class q , i.e., $t^q = m^q \times v^q$
L	Maximum number of coaches in a train
s_o	Starting section for OD pair o , $s_o \in K$
p_o^q	Ticket price for OD pair o in class q
d_o^q	Passenger demand for OD pair o in class q
ω	Minimum fraction of demand to be satisfied
qc	Product that represents coach c of class q
qcb	Product that represents cabin b of coach c in class q
$\alpha_{oo'}^{qc}$	penalty if OD pairs couple $(o, o') \in \Omega^q$ occupy seats of the product qc
$\beta_{oo'}^{qcb}$	Penalty if OD pairs couple $(o, o') \in \Phi^q$ occupy seats of the product qcb
ϵ	Target number of passengers in a cabin to maintain a uniform distribution
σ	Penalty per unit increase in passenger assignment exceeding ϵ

Table 2
Decision variables used for model formulation.

Notation	Description
h^{qc}	=1 if product qc is used for seat assignment; 0 otherwise
y_{ok}^{qcb}	Number of seats of the product qcb allocated for passengers of OD pair o in section k
$z_{o'}^{qc}$	=1 if any passenger of OD pair o is assigned to seat of the product qc ; 0 otherwise
g_o^{qcb}	=1 if any passenger of OD pair o is assigned to seat of the product qcb ; 0 otherwise
$\gamma_{oo'}^{qc}$	=1 if passengers of OD pairs couple (o, o') are assigned to seats of the product qc ; 0 otherwise
$\mu_{oo'}^{qcb}$	=1 if passengers of OD pairs couple (o, o') are assigned to seats of the product qcb ; 0 otherwise
$\gamma_k^{qcb+}, \gamma_k^{qcb-}$	Deviation from target assignment ϵ for the product qcb in each section k

Objective function

$$\text{Max } z = \sum_{o \in O} \sum_{q \in Q} \sum_{c \in C^q} \sum_{b \in B^q} p_o^q y_{os_o}^{qcb} - \sum_{q \in Q} \sum_{c \in C^q} \sum_{(o, o') \in \Theta^q} \alpha_{oo'}^{qc} y_{oo'}^{qc} - \sum_{q \in Q} \sum_{c \in C^q} \sum_{b \in B^q} \sum_{(o, o') \in \Phi^q} \beta_{oo'}^{qcb} \mu_{oo'}^{qcb} - \sigma \sum_{k \in K} \sum_{q \in Q} \sum_{c \in C^q} \sum_{b \in B^q} \gamma_k^{qcb+} - \sigma \sum_{k \in K} \sum_{q \in Q} \sum_{c \in C^q} \sum_{b \in B^q} \gamma_k^{qcb-} \quad (1)$$

The objective function (1) contains four terms: the first one indicates revenue generation due to seat allocation to different OD pairs. The following two terms represent penalties associated with undesirable seat assignment to different OD pairs within coaches and cabins, respectively. The value of penalty parameters α and β depend on the difference in infection intensity at the starting station of OD pairs o and o' and total interaction hours between them. Further, for the given OD pairs (o, o') , penalties $\alpha < \beta$ as virus diffusion risk in closed cabins is significantly higher. The last term aims to reduce the crowding of some cabins while others are being under-occupied, i.e., attempts to create a uniform distribution of passengers across cabins. This may enable virtual seat isolation under low demand for some sections of the train journey. Therefore, the objective function maximizes the overall revenue through seat inventory control and homogenizes passenger distribution within coaches and cabins based on the severity of virus diffusion risk.

Capacity constraints

$$\sum_{o \in O_k} y_{ok}^{qcb} \leq v^q h^{qc} \quad \forall k \in K, q \in Q, c \in C^q, b \in B^q \quad (2)$$

The cabin capacity constraints (2) ensure that total seat allocation to different OD pairs must satisfy cabin capacity in each section. Further, the overall capacity of a class can be determined by constraints (2) and (7).

Service constraints

$$\sum_{c \in C^q} \sum_{b \in B^q} y_{os_o}^{qcb} \leq d_o^q \quad \forall o \in O, q \in Q \quad (3)$$

$$\sum_{c \in C^q} \sum_{b \in B^q} y_{os_o}^{qcb} \geq \omega d_o^q \quad \forall q \in Q, o = (1, n) \quad (4)$$

$$\sum_{c \in C^q} h^{qc} \geq l^q \quad \forall q \in Q \quad (5)$$

Constraints (3) ensure that total seats allocated to OD pairs should not exceed their demand. Constraints (4) are the additional service constraints to provide a minimum service level guarantee for end-to-end OD demand. As long-distance train service is generally designated to meet passenger demand for end-to-end cities, allocating too many seats for ODs from intermediate stations will be detrimental to passenger service quality. In another scenario, when the ticket fare is non-linear (high fare per km for short-length ODs), intermediate ODs will be preferred as they are more profitable than end-to-end OD. Constraints (5) define the lower bound on the number of coaches for each class and deliver a minimum protection level.

Operational constraints

$$y_{ok}^{qcb} = y_{os_o}^{qcb} \quad \forall o \in O, k \in F_o, q \in Q, c \in C^q, b \in B^q \quad (6)$$

$$\sum_{q \in Q} \sum_{c \in C^q} h^{qc} \leq L \quad (7)$$

The operational constraints (6) and (7) define operative requirements and limitations of TOCs, respectively. Constraints (6) along with capacity restriction (2) ensure the joint seat regulation of rail operations, i.e., a passenger must complete her journey on the same seat. Constraint (7) ensures that the maximum number of coaches coupled to a train should not exceed a certain limit (generally determined by engine capacity, minimum platform stretch along its route, etc.).

Indicator forcing constraints

$$h^{qc} \leq \sum_{o \in O} \sum_{b \in B^q} y_{os_o}^{qcb} \quad \forall q \in Q, c \in C^q \quad (8)$$

$$\sum_{b \in B^q} y_{os_o}^{qcb} \leq t^q z_o^{qc} \quad \forall o \in O, q \in Q, c \in C^q \quad (9)$$

$$z_o^{qc} \leq \sum_{b \in B^q} y_{os_o}^{qcb} \quad \forall o \in O, q \in Q, c \in C^q \quad (10)$$

$$y_{os_o}^{qcb} \leq v^q g_o^{qcb} \quad \forall o \in O, q \in Q, c \in C^q, b \in B^q \quad (11)$$

$$g_o^{qcb} \leq y_{os_o}^{qcb} \quad \forall o \in O, q \in Q, c \in C^q, b \in B^q \quad (12)$$

Constraints (8) affirm that a coach c of class q will be coupled to the train only if any passenger is allocated a seat in product qc . Constraints (9) and (10) link variables z_o^{qc} with $y_{os_o}^{qcb}$. Similarly, constraints (11) and (12) relate variables g_o^{qcb} with $y_{os_o}^{qcb}$.

Virus diffusion limiting constraints

$$z_o^{qc} + z_{o'}^{qc} \leq 1 \quad \forall q \in Q, c \in C^q, (o, o') \in \Omega^q \quad (13)$$

$$g_o^{qcb} + g_{o'}^{qcb} \leq 1 \quad \forall q \in Q, c \in C^q, b \in B^q, r = \{1, \dots, m^q - 1\},$$

$$b' = \{\max\{1, b - r\}, \dots, \min\{m^q, b + r\}\}, (o, o') \in \Psi_r^q \quad (14)$$

$$z_o^{qc} + z_{o'}^{qc} - v_{oo'}^{qc} \leq 1 \quad \forall q \in Q, c \in C^q, (o, o') \in \Theta^q \quad (15)$$

$$\begin{aligned} g_o^{qcb} + g_{o'}^{qcb} - \mu_{oo'}^{qcb} &\leq 1 \\ \sum_{o \in O_k} y_{ok}^{qcb} + \gamma_k^{qcb^-} - \gamma_k^{qcb^+} &= \epsilon \end{aligned}$$

$$\forall q \in Q, c \in C^q, b \in B^q, (o, o') \in \Phi^q \quad (16)$$

$$\forall k \in K, q \in Q, c \in C^q, b \in B^q \quad (17)$$

The passenger safety constraints (13)–(17) ensure separation of passengers boarding from different cities in the seating space as well as their uniform distribution throughout the train. Constraints (13) make sure passengers from low infection zone are not allotted seats with high infection zone passengers in the same coach. Constraints (14) guarantee a minimum gap of r cabins within a coach between passengers of medium risk category. Higher the virus diffusion potential larger the gap. Constraints (15) and (16) along with the penalties in the objective function strive to homogenize seat allocation within cabins and coaches, respectively. The homogenization is in terms of the boarding station of passengers and virus diffusion potential between different OD pairs. Finally, constraints (17) along with the fourth term in the objective function (1) minimizes deviation in the number of seat assignments in each cabin from the target (ϵ). It aims to perform uniform distribution of passengers throughout the train. The value of ϵ can be derived from the fact that under best settings for minimizing virus outbreak, the number of passengers in each cabin at every section of train journey should be at most 1. This may be realized only under a weak demand scenario. Hence, this requirement is modeled as a goal rather than a hard constraint.

Variable domain

$$\begin{aligned} y_{os_o}^{qcb} &\in \mathbb{Z}_0^+ & \forall o \in O, q \in Q, c \in C^q, b \in B^q & (18) \\ y_{ok}^{qcb} &\geq 0 & \forall o \in O, k \in F_o, q \in Q, c \in C^q, b \in B^q & (19) \\ \gamma_k^{qcb^+}, \gamma_k^{qcb^-} &\geq 0 & \forall k \in K, q \in Q, c \in C^q, b \in B^q & (20) \\ z_o^{qc} &\in \{0, 1\} & \forall o \in O, q \in Q, c \in C^q & (21) \\ g_o^{qc} &\in \{0, 1\} & \forall o \in O, q \in Q, c \in C^q, b \in B^q & (22) \\ h^{qc} &\in \{0, 1\} & \forall q \in Q, c \in C^q & (23) \\ 0 \leq v_{oo'}^q &\leq 1 & \forall q \in Q, (o, o') \in \Theta^q & (24) \\ 0 \leq \mu_{oo'}^{qc} &\leq 1 & \forall q \in Q, c \in C^q, (o, o') \in \Phi^q & (25) \end{aligned}$$

Constraints (18) to (25) impose nonnegativity and integrality requirements to the decision variables. Constraints (6) and (18) imply that y -variables except for the starting section of an OD pairs will be automatically integer-valued. Further, we do not explicitly impose binary restrictions on v and μ variables since constraints (15), (16), (24), (25) and objective function (1) together with the binary-valued z and g variables force v and μ variables to be binary.

The optimal solution to this problem provides the amount of demand to be accepted for each OD pair that maximizes TOCs revenue and the actual seat assignment of passengers of all OD pairs to cabins such that the diffusion of SARS-CoV-2 during travel is minimized. The computational experience with the MILP model is presented in the next section.

5. Computational study

This section aims to show the validity of the proposed model using computational experiments on real-life instances.

5.1. Data

We consider the New Delhi (NDLS)–Howrah (HWH) corridor of Indian Railways for our computational study. However, our model can be applied to any other railway network, discussed at the end of this section. The NDLS–HWH route stretches over 1454 km and is one of the busiest corridors of Indian Railways. Fig. 8 illustrates the route of the NDLS–HWH corridor as well as the SARS-CoV-2 infection intensity at different districts along the line. The corridor runs multiple trains having different stop plans. Since the study considers each train independently, we perform several computational tests for a single train; however, the study can be easily applied to any other train. The passenger demand data was obtained from the Centre for Railway Information System (CRIS), Indian Railways. The ticket fare for different OD pairs is based on the baseline fare mentioned in Railways (2020). The Indian Railways generally exploit a *telescopic* pricing strategy, a non-linear pricing model where ticket price per kilometer is higher for shorter length OD pairs. Further, the penalty parameters α and β , discussed in Table 1, follow a telescopic strategy and are relative to ticket pricing. Finally, the minimum cabin gap between OD pairs within a coach varies from 1 to $(m^q \cdot 2)$.

Data pertaining to train and coach configuration utilized in the study are detailed in Table 3. Concerning stop plan and service type, the train has eight stoppages along the route and encompasses three different seating classes (1AC, 2AC and 3AC). The ticket price per seat in 1AC is higher than that of 2AC and 3AC for the same OD pair. Further, the 1AC is considered a premium class, and the operator places a high degree of demand satisfaction for 1AC compared to other classes. The protection limit for each class is based on passenger demand and the maximum permissible number of coaches. The lower limit assures a minimum demand satisfaction for each class, whereas TOC's operational practice governs the upper limit. The infection intensity at different stopping stations are reported in Table 4.

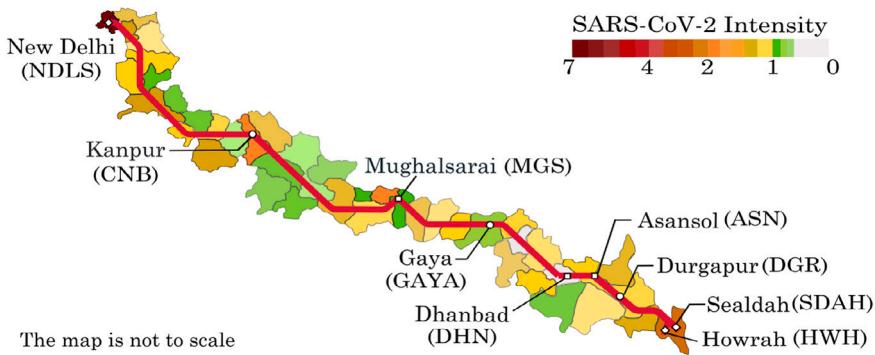


Fig. 8. NDLS–HWH corridor of Indian Railways (data for SARS-CoV-2 cases fetched from covid19india.org dated July 14, 2021).

Table 3
Parameter settings for train and coach configuration.

Class	Number of cabins		Total seats	Protection limit	
	Per coach	Per cabin		Lower	Upper
1AC	6	4	24	1	4
2AC	8	6	48	3	6
3AC	9	8	72	5	10

Table 4
Infection intensity at different stopping stations of the train under investigation.

Station	NDLS	CNB	MGS	GAYA	DHN	ASN	DGR	SDAH
Confirmed cases ^a	1435	82.81	1.61	3.38	1.64	95.4	95.4	309
Infection intensity ^b	8.55	1.81	0.83	0.77	0.61	1.23	1.23	2.07

Notes:

^aIn thousands (accessed on July 14 2021 from covid19india.org).

^b(number of cases/total population) × 100.

To identify overlapping OD pairs at a section, we draw an interval graph as shown in [Fig. 9](#). Each rectangular box represents an OD pair, and the region between two consecutive stations signifies a section. The overlapping OD pairs at a section can be easily obtained by drawing a perpendicular bisector at a section and observing the intersecting rectangular boxes.

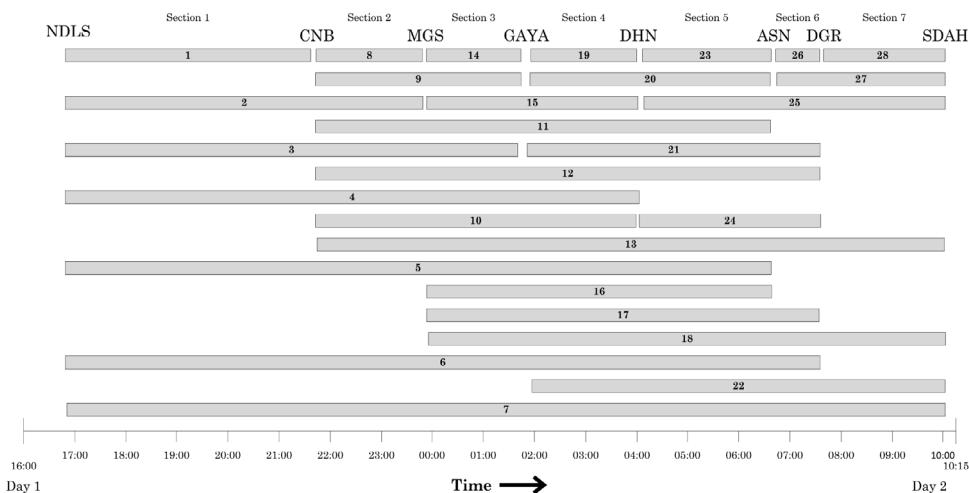


Fig. 9. Interval graph for OD pairs.

Next, to extend the applicability of the proposed model to other countries' rail operations, we present the following conceptualization. [Fig. 10](#) presents a general coach configuration of China HSR and regional rails in major European countries. Since these

trains do not have a physical cabin configuration, adjacent seats can be considered as a virtual cabin; see the dotted boxes in Fig. 10. The physical distancing can then be defined between virtual cabins based on local infection levels. Moreover, certain long-distance sleeper trains in China and regional night-jet trains in Europe have a coach configuration and stoppage plan similar to the case presented in this paper.

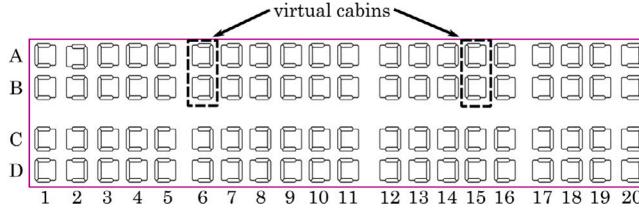


Fig. 10. A general seat map of China HSR and regional rails in Europe.

5.2. Results and discussion

The MILP model has been implemented using Visual C++, and the callable library of CPLEX 12.5.1 is used for solving the MILP applying branch-and-cut procedure with default settings. The experiments have been conducted on a Pentium Core i7 processor with 3.0 GHz clock speed running Windows 10.

To affirm the effectiveness of the proposed model on virus diffusion control, we create different test scenarios, detailed in Table 5. The major difference between these scenarios is capacity utilization (% of cabin capacity used for seat allocation) and the model used for seat assignment. Scenario S1 contemplates 50% capacity utilization and random assignment of seats in coaches, i.e., without considering the virus diffusion potential of the passengers. On the other hand, scenarios S2, S3 and S4 utilize our proposed seat allocation-cum-assignment model with 50%, 75% and 100% capacity utilization, respectively. Further, the minimum service guarantee (ω) for the end-to-end OD pair is set at 0.2 for all scenarios as a higher value may produce infeasibility in S1 and S2. Additionally, to perform a relative comparison among all the scenarios, the basic modeling parameters discussed in Table 1 are held constant in each.

Table 5
Different test scenarios.

Scenario	Capacity utilization	Seat assignment model
S1	50%	R
S2	50%	M
S3	75%	M
S4	100%	M

Note: R-random seat assignment; M-proposed MILP model.

To assess virus diffusion potential, we compute standard deviation (SD) and range of infection intensity in each coach at each section based on the actual seat assignment and virus intensity at passengers' boarding stations. The SD and range assist in identifying population characteristics across coaches, i.e., homogeneous or heterogeneous in terms of infection intensity. A large value of SD and range indicates the mixing of passengers from high and low-intensity locations and suggests a high possibility of virus diffusion. In contrast, a small value indicates passengers from similar infection intensity locations are seated in proximity and anticipate a controlled diffusion. Fig. 11(a)–(d) illustrate the SD and total revenue under scenarios S1–S4, respectively. Further, Fig. 12(a)–(d) report the range of virus intensity under scenarios S1–S4, respectively.

It is well evident from Figs. 11 and 12 that the SD and range of virus intensity are considerably low in scenario S2 than S1, while the reduction in revenue is around 5% only. Further, with increment in capacity utilization, i.e., scenarios S3 and S4, the increase in SD and range of virus intensity is negligible compared to scenario S2, see Figs. 11(c),(d) and 12(c),(d). Moreover, the surge in revenue is around 30%–65% compared to scenarios S1 and S2, see Table 6. This confirms that the proposed model produces competent results in restricting virus diffusion and improving revenue under varying capacity levels. Further, we can assert that merely reducing capacity utilization (50%) may not be an effective strategy to control virus outbreak, and TOCs may require additional measures. Table 6 also present the computational performance where the CPU run time was set to 3600 seconds, and optimality gap is reported if the MILP model is unsolved in this time limit.

Next, we investigate the actual seat allocation to OD pairs and passengers' seat assignment for scenario S4. Table 7 reports seat allocation to different OD pairs, where empty cells indicate OD pairs having zero demand for that seat class. It is interesting to note that if seat allocation for all the incoming and outgoing OD pairs for a station is zero, the train may be exempted from stopping at that station. Thus, the model may aid in redefining the train stoppage plan under pandemics. From Table 7, we see that majority of allocation is for end-to-end OD pair (OD #7). We also observe that all the demand for 1AC is satisfied in contrast to 2AC and 3AC. This may be due to a higher protection level for class 1AC relative to the demand.

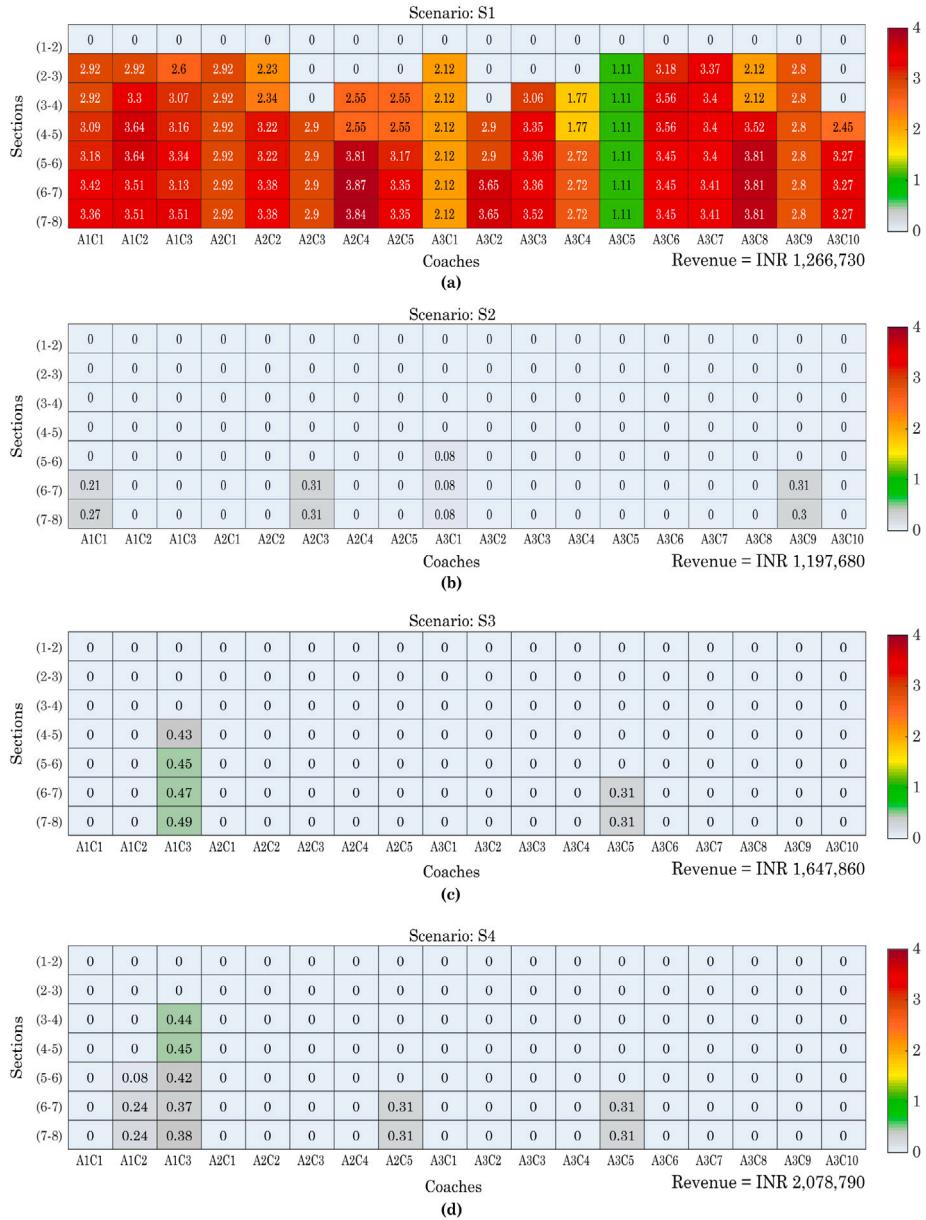


Fig. 11. Standard deviation of virus intensity in each coach and at each section under scenarios - (a) 50% capacity utilization and random seat assignment; (b), (c) and (d) seat assignment using proposed model with 50%, 75% and 100% capacity utilization, respectively.

Further, we review passengers' seat assignments where most coaches are occupied by end-to-end OD pair passengers' due to high demand. Fig. 13 illustrates seat assignment in different coaches of 2AC where there is a mix of passengers boarding from different stations.

Some of the critical observations based on the seat assignment in Fig. 13 are:

- (i) A coach level isolation between passengers of CNB and MGS (Section 3 onwards in coaches C₁-C₂) is maintained as the risk of virus diffusion is high.
- (ii) One cabin gap between passengers of MGS and GAYA inside a coach (coach C₂, cabins b₄-b₆), since there is a moderate risk of virus transmission among them.
- (iii) Similarly, passengers boarding from ASN and DHN come under medium-high risk category and maintain two-cabin gap within a coach (coach C₃, cabins b₂-b₅).
- (iv) Uniform distribution of passenger across cabins (coaches C₁ and C₂, Section 1) as the demand for OD# 1 (NDLS-CNB) is low.

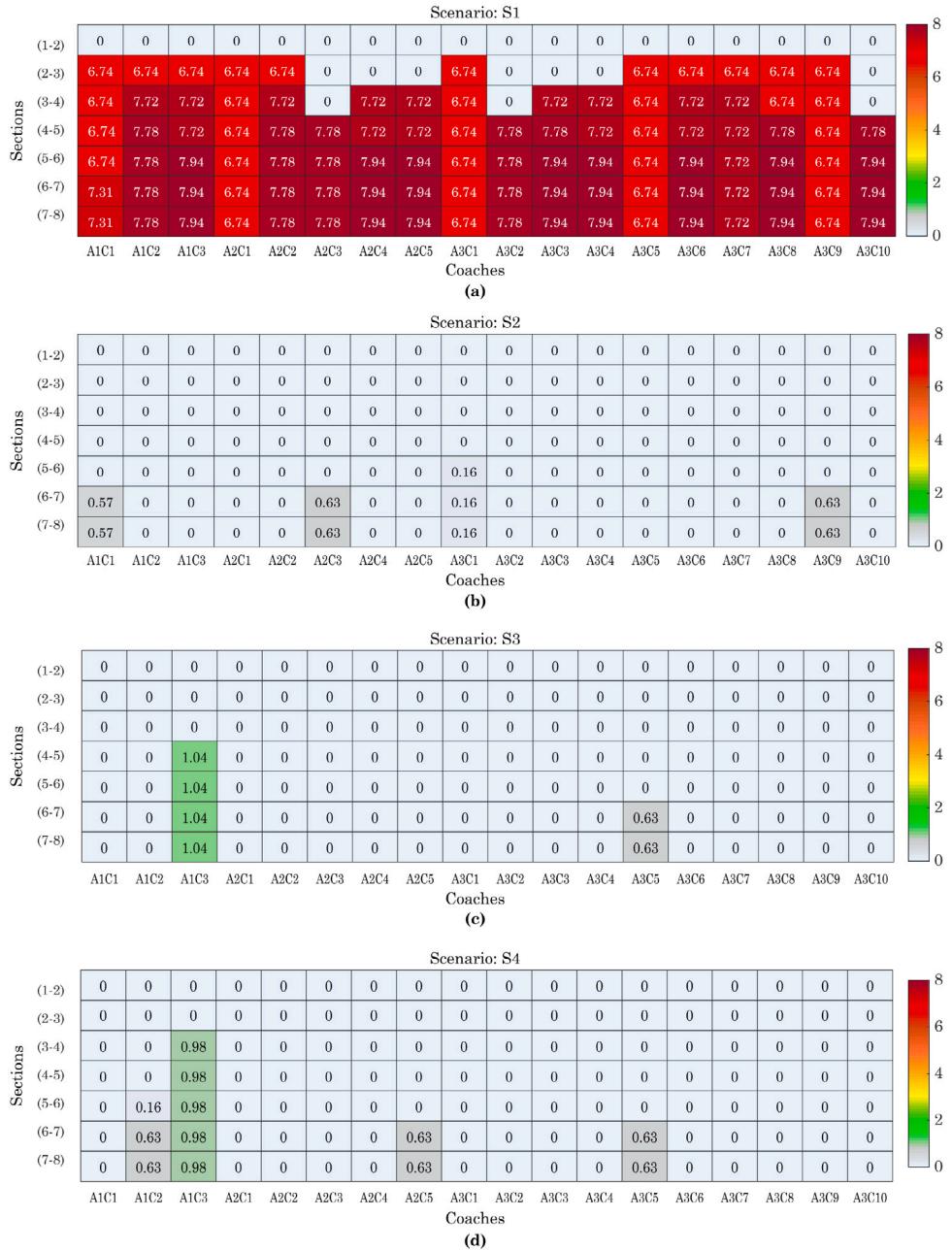


Fig. 12. Range of virus intensity in each coach at each section under scenarios - (a) 50% capacity utilization and random seat assignment; (b), (c) and (d) seat assignment using proposed model with 50%, 75% and 100% capacity utilization, respectively.

Table 6
Computational performance for different scenarios.

Scenario	Revenue (INR)	Demand rejections	% Optimality gap
S1	1,266,730	896	0.00
S2	1,197,680	957	1.62
S3	1,647,860	753	1.65
S4	2,078,790	528	1.78

Finally, to analyze the effect of joint optimization of train composition and seat allocation, we create different test scenarios by varying the protection level, see Table 8. Scenario S5 relaxes the minimum protection level, whereas S6 assumes a similar protection

Table 7
Optimal seat allocation to OD pairs under scenario S4.

OD pair	Org.	Dest.	Demand [Satisfied, Unsatisfied]			OD pair	Org.	Dest.	Demand [Satisfied, Unsatisfied]		
			1AC	2AC	3AC				1AC	2AC	3AC
1	NDLS	CNB	[4,0]	[9,0]	[46,0]	15	MGS	DHN	[1,0]	[0,1]	[0,1]
2	NDLS	MGS	[1,0]	[6,0]	[0,17]	16	MGS	ASN	[1,0]	[0,1]	[0,1]
3	NDLS	GAYA	[4,0]	[11,0]	[28,7]	17	MGS	DGR	[0,1]	[0,1]	[0,1]
4	NDLS	DHN	[1,0]	[11,0]	[44,0]	18	MGS	SDAH	[1,0]	[6,3]	[0,23]
5	NDLS	ASN	[1,0]	[18,0]	[0,57]	19	GAYA	DHN		[0,1]	
6	NDLS	DGR	[1,0]	[1,0]	[0,42]	20	GAYA	ASN		[0,1]	
7	NDLS	SDAH	[19,0]	[125,0]	[576,318]	21	GAYA	DGR		[0,1]	
8	CNB	MGS		[1,0]	[0,1]	22	GAYA	SDAH	[2,0]	[0,7]	[0,17]
9	CNB	GAYA	[1,0]	[1,0]	[0,1]	23	DHN	ASN			
10	CNB	DHN	[1,0]	[1,0]	[0,1]	24	DHN	DGR			
11	CNB	ASN	[1,0]	[1,0]	[0,1]	25	DHN	SDAH	[1,0]	[6,2]	[20,0]
12	CNB	DGR	[1,0]	[1,0]	[0,1]	26	ASN	DGR		[0,6]	
13	CNB	SDAH	[4,0]	[12,3]	[72,1]	27	ASN	SDAH	[1,0]	[0,5]	[13,6]
14	MGS	GAYA				28	DGR	SDAH	[1,0]	[1,0]	[3,0]



Fig. 13. Passengers seat assignment for a train in various coaches of 2AC under scenario S4..

Table 8
Scenarios to analyze effect of protection level.

Scenario	Capacity Utilization	End-to-end OD pair demand fulfillment (ω)	Protection level [LB,UB]		
			1AC	2AC	3AC
S5	100%	0.5	[0,18]	[0,18]	[0,18]
S6	100%	0.5	[1,4]	[3,6]	[5,10]

level defined in [Table 3](#). The value of ω for the end-to-end OD pair and the maximum number of coaches is fixed at 0.5 and 18, respectively. We perform multiple tests on scenarios S5 and S6 by changing the magnitude of demand and analyze its effect on the revenue and train composition. The demand is varied from 0.1 to 1.5 times the base demand with an increment of 0.10 for all OD

pairs. All the safety regulations discussed in Section 3 are ensured in both scenarios. Fig. 14(a),(b) highlight the effect of demand variation on revenue and train composition under both the scenarios (S5 and S6), respectively.

From Fig. 14(a), we observe an increase in revenue with a rise in demand in both scenarios S5 and S6. However, any increment in demand beyond its base value does not substantially improve revenue. This is primarily because the maximum coach limit for the train is reached. Moreover, we observe that the revenue is slightly higher in scenario S5, and there is a change in train composition with every increment in demand up to its base value, see Fig. 14(a),(b). The composition change is due to an increase in 3AC coaches and a simultaneous decrease of 2AC and 1AC coaches. This is against the general presumption that 1AC coaches are more profitable to TOC. Additional investigation reveals that, although the fare in 1AC and 2AC classes is about 2.4 and 1.4 times expensive than 3AC, the capacity of each coach of 3AC is 3.0 and 1.5 times higher than that of 1AC and 2AC. Therefore, every addition of a 3AC coach to the train is profitable to TOC against 1AC and 2AC coaches. This confirms that our model is sensitive to all the classes while maximizing revenue, as it is developed to be a multi-class optimization model.

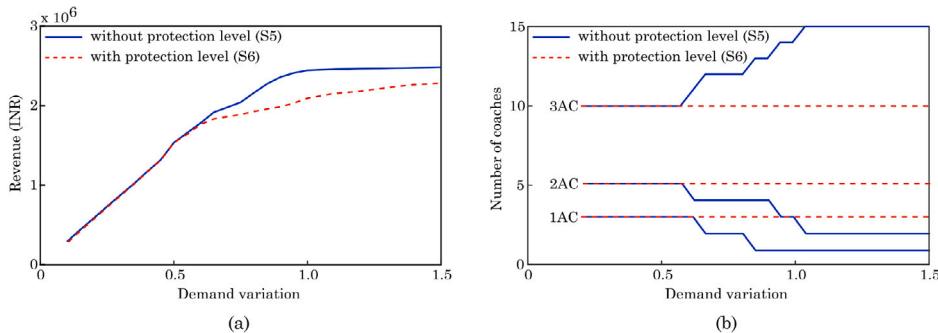


Fig. 14. Effect of variation in demand magnitude - (a) revenue and (b) train composition.

6. Conclusions

The SARS-CoV-2 pandemic has created an emergency condition worldwide, and usually, mathematical methods are known to be a reliable tool for combating such pandemics. The use of mathematical models in public transport with SARS-CoV-2 data enables operators to plan services such that the risk of virus diffusion during travel is minimized. Most articles published so far addressed new strategy designs such as no ticket checking, no restaurants at stations, etc. to control virus spread. Few studies utilized simulation-based tools to layout airlines' operations (boarding and deboarding) and effectively plan passenger movement trajectories that reduce passengers' contact. These early preventive measures might be followed for a long time to restrain virus spread.

To the best of our knowledge, this is the first attempt to utilize a mathematical optimization model that restrains virus diffusion via seat assignment and maximizes TOCs revenue through seat allocation to different OD pairs. The novel seat assignment policy effectively reduces virus diffusion by maintaining a sufficient gap between passengers and homogenizing seat distribution relative to infection intensity within coaches and cabins. Further, computational tests exhibit that even under full operating capacity, the proposed model outperforms the strategy to operate at 50% capacity only (Schraer, 2020). The benefits from our model in countering the diffusion of the SARS-CoV-2 virus may not be immediately noticeable; nevertheless, it will have a significant long-term impact on the post-SARS-CoV-2 pandemic control and operators' sustainability.

The results of the proposed model are highly encouraging, such that it calls attention to future research prospects and the importance of a new facet, “Safety in Revenue Management” for public transport. In continuation with the proposed seat assignment policy, we expect the present model may further strengthen passengers' safety by exploiting two-dimensional distancing, i.e., along the length and width of a cabin or coach based on coach configuration. The two-dimensional distancing is a seat-based control where the gap between passengers relies on individual seats. Moreover, some cutting-edge technology can be employed to obtain real-time data on passengers' vulnerability to the virus and execute a real-time seat assignment. For example, Chinese authorities exploit novel facial recognition technology to stifle virus outbreaks (Cadell, 2020). This real-time individual passenger-centric control may enhance safety against a city-based control where all the passengers boarding from a city are assumed to have a similar vulnerability to the virus.

Public transport operators (such as airlines) are investing heavily in health insurances related to SARS-CoV-2 to entice passengers. Since our seat assignment policy substantially reduces the risk of virus spread, the premium paid by the operator can be minimized, thereby making the operator competitive. A similar study prospect can be carried out for airlines or other public transport sectors having multiple legs in a journey. Since airplanes encompass a centralized air circulation with a single closed seating compartment, seat distancing constraints within a coach similar to our model can be utilized to minimize virus diffusion among passengers, see constraints (14).

Finally, we believe that this study opens up a plethora of new research topics in railway strategic planning that assist in reducing virus spread. For example, rail operators may develop a stoppage plan to contain the spread of SARS-CoV-2. In such a scenario, a group of train services stops at highly infectious cities only while others cater to the demand of medium-low infectious cities. Additionally, some connecting trains can be introduced to cater to the demand between high and medium infectious cities. Another interesting problem to explore will be seat assignment for group reservations while minimizing virus diffusion.

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References

- Armstrong, A., Meissner, J., 2010. Railway Revenue Management: Overview and Models. Working Paper, The Department of Management Science.
- Bharill, R., Rangaraj, N., 2008. Revenue management in railway operations: A study of the Rajdhani express, Indian railways. *Transp. Res.* A 42 (9), 1195–1207.
- Cadell, C., 2020. China's coronavirus campaign offers glimpse into surveillance system. URL: <https://www.reuters.com/article/us-health-coronavirus-china-surveillance-idUSKBN2320LZ>.
- Carpenter, T.G., 1994. The Environmental Impact of Railways. John Wiley & Sons, Chichester, England.
- Chang, Y.-H., Yeh, C.-H., 2004. A multiobjective planning model for intercity train seat allocation. *J. Adv. Transp.* 38 (2), 115–132.
- Chinazzi, M., Davis, J.T., Ajelli, M., Gioannini, C., Litvinova, M., Merler, S., Y Piontti, A.P., Mu, K., Rossi, L., Sun, K., et al., 2020. The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. *Science* 368 (6489), 395–400.
- Choerunnisa, D., Maula, F., Iman, H., 2020. The vulnerability of COVID-19 pandemic based on urban density (a case study of the core urban area in Cirebon city, west Java). In: IOP Conference Series: Earth and Environmental Science, Vol. 592. IOP Publishing, 012036.
- Ciancimino, A., Inzerillo, G., Lucidi, S., Palagi, L., 1999. A mathematical programming approach for the solution of the railway yield management problem. *Transp. Sci.* 33 (2), 168–181.
- EASA, 2021. COVID-19 aviation health safety protocol. URL: <https://www.easa.europa.eu/sites/default/files/dfu/Joint%20EASA-ECDC%20Aviation%20Health%20Safety%20Protocol%20Issue%203.pdf>.
- EURNEX, 2020. Impact of COVID-19 on rail. URL: http://www.eurnex.org/wp-content/uploads/2020/06/Covid_Rail_AT.pdf.
- Eurostat, 2021. Passengers transported. data retrieved from Eurostat. https://ec.europa.eu/eurostat/databrowser/view/RAIL_PA_QUARTAL/bookmark/table?lang=en&bookmarkId=bc01784f-47d7-4f24-8a0a-798f4cd7c966.
- Frost, N., 2020. How Covid-19 could change plane boarding. URL: <https://www.bbc.com/worklife/article/20200612-why-coronavirus-will-change-how-we-board-a-plane>.
- Gönsch, J., 2017. A survey on risk-averse and robust revenue management. *European J. Oper. Res.* 263 (2), 337–348.
- Gopalakrishnan, R., Rangaraj, N., 2010. Capacity management on long-distance passenger trains of Indian railways. *Interfaces* 40 (4), 291–302.
- Gorman, M.F., 2015. Operations research in rail pricing and revenue management. In: Handbook of Operations Research Applications at Railroads. Springer, pp. 243–254.
- Hensher, D.A., 1998. Intercity rail services: A nested logit stated choice analysis of pricing options. *J. Adv. Transp.* 32 (2), 130–151.
- Hu, M., Lin, H., Wang, J., Xu, C., Tatem, A.J., Meng, B., Zhang, X., Liu, Y., Wang, P., Wu, G., et al., 2020a. The risk of COVID-19 transmission in train passengers: an epidemiological and modelling study. *Clin. Infect. Dis.*
- Hu, X., Shi, F., Xu, G., Qin, J., 2020b. Joint optimization of pricing and seat allocation with multistage and discriminatory strategies in high-speed rail networks. *Comput. Ind. Eng.* 148, 106690.
- Hulse, J., 2013. Intrusion detection and prevention technologies available to rail transit. In: Proceedings of the 2013 APTA Rail Conference, Philadelphia, PA, USA, pp. 2–5.
- Hunter-Zaworski, K., 2017. Analysis of passenger incident data from five rail transit systems. *Safety* 3 (3), 21.
- ICAO, 2020. Effects of novel coronavirus (COVID-19) on civil aviation: Economic impact analysis. URL: <https://digitallibrary.un.org/record/3859860?ln=en>.
- Indigo, 2020. Travel guidelines during COVID-19. URL: <https://www.goindigo.in/information/corona-virus-travel-restrictions.html>.
- Kartal, M.T., Depren, O., Depren, S.K., 2021. The relationship between mobility and COVID-19 pandemic: Daily evidence from an emerging country by causality analysis. *Transp. Res. Interdiscip. Perspect.* 10, 100366.
- Klein, R., Koch, S., Steinhardt, C., Strauss, A.K., 2020. A review of revenue management: Recent generalizations and advances in industry applications. *European J. Oper. Res.* 284 (2), 397–412.
- Lam, W.H., Cheung, C., Poon, Y., 1998. A study of train dwelling time at the Hong Kong mass transit railway system. *J. Adv. Transp.* 32 (3), 285–295.
- Lin, D.-Y., Fang, J.-H., Huang, K.-L., 2019. Passenger assignment and pricing strategy for a passenger railway transportation system. *Transp. Lett.* 11 (6), 320–331.
- Love, A., 2020. Covid-19: could the pandemic bolster international rail travel? URL: <https://www.railway-technology.com/features/covid-impact-railways/>.
- Milan, J., 1993. A model of competition between high speed rail and air transport. *Transp. Plan. Technol.* 17 (1), 1–23.
- Milne, R.J., Cotfas, L.-A., Delcea, C., Crăciun, L., Molănescu, A.-G., 2020a. Adapting the reverse pyramid airplane boarding method for social distancing in times of COVID-19. *PLoS One* 15 (11), e0242131.
- Milne, R.J., Delcea, C., Cotfas, L.-A., Ioanăs, C., 2020b. Evaluation of boarding methods adapted for social distancing when using apron buses. *IEEE Access* 8, 151650–151667.
- Nag, D., 2020. Indian railways zero-based timetable: Travel time in long-distance trains to reduce. URL: <https://www.financialexpress.com/infrastructure/railways/indian-railways-zero-based-timetable-travel-time-in-long-distance-trains-to-reduce-check-details/2141321>.
- NewsWire, P., 2020. Airlines add COVID-19 insurance. URL: <https://www.prnewswire.com/news-releases/airlines-add-covid-19-insurance---why-you-should-still-consider-travel-insurance-301143809.html>.
- Nouvellet, P., Bhatia, S., Cori, A., Ainslie, K.E., Baguelin, M., Bhatt, S., Boonyasiri, A., Brazeau, N.F., Cattarino, L., Cooper, L.V., et al., 2021. Reduction in mobility and COVID-19 transmission. *Nature Commun.* 12 (1), 1–9.
- OECD, 2020. COVID-19 and the aviation industry: Impact and policy responses. URL: <http://www.oecd.org/coronavirus/policy-responses/covid-19-and-the-aviation-industry-impact-and-policy-responses-26d521c1/>.
- Pratiko, F.R., 2020. A practical approach to revenue management in passenger train services: A case study of the Indonesian railways argo parahyangan. *J. Rail Transp. Plan. Manage.* 13, 100161.
- Qin, J., Zeng, Y., Yang, X., He, Y., Wu, X., Qu, W., 2019. Time-dependent pricing for high-speed railway in China based on revenue management. *Sustainability* 11 (16), 4272.
- Railways, I., 2020. Train at a glance july 2019 - june 2020. URL: http://indianrailways.gov.in/railwayboard/view_section.jsp?id=0,1,304,366,537.
- Sato, K., Sawaki, K., 2012. Dynamic pricing of high-speed rail with transport competition. *J. Revenue Pricing Manage.* 11 (5), 548–559.
- Schraer, R., 2020. Coronavirus: What's the risk on transport? URL: <https://www.bbc.com/news/health-51736185>.
- Schultz, M., Fuchte, J., 2020. Evaluation of aircraft boarding scenarios considering reduced transmissions risks. *Sustainability* 12 (13), 5329.
- Sibdari, S., Lin, K.Y., Chellappan, S., 2008. Multiproduct revenue management: An empirical study of auto train at amtrak. *J. Revenue Pricing Manage.* 7 (2), 172–184.

- Stelzer-Braids, S., Oliver, B.G., Blazey, A.J., Argent, E., Newsome, T.P., Rawlinson, W.D., Tovey, E.R., 2009. Exhalation of respiratory viruses by breathing, coughing, and talking. *J. Med. Virol.* 81 (9), 1674–1679.
- Strauss, A.K., Klein, R., Steinhardt, C., 2018. A review of choice-based revenue management: Theory and methods. *European J. Oper. Res.* 271 (2), 375–387.
- Talluri, K.T., Van Ryzin, G.J., Karaesmen, I.Z., Vulcano, G.J., 2008. Revenue management: models and methods. In: 2008 Winter Simulation Conference. IEEE, pp. 145–156.
- Talluri, K.T., Van Ryzin, G., Van Ryzin, G., 2004. The Theory and Practice of Revenue Management, Vol. 1. Springer.
- Tirachini, A., Cats, O., 2020. COVID-19 and public transportation: Current assessment, prospects, and research needs. *J. Public Transp.* 22 (1), 1.
- UITP, 2020. Management of COVID-19: Guidelines for public transport operators. URL: https://cms.uitp.org/wp/wp-content/uploads/2020/06/Corona-Virus_EN.pdf.
- Wang, X., Wang, H., Zhang, X., 2016. Stochastic seat allocation models for passenger rail transportation under customer choice. *Transp. Res. E* 96, 95–112.
- Warpinski, J., 2020. Focused on safety, delta moves quickly to meet customer needs during coronavirus. URL: <https://news.delta.com/focused-safety-delta-moves-quickly-meet-customer-needs-during-coronavirus>.
- Wen, S., Zhang, Q., 2019. Design of seat allocation of high-speed trains. In: 2019 4th International Conference on Electromechanical Control Technology and Transportation (ICECTT). pp. 211–214.
- Xiaoqiang, Z., Lang, M., Jin, Z., 2017. Dynamic pricing for passenger groups of high-speed rail transportation. *J. Rail Transp. Plan. Manage.* 6 (4), 346–356.
- Yan, Z., Li, X., Zhang, Q., Han, B., 2020. Seat allocation model for high-speed railway passenger transportation based on flexible train composition. *Comput. Ind. Eng.* 106383.
- Yazdani, D., Omidvar, M.N., Deplano, I., Lersteau, C., Makki, A., Wang, J., Nguyen, T.T., 2019. Real-time seat allocation for minimizing boarding/alighting time and improving quality of service and safety for passengers. *Transp. Res. C* 103, 158–173.
- Yuan, W., Nie, L., 2020. Optimization of seat allocation with fixed prices: An application of railway revenue management in China. *PLoS One* 15 (4), e0231706.
- Yuan, W., Nie, L., Wu, X., Fu, H., 2018. A dynamic bid price approach for the seat inventory control problem in railway networks with consideration of passenger transfer. *PLoS One* 13 (8), e0201718.