Singapore Airlines: Profit Recovery and Aircraft Allocation Models during the COVID-19 Pandemic

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Abstract

COVID-19 has severely impacted the global aviation industry, causing many airlines to downsize or exit the industry. For airlines which attempt to sustain their operations, they will need to respond to the increase in passenger and cargo demand, as countries recover slowly from the crisis due to the availability of vaccines. We built a series of spreadsheet models to first project the COVID-19 recovery rates by countries from 2021 to 2025, then forecast the passenger and cargo demand, using historical data as base figures. Using the financial and operation data, the revenue, expense, and profit can be projected, then an optimization model is used to determine the optimal number of aircrafts to be allocated to passenger and cargo respectively, and the number of aircrafts to be put into storage. We applied our models to data extracted on 26 October 2020 to obtain insights on the impact of COVID-19 on Singapore Airline's profit recovery and aircraft allocation. Our sensitivity analysis shows that Singapore Airline's profitability and aircraft allocation in 2023 and 2024 will be very sensitive to the vaccine release date. Our models can be applied to another airline, by replacing the financial and operation data, to provide similar insights.

Keywords
COVID-19, Singapore Airlines, spreadsheets modeling, profit recovery, aircraft allocation

1. Introduction
As COVID-19 ravages through the world since early 2020, the global aviation industry was among the worst hit industries. Border controls and travel restrictions were dynamically being imposed as different countries' COVID-19 situations fluctuated, severely impacting the demand for air travel. Compared to the other major crises, like the oil crisis in the 1973, Iran-Iraq war in the 1980s, Gulf crisis and Asian Financial crisis in the 1990s, 9/11 attack and SARS in the 2000s, this COVID-19 pandemic is projected to cause the largest decline of between 54% to 60% in three months in the world total passengers, in 2020 as compared to 2019 (IATA 2020a). With extended travel restrictions, the decline is likely to be worse.

Many airlines around the globe are facing immense difficulties and responded differently to the crisis. Responses include retrenchment of workers and fleet reduction (e.g., Austrian Airlines and Brussels Airlines), obtain government aid and secure investments from investors (e.g., Lufthansa and Korean Air), or simply cease operations (e.g., Air Italy and Norwegian Air Shuttle). Singapore Airlines (SIA), the national carrier of the city state, experienced close to a standstill given that all its flights are international. Being a relatively strong player in the industry, the Singapore government is determined to see SIA survive this crisis to emerge stronger (Wong 2020). As countries recover slowly from the situation due to the availability of vaccines, airlines will need to respond to increase in passenger and cargo demand by allocating their aircrafts efficiently. It will be of paramount importance for airlines to have models which can provide insights to support informed decision making, to respond better through this crisis.

We attempt to build a series of spreadsheet models to project the COVID-19 recovery rates by countries from 2021 to 2025, and then forecast the passenger and cargo demand, using historical data. To determine the optimal number of aircrafts to be allocated to passenger and cargo respectively, and the number of aircrafts to be put into storage, we

optimize the profit generated, using financial and operational data obtained. We validated our models using COVID-19 data extracted on 26 October 2020 for analysis to obtain insights, and performed sensitivity analysis on the results obtained.

2. Literature Review

We focus our review on academic papers related to how the aviation industry responded to the pandemic, and mathematical models for impact analysis due to disruptions caused by pandemics. Amankwah-Amoah (2020) examined how airlines' have responded to the COVID-19 crisis and the factors that facilitated their responses. He developed a 2x2 matrix framework to offer insights into long-term and short term, against internally generated and externally imposed responses, adopted by airlines. Short term responses are operational and tactical, while long-term responses are strategic in nature. Externally imposed responses are driven by governments, industry bodies and societies, to ensure standardized responses to secure a wider participation, while internally generated responses are self-directed by the firm to ensure survival. Some specific responses undertaken by different airlines were documented, such as in-flight social distancing measure which will have long-term impact on seating density and in-flight services.

For European airlines, Albers and Rundshagen (2020) applied Wenzel et al.'s (2020) typology of crisis response strategies to analyse 148 news items published from 6 January 2020 to 2 June 2020, to differentiate the airlines' responses by retrenching, persevering, innovating and exiting. They found that most airlines (75 news items) went into retrenchment mode initially, while some financially strong players (37 news items) chose persevering to remain competitive post-crisis. Innovating (16 news items) involves strategically renewing the organization such as converting passenger aircraft to cargo aircraft to benefit from stable cargo demand during the crisis. The final response strategy, exit (11 news items), refer to closing the entire business, downsize operations or exit from certain markets. In addition, they provided broad implications for the European airline industry involving the governments acting as change agents to provide support with imposed conditions, resetting business model convergence, and halting the consolidation of the industry.

Rimmer (2020) analysed the key components of the aviation ecosystem including demand, airlines, airports, network connectivity and governance, based on data collected in September 2020. He discussed how each of these components will fare in the 'next normal' once an effective vaccine is introduced, and when the pandemic is over. For airlines, he expected that cargo demand will increase; passenger demand recovery will occur first in domestic and regional markets, rather than international markets; business travel recovery will be much slower due to cancellation of physical MICE events; leisure class recovery is expected only after 2024. Hence, airlines will respond by offering fewer flights, downsizing business classes, and reducing in-flight services.

While these papers discussed the different possible responses to the 'new normal' or 'next normal', these suggested responses can only be made when there is proper analysis of data to support such decision making. Rimmer (2020) concluded in his paper that airlines can be guided to transform through analysis by strategists and logisticians who would forecast and plan for the likely outcomes. Such planning and forecasting require carefully built models which can perform the analysis to obtain results and insights.

Complex system dynamics models such as the inoperability input-output model (IIM) and dynamic IIM (DIIM) have been used to provide insights into understanding the inoperability (the inability to satisfy as-planned production levels) into input-output modeling. Santos et al. (2009) applied the DIIM to account for economic and productivity losses resulting from a pandemic-caused workforce disruption. They applied the enhanced DIIM model to simulate three pandemic scenarios in the Commonwealth of Virginia, with three different attack rates. Their simulation results provided insights into identifying the vulnerable sectors, and productivity losses of the affected regional economy due to interdependencies, useful for effective policy making. Santos et al. (2013) and Haimar and Santos (2014) continued to apply DIIM to investigate the interdependent economic and productivity risks due to 2009 H1NI influenza epidemic induced workforce disruptions. The results from both studies were similar and suggested that sectors which suffered the most economic loss are those that contributed the most to GDP or with the most significant total production outputs, while sectors that suffered the most inoperability are involved in epidemic management, such as healthcare.

The COVID-19 pandemic has inspired several other works to apply the input-output models. Yu et al. (2020) applied persistent IIM (PIIM) to model the economic impact due to lockdowns imposed. Their results show that (1) sectors that suffered higher levels of inoperability during the lockdown may recover faster depending on their resilience; (2)

sectors which were initially unaffected can over time end up suffering higher inoperability than sectors which were directly affected; and (3) the economic impact on regions which were not in lockdown can also be significant. Santos (2020) applied DIIM to estimate the impact of workforce disruptions due to COVID-19 and simulated the impact of containment, suppression and mitigation for workforce continuity. Xiao et al. (2020) modeled the global value chain to provide insights into how trade will be affected due to factories shut down in some countries.

Apart from input-output models, mathematical models have been created to analyse data related to COVID-19 pandemic. Adiga et al. (2020) provided a non-exhaustive list of mathematical models with different modeling frameworks, underlying assumptions made, datasets, regions and timeframes. They compared models developed in the UK, US and Sweden, assessing the strengths and weaknesses of each model. These models are meant for policy makers to assess the evolution of the pandemic, to design and analyze control measures, and study various what-if scenarios. The UK model first developed by Ferguson et al. in 2005, is an agent-based simulation model to analyze the H5N1 pandemic considering household data, interaction points at schools, workplace and random meeting points, to simulate the disease transmission. Intervention actions such as case isolation, home quarantine, social distancing, and closure of schools were added to study the impact on the outcome. When applied to COVID-19 to study the impact of non-pharmaceutical interventions to reduce mortality and healthcare demand (Ferguson et al. 2020), the simulation results predicted a dire situation for UK and US, to consider complete lock downs.

The US model was applied to study the spread of influenza (Balcan et al. 2009, Venkatramanan et al. 2019), Ebola (Gomes et al. 2014), and Zika (Zhang et al. 2017). It is a spatial metapopulation model which constructs abstraction of the mixing patterns in the population, decomposed into subpopulations, connected through flow networks. When applied to COVID-19 (Kraemer et al. 2020), the results suggested that international importation could be contained substantially by strong travel ban. The simple model developed by Britton in 2020 for predicting the number of cases in Sweden used the R_0 and doubling time d, with calibration done using observed number of fatality cases, time between infection to death, and infection fatality risk. The model predicted that the Stockholm area would attain herd immunity within a short period, which was not the case. However, the advantage of this model is that it is transparent with few parameters, and one could see which parameters have biggest impact on the outcome.

In terms of using spreadsheets to build models to analyse the COVD-19 situation, Alvarez et al. (2020) developed a model using differential equations to follow the evolution of COVID-19 in large cities by adjusting the population density and aggressiveness of the response from a society or government to epidemics. Buxton (2020) built a model to analyse the projectile motion, evaporation and dispersion of respiratory droplets, for biology and health science students to explore the disease transmission. To our best knowledge, we have not found an academic paper which discusses spreadsheet models for business applications related to COVID-19.

We built spreadsheet models to project the COVID-19 recovery rates by countries from 2021 to 2025. Based on the predicted recovery rate for each country, and vaccine available date, the passenger and cargo demand of SIA will be forecasted, using historical data as base figures. Using the financial and operation data of SIA, the revenue, expense, and profit can be projected based on the forecasted passenger and cargo demand. To optimize the total profit, an optimization model is proposed to determine the number of aircrafts to be allocated to passenger and cargo respectively, and the number of aircrafts to be put into storage at Alice Springs in Australia. We applied our models to data extracted on 26 October 2020 to obtain insights on the impact of COVID-19 on SIA's profit recovery and aircraft allocation, in hope that SIA can respond better in this crisis to remain 'a great way to fly'.

Our work is different from previous works in two ways. Firstly, unlike input-output models which use complex system dynamics concepts and theories and simulation models, or mathematical models that applied agent-based and deep learning models, which are beyond the knowledge and skills of most business executives, our models are built using spreadsheets which are easy to understand, use and modify. Secondly, our models are applied at the company level, for an airline to assess the impact of COVID-19 on its financial and operation aspects to support better decision making, and not at an economic sectorial level to support informed policy decision making.

We will introduce our proposed models in Section 3, explain the results obtained using data related to SIA in Section 4, and finally provide concluding remarks in Section 5.

3. Proposed Solution Models

We built several spreadsheet models as shown in Figure 1 to perform the detailed computations including,

- COVID-19 recovery rate by country
- Passenger demand forecasting
- Cargo demand forecasting
- Revenue, expense and profit computations
- Optimal allocation of aircrafts

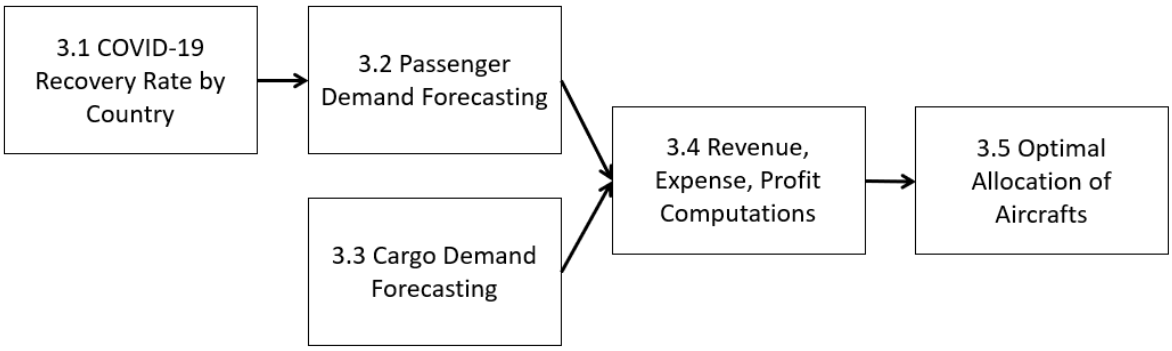

Figure 1. Proposed solution models

3.1 COVID-19 Recovery Rate by Country

Our first model is the COVID-19 recovery rate by country from 2020 to 2025. Based on the data extracted from https://ourworldindata.org/covid-cases (Ritchie et al. 2020), each country is assigned a risk profile using a traffic light system adapted from the European Center for Disease Prevention and Control (Riegert 2020). The traffic light colors (Green, Yellow and Red) for each country is determined as follows,

- Green is for countries reporting less than 1 new infection per 100,000 inhabitants in the last 14 days
- Yellow is for countries reporting more than 1 new infection per 100,000 inhabitants and the trend of daily new cases is going down in the last 14 days
- Red is for countries reporting more than 25 new infection per 100,000 inhabitants and the trend of daily new cases is going up in the last 14 days

As an illustration, we extracted the latest 14 days COVID cases data on 26 October 2020 for 31 countries, where SIA has operating flights. When the maximum value of the number of new infections per 100,000 inhabitants, within the latest 14 days, fall within each range with an upward or downward trend, the respective traffic light color will be assigned. Table 1 lists the 31 countries which were assigned to the different traffic light colors, as of 26 October 2020.

Table 1. Traffic light color for 31 countries as of 26 October 2020

Traffic light color	Countries
Green	Japan, New Zealand, South Korea, Brunei, Hong Kong, Australia, Taiwan, Thailand, Vietnam, China
Yellow	Maldives, India, Philippines, Bangladesh
Red	Switzerland, Spain, France, Netherlands, UK, Italy, USA, Germany, UAE, Denmark, Russia, Sri Lanka, Malaysia, South Africa, Myanmar, Turkey, Indonesia,

Based on the traffic light color assignment, two sets of opening dates will be determined for each country. Partial opening date refers to the date at which the country will open for business and essential travel only, while full opening date refers to opening for non-restricted travel, which is assumed to be one year after vaccine is available (Mahase 2020). Table 2 lists the partial opening and full opening dates for each color. These opening dates are important as they will be used to forecast the passenger demand on SIA from 2021 to 2025.

Table 2. Traffic light color, and its partial and full opening dates

Traffic light color	Partial opening date	Full opening date
Green	Currently partially open	One year after vaccine is available
Yellow	Date to be determined based on Log-Normal Fit	One year after vaccine is available
Red	NA	One year after vaccine is available

For countries which were assigned yellow color, the daily new cases will be projected using a curve-fitting of past data with a Log-Normal distribution to meet the asymmetrical feature of the distribution of new cases (Nishimoto and Inoue 2020). The Log-Normal distribution is given by the function,

$$f(t) = \frac{a}{t} \cdot \exp\left(-\left(\frac{\log(t) - b}{c^2}\right)^2\right)$$

where t = time, a = peak height, b = peak position, and c = width

We will use Solver to minimize the sum of the squared error from the fitted curve value and the actual daily COVID-case per million of inhabitants, to optimize the parameters of the Log-Normal curve, a, b, and c. Then, the partial opening date will be read from the best fitted curve where there will be 14 consecutive days of less than 1 new infection per 100,000 inhabitants. Using the past data up till 25 October 2020, the best fitted curves for the four countries assigned the yellow color are shown in Figure 2.

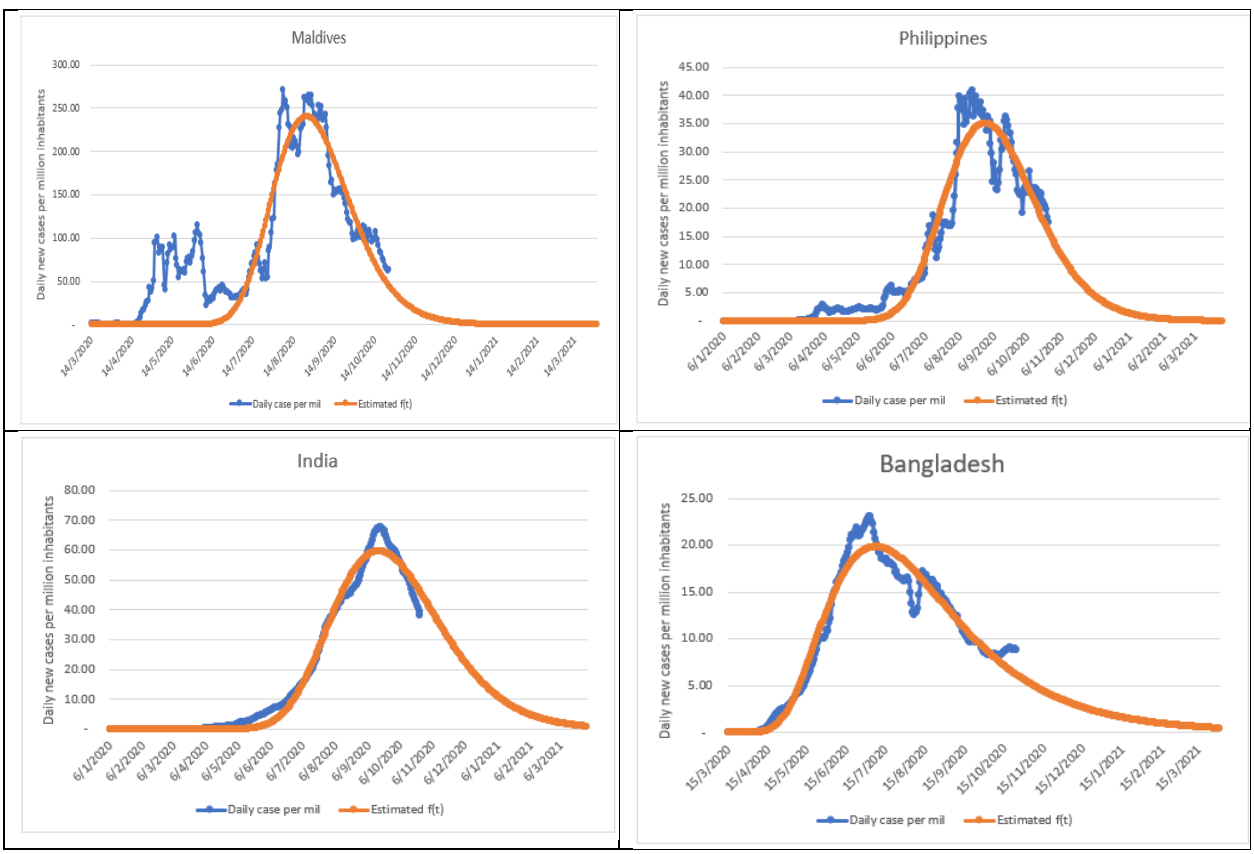

Figure 2. Log-Normal curve fitting for yellow color countries

The estimated dates for the four countries assigned yellow color are given in Table 3.

Table 3. Estimated partial opening dates for countries assigned yellow color as of 26 October 2020

Yellow color countries	Partial opening date
Maldives	14 January 2021
India	12 April 2021
Philippines	27 January 2021
Bangladesh	25 February 2021

3.2 Passenger Demand Forecasting

SIA's passenger demand in 2020 was a mere 1.5% of the pre-COVID level (Yahoo News 2020). It was projected by SIA that partial opening will bring in an additional 15% demand, to 16.5%, increasing gradually over the months with partial opening status. Thus, our passenger demand forecasting model will match this gradual increase, increasing linearly from 1.5% to 16.5%, in equal steps using 15% divided by the number of months with partial opening status, for each country. We assume that all countries will have full opening date one year after the vaccines become available (Mahase 2020). With several vaccines on different clinical trial stages, different vaccines will be approved for use over time from late 2020 onwards. The vaccination programme in each country will differ, and countries with bigger populations will require a longer duration to vaccinate a significant portion of their people. Using a conservative estimate, we assume that vaccines will become widely available by December 2021, making the full opening date to be one year later in December 2022. From the full opening date in December 2022 to December 2025, a duration of three years, we assume that the passenger demand will increase linearly in equal steps to reach 100%, back to the pre-COVID level. This is in line with IATA which predicted that it would take 5 years from year 2020, for passenger demand to return to pre-COVID level (IATA 2020b). Table 4 depicts the linear increase method applied to different countries assigned different traffic light colors.

Table 4. Passenger demand forecasting

Color	Current to partial open date	From partial open date to Dec 2022	From Dec 2022 to Dec 2025
Green	Increase from 1.5% to 16.5%		Increase from 16.5% to 100%
Yellow	Remain as 1.5%	Increase from 1.5% to 16.5%	Increase from 16.5% to 100%
Red	Remain as 1.5%	Remain as 1.5%	Increase from 1.5% to 100%

After the monthly passenger demand has been forecasted, the average values for each year will be computed to be applied on a yearly basis. Table 5 lists the yearly forecasted passenger demand for SIA from 2021 to 2025. The average values in the last row will be used to estimate the passenger demand from 2021 to 2025. 1.5% will be used as the average value for 2020 (Yahoo News 2020).

Table 5. SIA's forecasted passenger demand from 2021 to 2025 using data on 26 October 2020

		Forecasted Passenger Demand				
Color	**Number of countries**	**2021**	**2022**	**2023**	**2024**	**2025**
Green	10	6.2%	13.8%	33.4%	60.5%	87.6%
Yellow	4	5.1%	13.5%	33.4%	60.5%	87.6%
Red	17	1.5%	1.5%	19.3%	52.1%	85.0%
	Average	**4.2%**	**8.9%**	**27.9%**	**57.2%**	**86.6%**

3.3 Cargo Forecasting

Apart from serving passengers, SIA owns seven cargo planes which it will continue to service cargo demand during the COVID-19 period and beyond. We assume that cargo demand will remain the same as in 2019, from 2020 to 2025. This assumption is reasonable as air cargo demand will remain resilient (ICAO 2020), thus will not decrease. There could be an increase in cargo demand due to the transportation of vaccines and increased e-commerce activities, which may lead to SIA converting some passenger planes to cargo planes. Our model will permit the user to enter the

estimated increase, and the number of cargo planes allocated will increase accordingly. SIA can look at converting passenger aircraft to cargo aircraft, with either minor or major retrofitting (Lim 2020). However, the cost of conversion is not part of the study, and thus will not be considered.

3.4 Revenue, Expense and Profit Computations

To allocate the aircrafts to serve passenger or cargo demand, or for storage at the Alice Springs in Australia, we need to perform some detailed financial computations, and to use an optimization model to allocate the number of aircrafts (to passenger or cargo), trading off between revenues and expenses. We first obtain the financial and operation data of SIA including,

- Fleet information from mainlymiles.com, centreforaviation.com, and planespotters.net, where we note that SIA has a total of 133 aircrafts, of which seven are cargo planes.
- 2019 financial report from SIA website at https://www.singaporeair.com/saar5/pdf/Investor-Relations/Annual-Report/annualreport1920.pdf. Note that 2020 financial report has not been released.
- Airport charges for storage of aircraft at Alice Springs from https://www.alicespringsairport.com.au/airport-charges

Based on the actual financial and operation data in 2019 (indicated as figures with ^ in Table 6 in the 2019 column), we can compute the unit price, unit expense, and passenger and cargo demand per aircraft in 2019, to apply them into future years from 2020 to 2025 (indicated as figures with →),

- Unit price per passenger (B.1.2)
- Unit expense per passenger aircraft (B.2.2)
- Passenger demand per aircraft (B.2.3)
- Unit price per tonne-km for cargo (C.1.2)
- Unit expense per cargo aircraft (C.2.2)
- Cargo demand per aircraft (C.2.3)

For 2020 onwards, the forecasted passenger demand and cargo demand are,

- Passenger demand (B.1.1) – this value will be forecasted based on the forecasting model described in section 3.2
- Cargo demand (C.1.1) – this value will be projected as described in section 3.3.

Based on the trade-off between the revenues generated and expenses incurred, the optimal number of aircraft will be allocated for passenger (B.2.1) and cargo service (C.2.1) respectively. Due to optimal allocation, the final number of passenger and cargo demand served may be lower than the forecasted demand in B.1.1 and C.1.1, if the incremental revenue generated is not sufficient to offset the increase in expense. Once the number of aircraft allocated to passenger and cargo services are determined, the remaining aircrafts will be placed into storage (D.2).

Table 6. Revenue, expense and profit computations

Annual figures	2019	2020 onwards
A. Total profit	655,131,500^	B + C – D
B. Total passenger profit (= B.1 – B.2)	485,129,400^	B
B.1 Total passenger revenue	11,130,878,000^	B.1.2 * final number of passengers served
B.1.1 Passenger demand	22,198,000^	forecasted
B.1.2 Unit price per passenger (= B.1/B.1.1)	501.44 →	501.44
B.2 Total passenger expense	10,645,748,600^	B.2.1 * B.2.2
B.2.1 Number of passenger aircrafts allocated	212^	optimized
B.2.2 Unit expense per passenger aircraft (= B.2/B.2.1)	87,260,234 →	87,260,234
B.2.3 Passenger demand per aircraft (= B.1.1/B.2.1)	181,951 →	181,951
C. Total cargo profit (= C.1 – C.2)	170,002,100^	C

C.1 Total cargo revenue	1,968,908,400^	C.1.2 * final amount of cargo served
C.1.1 Cargo demand (million tonnes-km)	6,605,000,000^	forecasted
C.1.2 Unit price per tonne-km (= C.1/C.1.1)	0.3 →	0.3
C.2 Total cargo expense	1,798,906,300^	C.2.1 * C.2.2
C.2.1 Number of cargo aircrafts allocated	**7**	optimized
C.2.2 Unit expense per cargo aircraft (= C.2/C.2.1)	256,986,614 →	256,986,614
C.2.3 Cargo demand per aircraft (= C.1.1/C.2.1)	943,571,429 →	943,571,429
D. Total storage expense (= D.1 * D.2)	0^	D
D.1 Storage cost per aircraft per year (= storage cost per MTOW * average aircraft tonnage = 4.01 * 337)	492,852 →	492,852
D.2 Number of aircraft allocated to storage	133 – B.2.1 – C.2.1	133 – B.2.1 – C.2.1

3.5 Optimal Allocation of Aircrafts

The proposed optimization model is given as,

Maximize $Z = \sum_i (R_i - E_i)$

Subject to, $F_i = Min(X_i N_i, P_i), \quad \forall i \quad \ldots (1)$

$R_i = F_i r_i, \quad \forall i \quad \ldots (2)$

$E_i = X_i e_i \quad \forall i \quad \ldots (3)$

$0 \leq X_i \leq T, \quad \forall i \quad \ldots (4)$

$$0 \leq \sum_i X_i \leq T, \quad \ldots (5)$$

$X_i \; integer, \quad \forall i \quad \ldots (6)$

Where,

- i = index for passenger, cargo or storage
- T = total number of aircraft
- R_i = total revenue earned from the service, where the service can be passenger or cargo. There is no revenue from storage
- E_i = total expense incurred for providing the service, where the service can be passenger, cargo or storage
- P_i = projected demand for the service, where the service can be passenger or cargo
- F_i = final demand served for the service, where the service can be passenger or cargo, where $F_i <= P_i$
- N_i = average demand per aircraft for the service, where the service can be passenger or cargo
- r_i = revenue earned per unit demand for the service, where the service can be passenger or cargo
- e_i = expense incurred per aircraft for the service, where the service can be passenger or cargo
- X_i = number of aircraft allocated for the service, where the service can be passenger or cargo

The model attempts to maximize the profit from the passenger service and cargo service, accounting for the expense incurred due to storage of planes, by trading off the revenues generated and expenses incurred. The constraints include,

- Constraint (1) – ensures that the final demand served should not exceed the forecasted demand figures. It is due to this constraint and the objective function, that the number of aircraft allocated will be optimized.
- Constraint (2) – computes the total revenue generated from providing the service which is equal to the final demand served multiply by the revenue earned per unit demand for the service.

- Constraint (3) – computes the total expense incurred for providing the service which is equal to the number of aircraft allocated multiply by the expense incurred per aircraft for the service.
- Constraint (4) – ensures that the number of aircraft allocated for each service cannot exceed the total number of aircraft T.
- Constraint (5) – ensures that the total number of aircraft allocated for all services cannot exceed the total number of aircraft T.
- Constraint (6) – is the integer constraint for the number of aircraft allocated.

4. Results and Discussion

4.1 Results for SIA

Using the data extracted on 26 October 2020, and the results from the proposed forecasting, financial computations, and optimization model, we present SIA's forecasted total profit chart in Figure 3. SIA's profits will increase gradually from 2021 to 2025, with steep increase happening only from 2023 onwards. Even in 2025, SIA's profit will not be able to reach that of pre-COVID level.

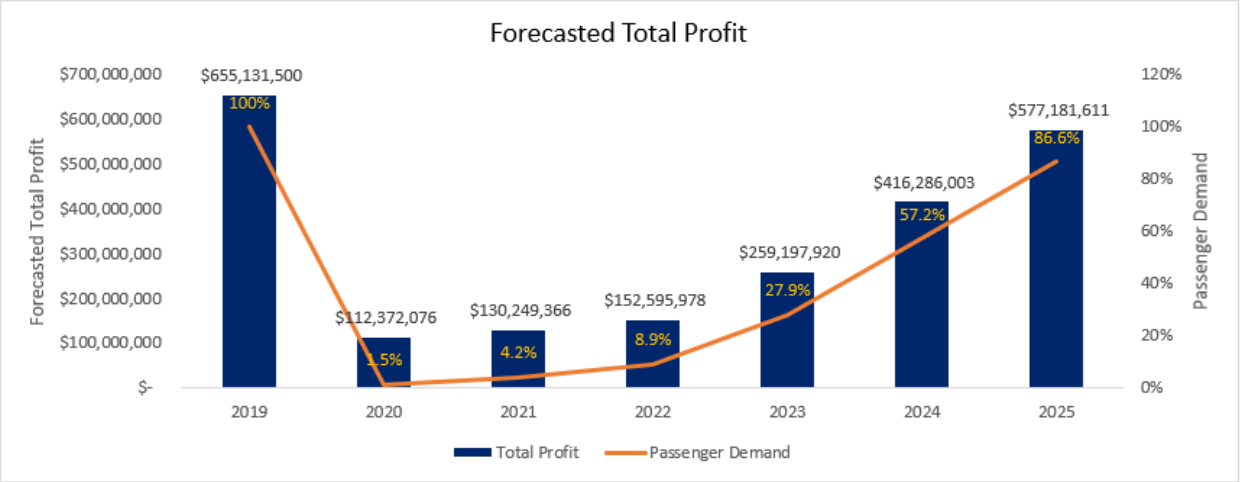

Figure 3. SIA's forecasted total profit versus passenger demand growth

The optimal number of aircrafts allocated to passenger, cargo or for storage is given in Table 7. As we have assumed that cargo demand will remain constant, the allocation of aircrafts will be between passenger service and storage. Having said that, the forecasted cargo demand can be adjusted in the model, and the optimal cargo aircraft allocation will be determined accordingly. From our results, we can see that even in 2025, there will be 21 aircrafts still parked in storage. Therefore, it may be worthwhile for SIA to consider retiring a few older aircrafts which are nearing their 25 years of age (IATA 2018) or scrap or sell them instead of storing, if it makes better economic sense.

Table 7. SIA's aircraft allocation from 2021 to 2025 using data on 26 October 2020

	2021	2022	2023	2024	2025
Passenger	5	10	34	69	105
Cargo (assume constant cargo demand)	7	7	7	7	7
Storage	121	116	92	57	21

4.2 Sensitivity Analysis

The results of our analysis are highly dependent on several input values, especially the forecasted passenger demand which is in turn dependent on the vaccine release date. When the vaccine release date is modified to different dates (Dec 2020, Jun 2021, Dec 2021, Jun 2022, and Dec 2022), in steps of 6 months, SIA's forecasted total profit will change according to Figure 4. We can see that the different vaccine release dates will not have much impact on SIA's

profits in 2021 and 2025, but will have the most significant impact in 2023, followed by 2024. Similarly, in Figure 5, the number of passenger aircraft allocated is also very sensitive to the vaccine release date, especially in 2023 and 2024. SIA can take note of how the different vaccine release dates will adversely affect its profitability and aircraft allocation, particularly in 2023 and 2024.

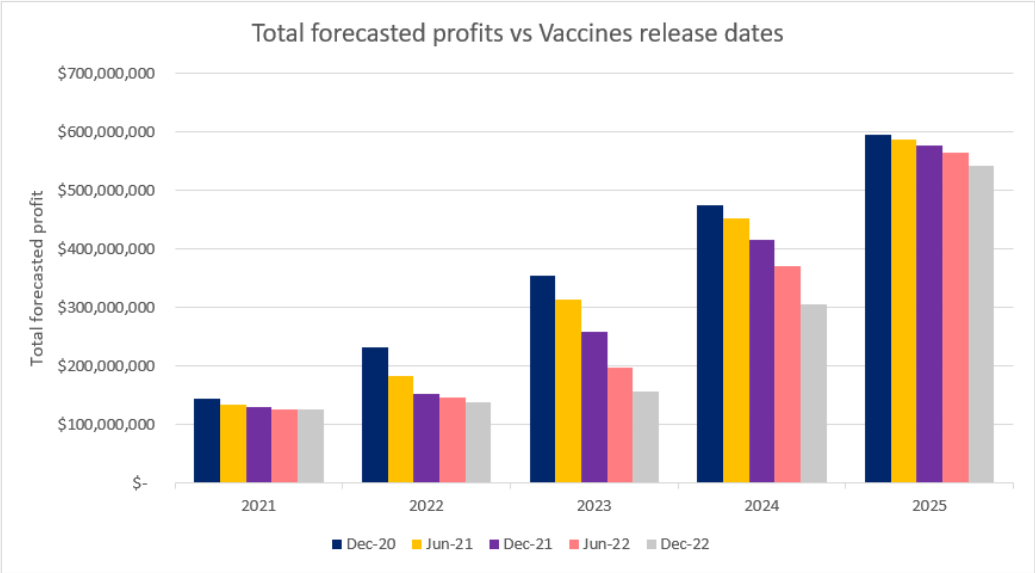

Figure 4. SIA's forecasted total profit for different vaccine release dates

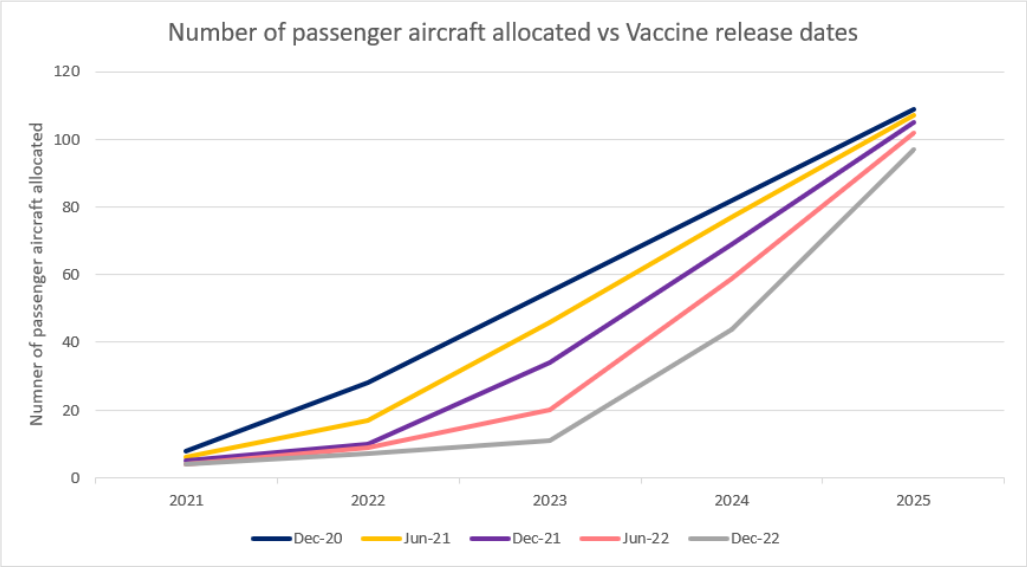

Figure 5. Number of passenger aircraft allocated for different vaccine release dates

5. Conclusion

In the face of immense uncertainty of the COVID-19 situation, our models were built based on several reasonable assumptions. Based on the analysis of COVID-19 new cases data extracted on 26 October 2020, we have performed detailed analysis to shed some insights into how SIA can expect its profit to recover, the number of aircrafts to be allocated to serve passengers and cargo, as well as the number of aircraft which will go to storage, from 2021 to 2025. Our sensitivity analysis shows that SIA's profitability and aircraft allocation in 2023 and 2024 will be very sensitive

to the vaccine release dates. Our models can be applied to another airline, by replacing the financial and operation data, to provide similar insights. In interpreting the models, analysis and results presented in this paper, one must bear in mind that the pandemic is still on-going. As the COVID-19 situation unfolds, some assumptions made may become invalid, and some countries may perform better or worse than expected. Therefore, it only represents a viable solution methodology for SIA or any other airlines to perform sufficient analysis to guide better decision making.

References

Adiga, A., Dubhashi, D., Lewis, B., Marathe, M., Venkatramanan, S., and Vullikanti, A., Mathematical models for COVID-19 pandemic: A comparative analysis, *Journal of Indian Institute of Science*, vol. 100, no. 4, pp. 793-807, 2020.

Albers, S., and Rundshagen, V., European airlines' strategic responses to the COVID-19 pandemic (January-May, 2020), *Journal of Air Transport Management*, vol. 87, 2020. DOI: 10.1016/j.jairtraman.2020.101863

Alvarez, M.M., Gonzalez-Gonzalez, E., and Santiago, G.T., Modeling COVID-19 epidemics in an Excel spreadsheet: Democratizing the access to first-hand accurate predictions of epidemic outbreaks, 2020. Available: https://www.medrxiv.org/content/10.1101/2020.03.23.20041590v2

Amankwah-Amoah, J., Note: Mayday, Mayday, Mayday! Responding to environmental shocks: Insights on global airlines' responses to COVID-19, *Transportation Research E: Logistics and Transportation Review*, vol. 143, 2020. DOI: 10.1016/j.tre.2020.102098

Balcan, D., Colizza, V., Goncalves, B., Hao, H., Ramasco, J.J., Vespignani, A., Multiscale mobility networks and the spatial spreading of infectious diseases, *Proceedings of National Academy of Sciences*, vol. 106, pp. 21484-21489, 2009.

Britton, T., Basic prediction methodology for COVID-19: Estimation and sensitivity considerations, 2020. Available: https://www.medrxiv.org/content/10.1101/2020.03.27.20045575v2.full

Buxton, G., Spreadsheet model of COVID-19 transmission: evaporation and dispersion of respiratory droplets, Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3582665

Ferguson, N.M., Cummings, D.A.T., Cauchemez, S., Fraser, C., Riley, S., Meeyai, A., Iamsirithaworn, S., and Burke, D.S., Strategies for containing an emerging influenza pandemic in Southeast Asia, *Nature*, vol. 437, pp. 209-214, 2005.

Ferguson, N.M., Laydon, D., Nedjati-Gilani, G., Imai, N., Ainslie, K., Baguelin, M., Bhatia, S., Boonyasiri, A., Cucunuba Z., Cuomo-Dannenburg G., et al., Report 9: Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand, 2020. Available: https://www.imperial.ac.uk/mrc-global-infectious-disease-analysis/covid-19/report-9-impact-of-npis-on-covid-19/

Gomes, M.F.C., y Piontti, A.P., Rossi, L., Chao, D., Longini, I., Halloran, M.E., Vespignani, A., Assessing the international spreading risk associated with the 2014 West African Ebola outbreak, *PLOS Current*, 6. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4169359/

Haimar, A.E., Santos, J.R., Modeling uncertainties in workforce disruptions from influenza pandemics using dynamic input-output analysis, *Risk Analysis*, vol. 34, no. 3, 2014. DOI: 10.1111/risa.12113

ICAO, Air cargo resilience in the times of COVID-19, Available: https://etradeforall.org/icao-air-cargo-resilience-in-the-times-of-covid-19/, May 11, 2020.

IATA, Best industry practices for aircraft decommissioning (BIPAD), Available: https://www.iata.org/contentassets/ffbed17ac843465aad778867cb23c45c/bipad.pdf, 2018.

IATA, IATA economics' chart of the week: What can we learn from past pandemic episodes?, Available: https://www.iata.org/en/iata-repository/publications/economic-reports/what-can-we-learn-from-past-pandemic-episodes, 2020a.

IATA, IATA economics' chart of the week: Five years to return to the pre-pandemic level of passenger demand, Available: https://www.iata.org/en/iata-repository/publications/economic-reports/Five-years-to-return-to-the-pre-pandemic-level-of-passenger-demand/, 2020b.

Kraemer, M.U.G., Yang, C-H., Gutierrez, B., Wu, C-H., Klein, B., Pigott, D.M., Plessis, L.D., Faria, N.R., Li, R., Hanage, W.P., The effect of human mobility and control measures on the COVID-19 epidemic in China, *Science*, vol. 368, no. 6490, pp. 493-497, 2020. DOI: 10.1126/science.abb4218

Lim, J., Coronavirus: SIA's Scoot modifies aircraft to carry only cargo, 2020, Available: https://www.straitstimes.com/singapore/transport/coronavirus-sias-scoot-modifies-aircraft-to-carry-out-cargo-deliveries#:~:text=SINGAPORE%20%2D%20Budget%20carrier%20Scoot%20has,capacity%20to%20nearly%2020%20tonnes.

Mahase, E., Covid-19:Vaccine roll out could take a year and will require difficult prioritization decisions, Available: https://www.bmj.com/content/371/bmj.m3846, October 01, 2020.

Nishimoto, Y., and Inoue, K., Curve-fitting approach for COVID-19 data and its physical background. Available: https://www.medrxiv.org/content/10.1101/2020.07.02.20144899v2, July 2020. DOI: 10.1101/2020.07.02.20144899

Riegert, B., Coronavirus: What the EU's new traffic light system means: DW:14.10.2020. Available: https://www.dw.com/en/coronavirus-what-the-eus-new-traffic-light-system-means/a-55265476, October 14, 2020.

Rimmer, P.J., Aviation and COVID-19 pandemic: Towards the 'next normal', *Journal of International Trade, Logistics and Law*, vol. 6, no. 2, pp. 119-136, 2020.

Ritchie, H., Roser, M., Giattino, C., Macdonald, B., Hassell, J., Matheiu, E., and Ortiz-Ospina, E., Coronavirus (COVID-19) Cases – Statistics and Research, Available: https://ourworldindata.org/covid-cases, October 2020.

Santos, J.R., Using input-output analysis to model the impact of pandemic mitigation and suppression measures on the workforce, *Sustainable Production and Consumption*, vol. 23, pp 249-55, 2020.

Santos, J.R., Orsi, M.J., and Bond, E.J., Pandemic recovery analysis using the dynamic inoperability input-output model, *Risk Analysis*, vol. 29, no. 12, 2009. DOI: 10.1111/j.1539-6924.2009.01328.x

Santos, J.R., May, L., and Haimar, A.E., Risk-based input-output analysis of influenza epidemic consequences on interdependent workforce sectors, *Risk Analysis*, vol. 33, no. 9, 2013. DOI: 10.1111/risa.12002

Venkatramanan, S., Chen, J., Fadikar, A., Gupta, S., Higdon, D., Lewis, B., Marathe, M., Mortveit, H., Vullikanti, A., Optimizing spatial allocation of seasonal influenza vaccine under temporal constraints, *PLOS Computational Biology*, vol. 15, no. 9, 2019.

Wenzel, M., Stanske, S., and Lieberman, M.B., Strategic responses to crises, *Strategic Management Journal*, vol. 41, 2020. DOI: 10.1002/smj.3161

Wong, K.Y., Government determined to see SIA through COVID-19 crisis: Lee Hsien Loong, Available: https://www.straitstimes.com/singapore/government-determined-to-see-sia-through-covid-19-crisis-pm-lee-hsien-loong, April 30, 2020.

Xiao, H., Meng, B., Ye, J., and Li, S., Are global value chains truly global? *Economic Systems Research*, vol. 32, no. 4, 2020. DOI: 10.1080/09535314.2020.1783643

Yahoo News, Changi Airport now world's 58th busiest, serving 1.5% of usual passenger volume: Ong Ye Kung, Available: https://sg.news.yahoo.com/changi-airport-now-worlds-58th-busiest-serving-15-of-usual-passenger-volume-ong-ye-kung-075644907.html, October 06, 2020.

Yu, K.D.S., Aviso, K.B., Santos, J.R., and Tan, R.R., The economic impact of lockdowns: A persistent inoperability input-output approach, *Economies*, vol. 8, no. 109, 2020. DOI: 10.3390/economies8040109

Zhang, Q., Sun, K. Chinazzi, M., y Piontti, A.P., Dean, N.E., Rojas, D.P., Merler, S., Mistry, D., Poletti, P., Rossi, L., Bray, M., Halloran, M.E., Longini, I.M., Vespignani, A., Spread of Zika virus in the Americas, *Proceedings of National Academy of Sciences*, vol. 114, no. 22, 2017.

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