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# Modeling Impacts of Aviation Mitigations & ATC Delay on Passenger COVID-19 Infection Risk*

Richard A. DeLaura & Tom G. Reynolds
Air Traffic Control Systems Group
MIT Lincoln Laboratory
Lexington, MA, USA

***Abstract*—The aviation system has been hugely impacted by COVID-19 but will be a critical enabler of economic recovery. There is an urgent need for models to help understand the potential infection risks posed by air travel, as well as the impact of different mitigations available to aviation stakeholders. This paper presents a modeling system to address these needs. Elements of the model are described and it is then exercised to explore the relative effectiveness of airport and aircraft cabin passenger density restrictions, air turnover rate and passenger mask utilization. The model is then extended to explore the impacts on infection risk of different ATC delay scenarios. The model can be built upon in the future to not only help in the recovery from COVID, but also to develop system robustness strategies to better prepare for future challenges.**

***Keywords—COVID-19, infection risk, mitigations, aviation delay.***

## I. INTRODUCTION

The COVID-19 pandemic has had a profound impact on most areas of life during 2020, but the aviation sector has been hit especially hard due to travel restrictions and a lack of consumer confidence in the safety of airline travel. As a result, aviation activity fell precipitously as the COVID-19 pandemic spread around the globe. Figure 1 shows US passenger and flight counts over the "post-COVID" outbreak period 1 March 2020 through 28 February 2021 compared to the equivalent "pre-COVID" period one year earlier.

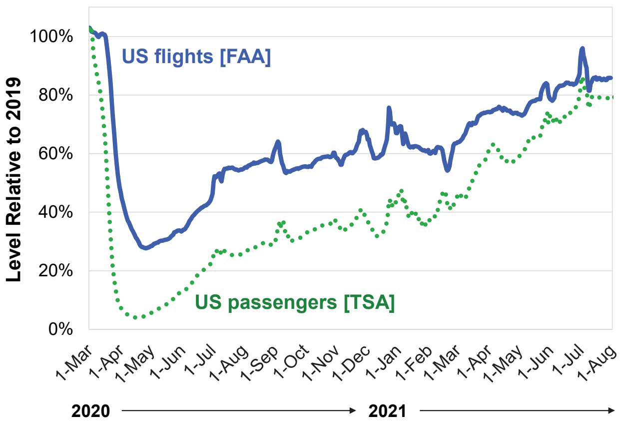


**Figure 1. Pandemic vs. Pre-Pandemic US Flights and Passenger Levels (7 day rolling average)**

During the six week period from 1 March through 15 April 2020, passenger numbers being screened by the US Transportation Security Administration (TSA) fell from 100% to just 4% of the levels the previous year. By the end of February 2021, passenger levels were still less than 50% of what they had been a year earlier. Flight levels are somewhat higher over this same period (reflecting significantly reduced load factors on aircraft), but by the end of February 2021 were still only around 60% of what they had been pre-COVID. Similar traffic and flight trends have been observed in other world regions, including Europe, SE Asia, and Australasia. There has been a rise in flights and passenger numbers over the summer of 2021, but future trends will be impacted by the complex interactions between emerging variants of COVID and vaccinations.

It is critical that stakeholders understand what role the aviation system is playing in both the risk of further spread of infection and also in the global recovery from the pandemic. This understanding is essential not only for the current COVID crisis, but also to help prepare for any similar future risks. Therefore, models need to be developed that help stakeholders understand the key interactions between aviation system performance and infectious disease dynamics. This work develops a modeling system to explore this and the impact of mitigations available to aviation stakeholders to manage air travel infection risk, such as limiting aircraft load factors, increasing air turnover rates in the aircraft or airport terminals, and enforcing strict masking requirements. The model is then extended to specifically focus on the role that ATC delays can play in modifying infection risk.

The paper is structured as follows. Section II provides background information on related current activities which motivates the need for a new modeling approach. The modeling framework being leveraged in this work is described in Section III. Section IV presents results from an assessment of the relative efficacy of load factor (passenger density) restriction controls, physical distancing measures, air turnover rates, and masking usage on infection risk in an airport terminal and aircraft cabin environment. Section V presents a case study application of the modeling framework for a range of different ATC delay scenarios. Finally, Section VI presents key takeaways and proposed next steps.

## II. RELEVANT PRIOR WORK

There is significant uncertainty associated with many of the key factors that affect disease transmission across all phases of air transport. The prevalence of disease among incoming passengers is unknown, and estimation methods are difficult to validate [1][2]. The rate of viral emission by infected passengers is also not well known. Published estimates suggest that the some infected passengers may be as much as 1000x more infectious (as defined by their virus emission rate) than the least infectious passengers [3][4]. However, the authors have not found any estimate of the probability distribution of infectiousness among the general population. The community's primary understanding of virus transmission in air travel is based on case studies such as those reviewed in [5] which, while informative, do not provide sufficient data to calibrate a general model for in-transit transmission.

There are gaps in our understanding of the environmental factors that affect transmission as well. Some aviation-specific studies are currently underway involving simulant releases in aircraft cabin interiors (e.g., [6]). Although these can lead to valuable data, they suffer from lack of realism in that they often involve empty aircraft parked on the ground which do not properly capture operational conditions. Several studies of indoor COVID transmission in mostly small and poorly ventilated indoor spaces [7][8] have been published, but the authors have been unable to find published studies concerning airflow and viral transmission in large public spaces such as transportation terminals. In any event, published studies to date have relied on details of a particular transmission event or specific indoor environment, rendering them inadequate to address the wide range of uncertainty encountered in modeling dynamic, real-world conditions in environments such as airport terminals or actual aircraft cabins. Therefore, a new modeling system was needed in order to address the objectives of the work described here.

## III. AVIATION/COVID-19 MODELING SYSTEM

Figure 2 presents the elements of the overall Aviation/COVID-19 modeling framework developed to address the needs identified above. At the left of the diagram are examples of mitigations under the control of different aviation stakeholders. For example, an airport operator can control passenger densities at different parts of the airport experience, from check-in, through security, concessions and at the gate. Airlines can similarly control aircraft cabin passenger densities (e.g., by blocking off middle seats), as well as controlling cabin air recycling and filtration rates, and also imposing and enforcing strict mask usage policies on passengers. Similarly, passengers themselves can mitigate risks by reliably self-certifying their fitness to travel and strictly complying with Personal Protective Equipment (PPE) and hygiene standards. Finally, government agencies have important roles to play by setting and disseminating appropriate public health guidelines.

The system represented by the simplified illustration in the middle box of Figure 2 defines the key system elements and their interactions. For this application, it includes the traditionally interconnected elements of aviation supply and demand, economic factors and public policy, which are significantly complicated by the impacts of COVID-19 dynamics on all factors. The rightmost box of Figure 2 contains the key outputs of interest: the relationship between infection rates and the total number of passengers transported for different mitigation strategies. These relationships can form the basis of a comprehensive cost/benefit analysis that takes into account factors such as mitigation effectiveness, and the cost and ease of mitigation implementation.

This work follows a multi-scale modeling approach inspired by [9] in which a complex system is decomposed into components that model system processes at different scales and the interfaces between them. In this way, models of system processes may be developed at a resolution that is appropriate to what is known about the process. Consistency across scales is tested by integrating results back into the

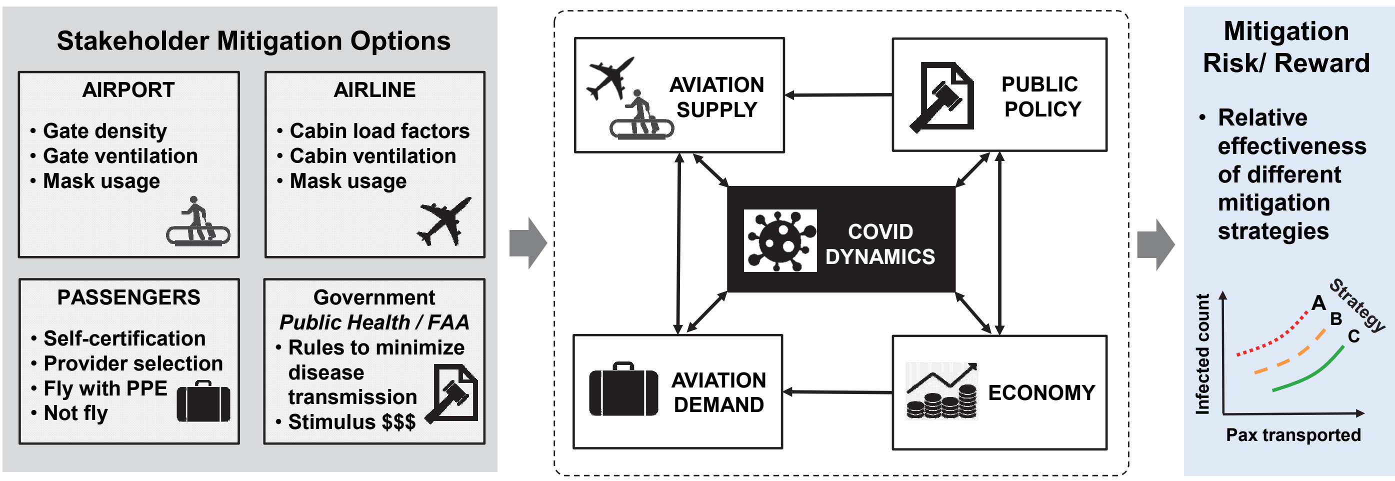


**Figure 2. Aviation / COVID-19 Modeling System**

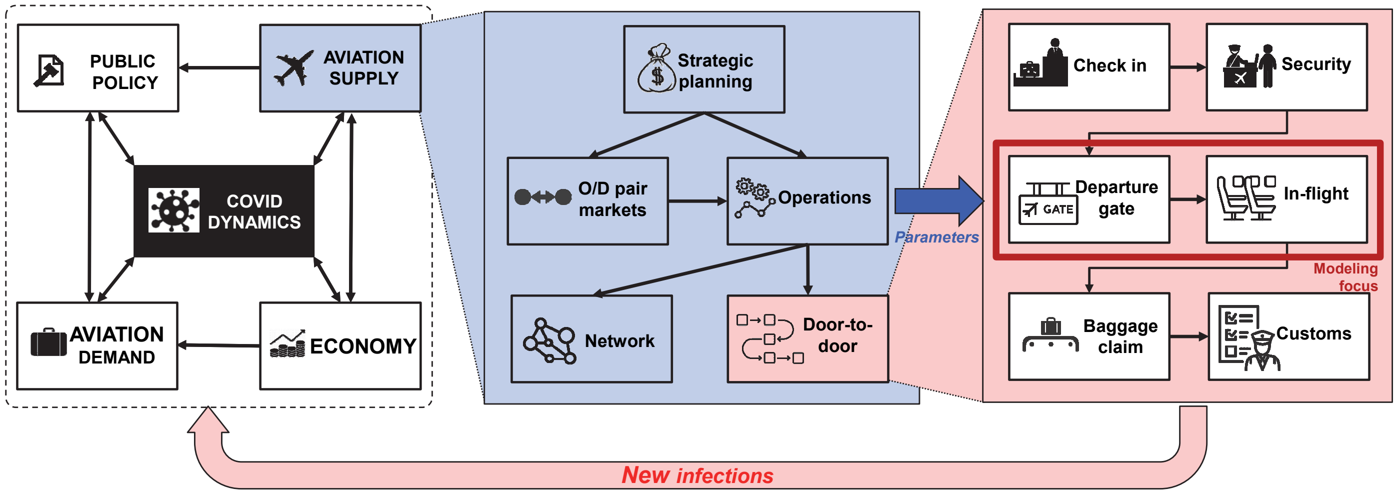


**Figure 3. Example of Aviation Supply and Door-to-Door Modeling**

comprehensive system model. For example, Figure 3 shows how the aviation supply block was decomposed into lower level elements of strategic planning, origin/destination (O/D) pair markets, operations, network design and gate-to-gate elements, the latter of which was further decomposed into process elements experienced by passengers as they flow through the aviation system.

The reintegration of component models back into the comprehensive complex system model is important for several reasons. Not only does it serve as a validation check to ensure that component system behaviors at fine resolutions are consistent with the larger scale behaviors of the complex system as a whole, but it also increases the likelihood that the model will capture unintended consequences that may have costly effects. The contextualization of system component models in the system environment also provides a framework in which component models can serve the needs of multiple stakeholders.

To illustrate the potential value of this framework, consider the viewpoints of two hypothetical stakeholders: airline operators and public health officials. Both stakeholders share a goal to minimize disease transmission in transit, subject to the needs for travel and economic sustainability. For the airline operator, this goal may be expressed as a reduction in transmission risk for an *individual passenger* to a level that is low enough to encourage flyers to return to the skies. For the public health official, the concern is *aggregate transmission risk*; that is, how many new cases per day will result from in-flight transmission and what will be the effect of those new cases on the disease reproduction number (R0) in different travel markets. For the epidemiologist, a small probability of transmission may still be cause for concern if travel volume is very high. Furthermore, an increase in community transmission in different travel markets may have a potential second-order effect of suppressing demand despite the relatively low risk of air travel. Finally, estimates of individual and population risks from different models or experiments should be consistent. While modeling of these complex system interactions is beyond the scope of the work presented here, it is one of the aspirational longer-term goals of this research.

## IV. AVIATION COVID-19 MITIGATION MODELING FOR INDIVIDUAL FLIGHTS

### A. *Approach*

In order to develop insights about transmission across a wide range of potential operational environments characterized by significant uncertainty about every aspect of transmission, we have opted for a modeling approach that emphasizes flexibility and speed over detail. The relationships among experimental and ill-defined factors such as disease prevalence, emission rate, and environmental conditions have been modeled using rather coarse approximations that are easily parameterized, calculated, and revised as new knowledge becomes available. The intent of the model is not to describe behavior in fine detail but rather to provide an objective and quantitative foundation for comparison of system behaviors and the relative merit of different mitigation strategies under a range of operating conditions. These insights may guide the focus and efforts of modelers and decision makers as they explore different aspects of the transmission problem in greater depth. This approach to strategy formulation under "deep uncertainty" is informed by [10].

In order to further manage complexity, we opted to partition model development to focus on different phases of the door-to-door air travel experience. The initial exploration focuses on the probability that an individual susceptible traveler will be infected due to exposure during a trip. To further reduce complexity, the initial model exploration is limited to the departure gate and in-flight processes highlighted in red in Figure 3. The objectives of the initial model exploration are:

- GIVEN PARAMETERS defining the exogenous factors of prevalence (i.e., the baseline probability of COVID infection) & virus emission rate, then apply…

- STAKEHOLDER MITIGATIONS of varying passenger density, air exchange rates (in both airport and aircraft settings) & masking usage/efficiency in order to estimate…
- OUTPUTS of the probability of infection with different combinations of mitigations applied.

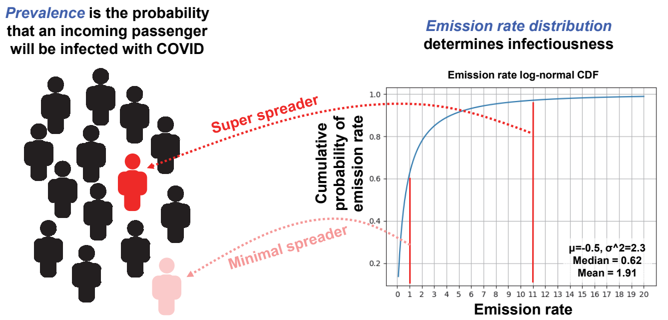


**Figure 4. Incoming Infection Parameters**

The disease transmission model has four components: a simplified epidemiological model, an operational model, an environmental model, and a virus transmission model. The epidemiological model presented in Figure 4 accounts for two transmission elements: the prevalence of infection among incoming passengers and the rate of virus emission among those passengers. Prevalence is an input assumption and the viral emission rate may be fixed or drawn from a log-normal curve whose parameters may be varied as experimental variables as well. Emission rate is defined as *disease quanta / hour*, and a disease quantum is defined in [12] as the amount of virus that results in a *probability of infection = (1 – 1/e)*.

The operational model governs the distribution of passengers in the departure gate and aircraft cabin, including any social distancing rules that may be in place.

The environmental model describes the spaces that the passengers inhabit: the physical dimensions of the spaces and the *transmission environment*, which models the key processes that govern transmission of airborne virus in the environment: air replacement, virus deposition, inactivation [11] and diffusion. Diffusion is modeled by a simple Gaussian kernel that estimates the fall-off in virus concentration with distance from the emitter.

Finally, the virus transmission model is based on the Wells-Riley equation [11][12], a widely used estimator for the probability of infection given a susceptible person's exposure to a pathogen. The virus transmission model includes the effects of passenger masking as well, as shown in Figure 5.

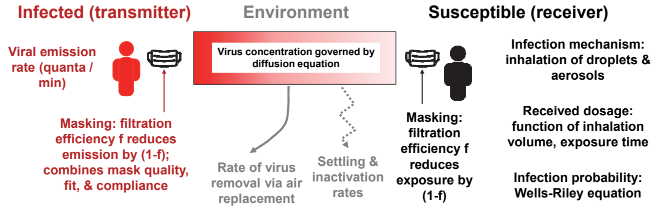


**Figure 5. Environment & Virus Transmission Interaction**

These elements are integrated into a flight simulation illustrated in Figure 6. Input parameters, transmission mitigations, and simulation outputs are highlighted in blue, red and green text respectively. In the *initialization phase* (shown in the grey box), the physical environments are characterized, a passenger list (including both incoming infected and uninfected passengers) is generated, and passengers are distributed randomly around the departure gate and aircraft cabin environments. The prevalence parameter is specified as a simulation input, and the virus emission rate of infected passengers is modeled using a log-normal cumulative density function as shown in Figure 4. Emission rates drawn from the distribution make it possible to generate a range of spreading events from minimal to super-spreader. The choice of the log-normal distribution was somewhat arbitrary, but was guided by studies suggesting that a potentially wide range of virus emission rates from infected people [3][4].

Then an *exposure phase* (shown in the pink box of Figure 6) implements the interactions between the environmental and virus transmission models. Infected passengers emit virus into the environment, virus is transported throughout the environment as governed by the characteristics of the ventilation system and the diffusion model, susceptible passengers are exposed to differing amounts of virus, depending on their location and the duration of their stay in the environment, and the probability of infection for each exposed passenger is calculated using the Wells-Riley equation. Finally, the expected value of the number of infected passengers and the overall probability of infection under each given set of mitigations are computed in the post-process step illustrated at the right in Figure 6.

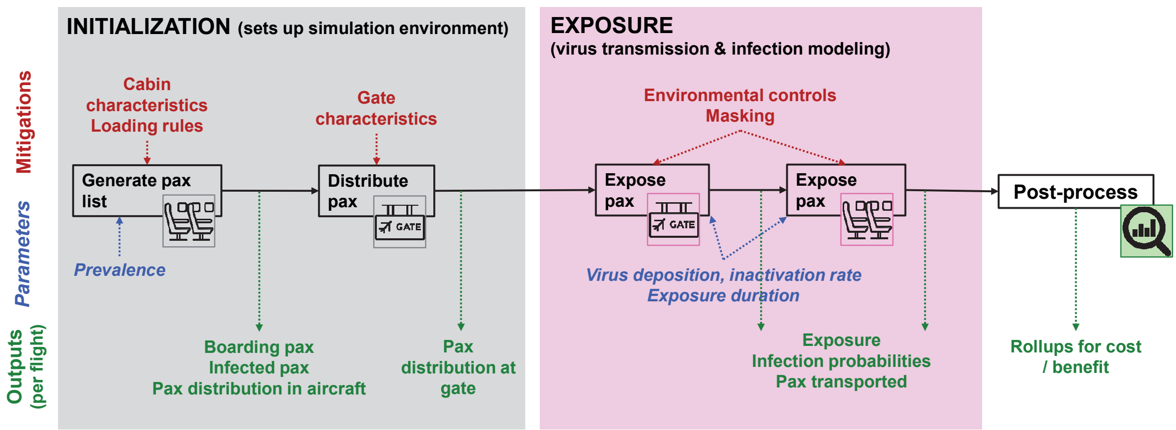


**Figure 6. Departure Gate & In-Flight Modeling Approach**

## B. *Results*

The modeling infrastructure discussed above was exercised using the modeling parameters detailed in Table 1 below. The key goals of this analysis were to (1) identify the most effective terminal gate management mitigations; (2) evaluate the effect of mask requirements on outcomes; and (3) couple terminal management mitigations to flight operations decisions.

**Table 1. Mitigation Analysis Modeling Parameters**

| Factor (goal) | Levels | Results Coding | Model Step |
|---|---|---|---|
| **Gate area (1)** | Low (150 $m^2$)<br>High (300 $m^2$) | —<br>— | |
| **Gate air removal rate (1)** | Low (4 / hour)<br>High (12 / hour) | ▼<br>▲ | |
| **Mask filtering (2)** | None (0.0)<br>Low (0.25)<br>Moderate (0.5)<br>High (0.75) | ······<br>—·—<br>– – –<br>—— | |
| **Aircraft load factor (3)** | Low (0.5)<br>Moderate (0.67)<br>High (0.9) | ······<br>– – –<br>—— | |

There are many potential combinations of parameters given this analysis space, but illustrative results against each of the goals are discussed here. The results curves presented are specific examples of the generic trade-off curves as a function of mitigation illustrated on the right side of Figure 2.

Results for goals (1) & (3) are presented in the top panel of Figure 7 for a case of fixed masking efficiency of 0.25. The plot at the top left only considers the gate area exposure. It shows that increasing gate area for a given passenger load factor has a bigger impact than increasing air removal rate to mitigate transmission risk at the departure gate. The plot on the top right adds in the exposure impacts from the aircraft cabin exposure for a 4 hour flight in a narrow body aircraft. These results show that the aircraft cabin exposure in this case can add significant additional exposure risk compared to the gate only results. The relative infection probability impact depends on the mitigation case being considered.

Sample results for goal (2) are presented in the bottom panel of Figure 7. These plots show how the passenger infection probability varies as a function of aircraft load factor with different mask filtration efficiencies for different airport gate mitigations including "best case" (low passenger density/high air turnover rate [left]) and "worst case" (high passenger density/low air turnover rate [right]) gate scenarios. If a notional target infection probability of 0.002 (or 0.2%) is postulated (as shown by the cyan dashed line in the plots), some sample insights from these results are:

- "No mask" usage cannot achieve the target infection rate.
- The target infection rate will be met for any load factor above 50% for the best-case gate mitigation scenario for any masking efficiency above 25%.
- At 67% load factor (all middle seats empty), mask efficiencies of 0.25 and higher can achieve the target

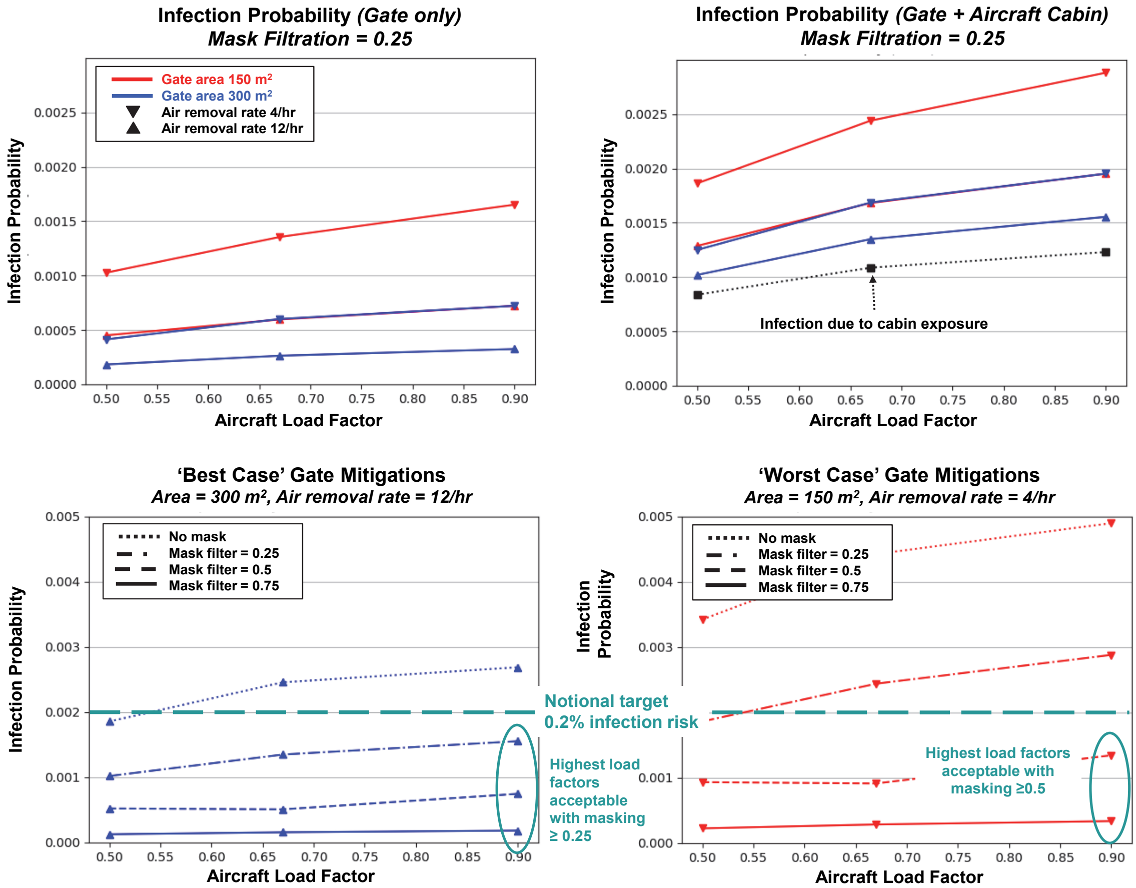


**Figure 7. Effects of Load Factor, Air Removal Rate, and Departure Gate Area (top panel) and Passenger Mask Usage and Efficiency (bottom panel) on Infection Probability**

infection rate under the best case gate mitigation, but only mask efficiencies of 0.50 or greater will achieve the target rate under the worst case gate mitigation case.
- At 90% load factor, only mask efficiencies of 0.50 or greater will achieve the target infection rate under both gate mitigation cases.

These results indicate that high quality, high compliance masking enables higher passenger density to be achieved for a given infection risk even with less effective gate mitigations. These results present only a small selection of the results that the modeling system can provide, but they illustrate how the tool can provide insights to stakeholders regarding the relative impact of a range of mitigation options available to them. Given that the cost of implementation of different mitigations can be highly variable (e.g., imposing strict mask requirements will be much less costly than blocking aircraft seats or re-designing airport infrastructure), a modeling system such as this can help determine the most cost-effective way of driving down infection risk in the aviation system.

### C. *Validation Efforts*

Validation of this type of model presents several significant challenges. Pre- and post-flight COVID testing, required to identify potential index cases (passengers who were already infected upon boarding) has still not become commonplace. Contact tracing to identify passengers likely to have been infected during air transit also presents several challenges. Contact tracing is labor intensive, response rates from contacts are often low, and travelers move through many environments during their travel [5][13]. Furthermore, there are few guidelines for operators to implement policies for collecting and sharing passenger data needed to inform public health decision as novel infectious disease threats emerge [5]. Addressing these shortfalls will require significant effort to develop technologies for data collection and sharing, as well as policies to govern their use.

We addressed this lack of validation data in two ways: comparison of our model results to other probability estimates derived by other methodologies (e.g., [14]) and comparison to infection rates reported across a range of case studies [5]. We did not consider various assertions of infection probability published on websites that did not include references to published studies in which the methods and datasets were clearly described.

In [14], Barnett uses basic principles of probability to estimate the probability of passenger infection as a function of aircraft cabin density (empty middle seat and filled to capacity) without simulation. After adjusting his assumed prevalence and masking effectiveness to match ours, we found our infection probability estimates to be roughly 5 – 6 times higher. Given the large range of uncertainty and differences in methods, we consider this to be reasonable agreement, but is a clear indication of the need for on-going cross-comparison between models as they continue to emerge in the literature.

In [5], the authors review 18 flights for which sufficient information was available to analyze possible transmission. Conditions such as number of index passengers, total number of passengers on the flight (when available), aircraft types, and mask use varied considerably across the cases. In all, 9 of 18 flights had one or more likely infections associated with air travel, of which 4 had multiple infections. Eight of the 18 reported no infections, and flight-related transmission could not be determined in one flight. Again, our model is in rough agreement with the range reported in the case studies. Each flight simulated had, on average, 1 or 2 index passengers. On average, we observed transmission on roughly 1 in 2 flights for the least effective mitigations and roughly 1 in 25 flights for the most effective.

## V. ATC Delay Impact Modeling

### A. *Approach*

Extensions to the model described in the previous section were made to analyze the infection impacts of ATC delay by adding an aircraft scheduling element to support the simulation of a 20-hour day of departure terminal operations. Although ATC delays were much lower than normal during the traffic downturn in 2020, significant traffic levels have returned in summer 2021 despite high COVID infection rates, so an assessment of the impact of ATC delay on infection rates is valuable. The simulation provides insights into the *system-wide infection rates* that may be expected under different operating conditions. While the probability of an individual passenger becoming infected may be estimated here as well, the finer-grained model presented in the previous section provides a better-tuned estimate of individual risk. Nonetheless, the results of the system-wide analysis should be (and are shown to be) consistent with the more detailed single flight analysis.

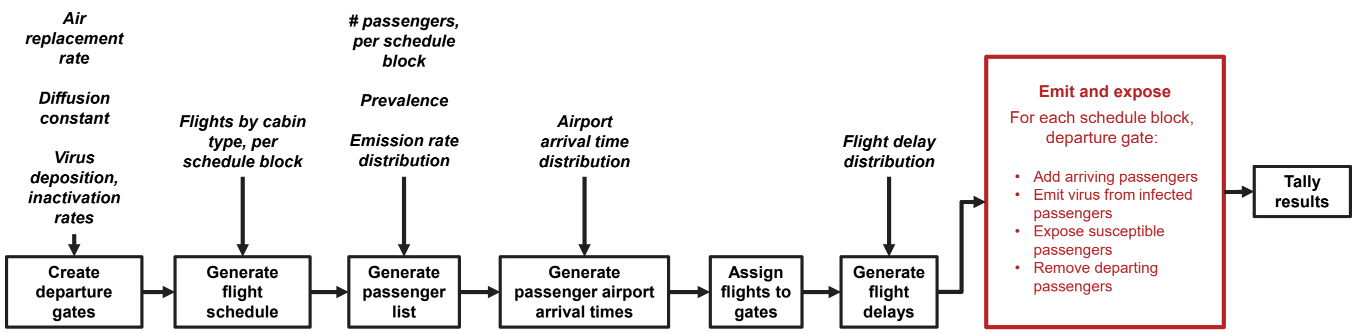


**Figure 8. ATC Delay Impact Simulation**

The full-day terminal operational model and simulation are more complex and dynamic than that used in the single flight analysis: see Figure 8. The terminal is defined as a list of departure gates, each of which is characterized by its dimensions, "passenger packing" grid, and the virus transmission environment discussed in the previous section that describes airflow and other viral-transmission parameters. All gate dimensions and environments were assumed to be identical.

For each schedule time block, passengers arriving during that time block are transferred directly to the departure gate to which their flight has been assigned. Newly arriving passengers are assigned seats randomly in the departure gate waiting area; if all seats are taken, they are "packed" into standing areas in the departure gate. If all seats and standing areas are occupied, the arriving passengers are rejected (this rarely occurred). Figure 9 illustrates gate occupancy at a given time block.

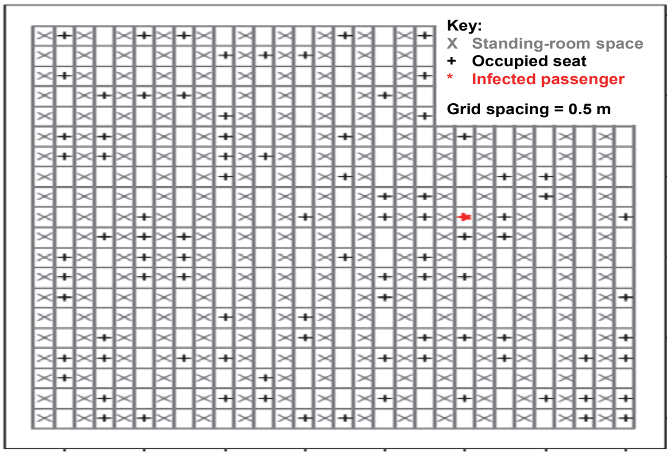


**Figure 9. Illustration of Gate Occupancy**

Passengers are assumed to wait at their assigned locations until their flights depart. Once the arriving passengers are situated, the concentration of airborne virus is calculated for each departure gate. Airborne virus is assumed to stay within the bounds of its departure gate; it does not pass from one gate to another. The Gaussian spatial distribution used in the previously described model was replaced by the diffusion equation solution described by Drivas [15], with the simplifying assumptions that airborne virus does not reflect off terminal walls and that there is not significant diffusion of virus in the vertical direction. Removal of virus from the environment due to vertical air motion is already accounted for by the viral deposition rate that characterizes the environment. The Drivas method was chosen because it provides greater detail in the spatial-temporal diffusion and decay of the virus in the environment (at a commensurate computational cost). The viral exposure of susceptible passengers at each departure gate is then updated. Finally, departing flights are identified and their passengers are removed from the departure gate environment.

The simulation generates several state variables for each departure gate/schedule block, including total occupancy, total number of infected passengers, total rate of virus emission into the environment (integral of virus emission rates over all infected passengers), and total airborne virus. Each of these may be aggregated over all gates to provide a time series of the departure terminal state over the course of the day or aggregated over all time blocks and gates to provide full-day performance measures for terminal operations. Additional full-day statistics also include total number of delayed flights, total/average flight delay, and, of course, the expected value of new infections resulting from the day's operations.

### *B. Results*

The objective of the experiments presented next was to assess the impacts of two factors on disease transmission in the departure terminal: departure delays and aircraft cabin load factor. In order to focus clearly on the effects of those two factors only, many of the simulation parameters were fixed at values shown in Table 2.

Airport arrival times were drawn from the distribution shown in Figure 10 which assumes passengers arrive anywhere from 60-120 minutes prior to the scheduled departure time, with 90 minutes being the most likely. Other experimental factors are described in Table 3. Daily operations were simulated for a perfectly executed departure schedule (the no-delay baseline), as well as "moderate" and "severe" departure delay profiles illustrated in Figure 11. The delay scenarios are modeled on typical delay profiles observed in the operational system, for example due to moderate or severe weather impacts respectively.

**Table 2. ATC Delay Analysis Modeling Parameters**

| Variable | Units | Value | Source |
|---|---|---|---|
| **Epidemiology** | | | |
| Prevalence | | 0.01 | |
| Emission rate | Quanta/hr | 30 | [4] |
| **Schedule** | | | |
| Hours of ops | | 20 | |
| Aircraft capacity | # passengers | 150 | |
| **Environment** | | | |
| Air replacement | Air change/hr | 6 | [16] (shopping center comparable) |
| Diffusion constant | $m^2$/min | 0.03 | [15] (reduced for large space) |
| **Virus transmission** | | | |
| Mask filtration | | 0.5 | [17][18] |

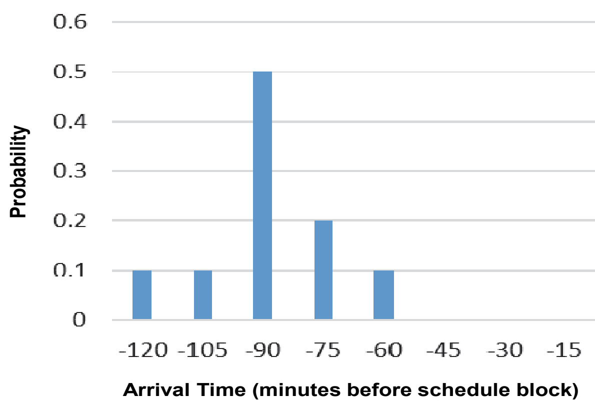


**Figure 10. Assumed Passenger Arrival Time Distribution**

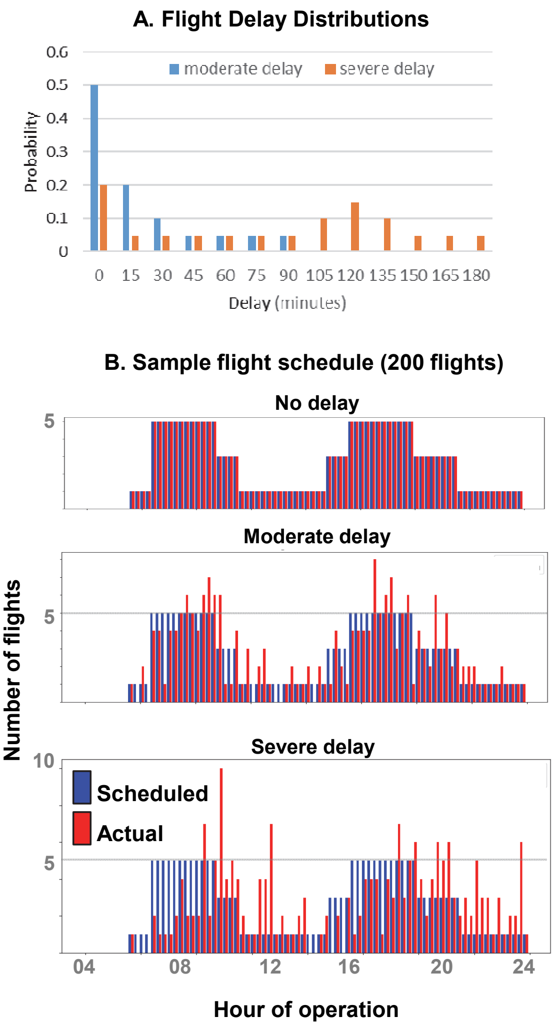


**Figure 11. Flight Delay Distribution and Sample Schedules**

The no delay, moderate, and severe delay cases were run for two load factors: 67% (0.67) corresponding to the empty middle seat case and 85% (0.85), roughly corresponding to 2019 levels for US domestic air traffic. Because the total daily number of traveling passengers was fixed at 20,000, the higher load factor resulted in fewer flights per day (156 vs. 200). A total of 30 days of operations was simulated for each delay profile/load factor combination (180 simulated operational days in all). Passenger arrival times, assignment of passengers as infected or susceptible, and individual flight delays were the factors randomized across simulations.

**Table 3. ATC Delay Analysis Experimental Factors**

| | Load factor = 0.67 | Load factor = 0.85 |
|---|---|---|
| Delay profiles | None, moderate, severe | None, moderate, severe |
| # Passengers | 20000 | 20000 |
| # Flights | 200 | 156 |
| # days | 30 | 30 |

Results are summarized in Figure 12. All plots provide comparisons of outputs as a function of delay modes (x-axis) and load factor (blue=67%, red=85%). The results presented are daily and terminal-wide averages of the instantaneous (per schedule block) outputs across all 30 simulations. The upper left plot shows the total flight delay. While the average per-flight delay is determined by the delay mode distributions (and hence roughly equal for both delay modes), the total flight delay is higher for the lower load factor operations because there are more flights. Terminal occupancy (lower left) is consistent across both load factors since this is driven by factors common to both: *passenger demand* schedule and delay profile. Average airborne virus loads (upper right), expressed as disease quanta, follows from terminal occupancy. Finally, the expected number of new infections (lower right) is calculated by applying the Wells-Riley equation to estimate the probability of infection for each susceptible passenger

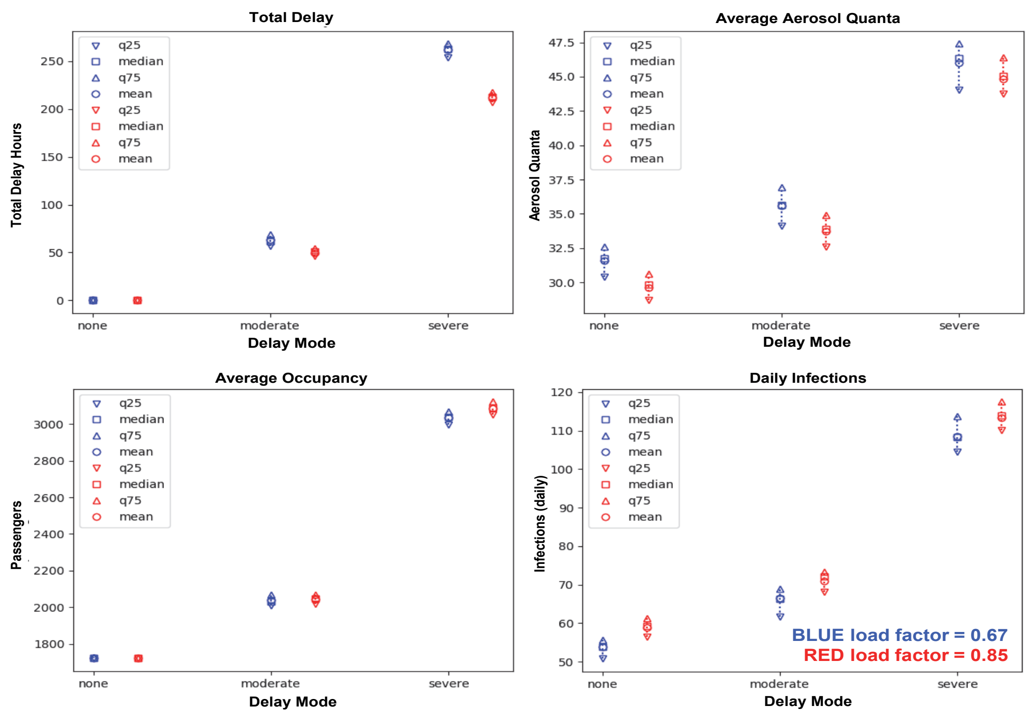


**Figure 12. ATC Delay Impact Results (Terminal-wide Daily Quartiles and Mean)**

given their exposure and summed up over all passengers. It is a function of both the occupancy and airborne virus.

Qualitatively, the results are not surprising. Increased delays result in higher terminal occupancy, which, in turn, results in higher levels of airborne virus and infection rates. But it is the quantitative relationships that are of interest. The mean total infections in the no delay case is approximately 9% greater for the 0.85 load factor than for the 0.67 load factor. Furthermore, the bottom quartile of the infection count for the higher load factor is greater than the top quartile infection count for the lower load factor, suggesting that the difference is statistically significant. Even though the terminal-wide occupancy is similar for the no-delay simulation for both load factors, passengers are distributed across fewer flights and departure gates in the high load factor case, resulting in higher local densities of waiting passengers. This finding is consistent with the increase in individual risk observed on flights with higher load factors in the previous analysis.

The difference in infection count between load factors narrows and there is considerable overlap between the quartile ranges as delays increase. As more flights are delayed, terminal occupancy increases, and in the severe delay case, passenger density at some individual gates may increase significantly as passengers from a delayed flight mix with newly arriving passengers for a later scheduled flight. Since there are more flights scheduled (and delayed) in the lower load factor case, more departure gates are likely to be impacted by delay-driven density increases. The increased local density, in turn, drives a greater increase in passenger exposure and infection, thus narrowing the gap in infection count between the two load factors.

Intraday terminal state averages for each load factor and delay scenario are shown in Figure 13. Intraday averages were calculated by averaging terminal-wide simulation outputs for each schedule block across all 30 simulated days. Delays lead to higher passenger occupancy (and hence higher airborne virus levels) as passengers pile up in the terminal awaiting their flight's departure, as evidenced by the differences in peak values observed during each of the two schedule peaks.

However, the effects are far more persistent in the severe delay profile. Intraday averages for the moderate delay case track the no delay schedule outputs closely throughout the day. On the other hand, impacts from severe delays clear more slowly as is evidenced by the wider peaks and inability of operations to recover and "reset" during the inter-peak schedule lull. The dynamic system behavior appears to be consistent across both load factors.

Intraday profile models could provide the basis for more dynamic operational mitigation planning. For instance, when intraday models predict that airborne virus concentration is likely to approach or exceed a critical risk threshold, it could trigger the implementation of targeted mitigations to limit passenger density at specific departure gates, such as utilization of passenger overflow areas and timed entry to departure gates.

## VI. Conclusions

In this work we considered the question of susceptibility of travelers to in-transit COVID infection from two points of view: the risk to an individual traveler of becoming infected on a particular flight conditioned on several operational factors, and the epidemiological risk estimated as the number of new infections generated in the departure terminal during a "typical" daily operational schedule under different delay and load factor conditions. For the individual traveler, masking compliance, and social distancing (implemented either via

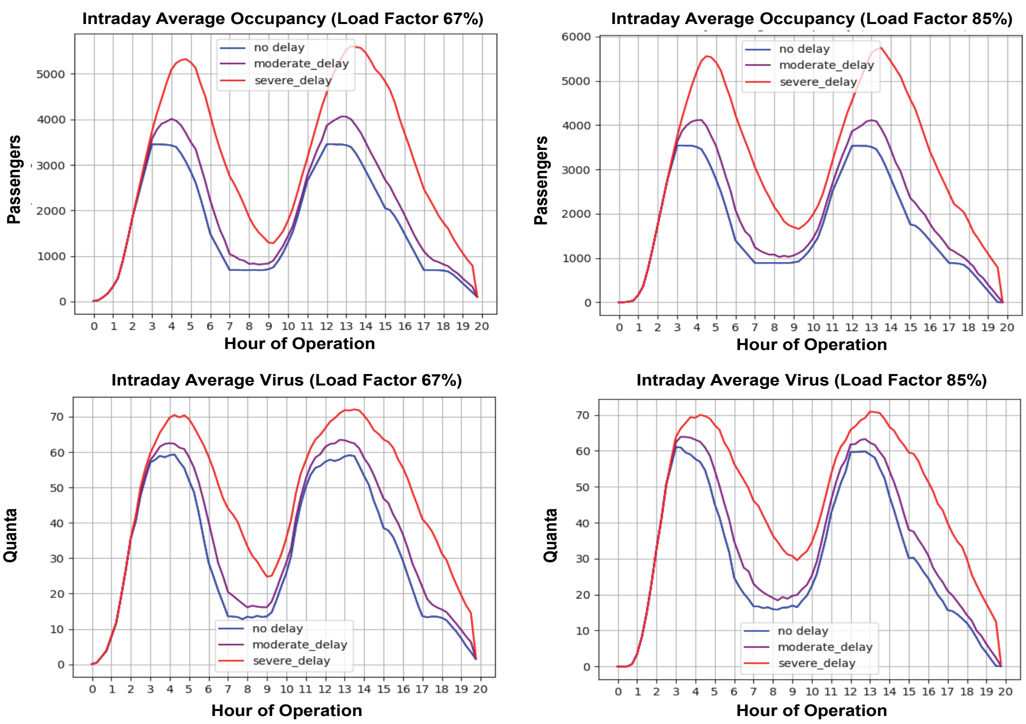


**Figure 13. ATC Delay Impact Results (Intraday Terminal-wide Averages)**

larger departure gate waiting areas and / or lower load factors) are identified as the most effective mitigations to reduce the probability of infection (anywhere from 50 – 90% reduction from no-mask operations). Consistent with these findings, a daily schedule with fewer, higher density flights posed a greater transmission risk than one with more but lower density flights in the case where there were no departure delays. However, as delays increase, terminal occupancy increases, as does the density of passengers at individual departure gates. This effect is more pronounced in a schedule characterized by a larger number of low density flights, and as a result, the difference in infection counts between schedules of high and low density flights narrows. The observed system-wide behavior was found to be consistent with the results of the individual flight simulations.

This initial exploration suggests several possibilities for future work. Operational and environmental transmission models are being developed for more dynamic phases of air transport such as security, check-in, and customs queues to extend the scope to more phases of the door-to-door experience. Exposure and infection models must be applied to airport and airline employees. Larger scale simulations that sweep a wider range of operational and epidemiological parameters could generate a database of results that can be mined with sophisticated statistical and machine learning techniques to uncover the critical factors that drive infection rates and the combination of mitigations that are most effective at reducing infection rates under different operating conditions. Model validation has already been highlighted as a key need and should continue as more empirical data becomes available. Finally, interfaces to models for demand and disease propagation in the world at large should be developed, work which has been started in [19]. All of these activities need to provide industry and public health planners with the information they need to set policies that are effective both from the standpoint of business and public health and to better prepare them to respond proactively to future unforeseen challenges.

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## AUTHOR BIOGRAPHIES


**Richard DeLaura** is Technical Staff in the ATC Systems Group at MIT Lincoln Laboratory. For the past 20+ years he has focused on the analysis of complex systems and development of decision support in the air traffic and military operational medicine domains.

**Tom Reynolds** is Leader of the ATC Systems Group at MIT Lincoln Laboratory. He has a Ph.D. in Aerospace Systems from MIT. He has worked on the research staff at MIT and the University of Cambridge, and in industry at British Airways Engineering.