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TEAM BASED, RISK ADJUSTED STAFFING DURING A PANDEMIC: AN AGENT BASED APPROACH

Vishnunarayan Girishan Prabhu
Kevin Taaffe
Caglar Caglayan
Tugce Isik
Yongjia Song

Department of Industrial Engineering
Clemson University
100 Freeman Hall
Clemson, SC 29634, USA

William Hand

Department of Anesthesiology
PRISMA Health - Upstate
701 Grove Road
Greenville, SC 29605, USA

ABSTRACT

Since the World Health Organization declared the novel coronavirus disease a pandemic, more than 2 million cases of infections and 140,000 deaths have been reported across the world. Specialty physicians are now working as frontline workers due to hospital overcrowding and a lack of providers, and this places them as a high-risk target of the epidemic. Within these specialties, anesthesiologists are one of the most vulnerable groups as they come in close contact with the patient's airway. An agent-based simulation model was developed to test various staffing policies within the anesthesiology department of the largest healthcare provider in Upstate South Carolina. We demonstrate the benefits of a restricted, no mixing shift policy, which segregates the anesthesiologists as groups and assigns them to a shift within a single hospital. Results consistently show a reduction in the number of deaths, anesthesiologists not available to work, and the number of infected anesthesiologists.

1 INTRODUCTION

Approximately 2.9 million cases of infections and 200,000 deaths have been recorded around the world under the current outbreak of severe respiratory syndrome coronavirus 2 (SARS-CoV-2) (John Hopkins University and Medicine 2020). Of these, more than one-third of the infections and one-fourth of the deaths are recorded in the US, placing the country in a unique, unprecedented public health emergency situation (Centers for Disease Control and Prevention 2020a). The rapid proliferation of the virus and surge in cases has overwhelmed the health systems, first responders, and providers. Additionally, lack of resources, including hospital beds, testing kits, ventilators, and providers, has created a significant delay in providing patient care and has resulted in significant hospital overcrowding. This additional patient demand on healthcare facilities has various negative impacts, one being the increased risk of infection transmission within the healthcare facility (Ng et al. 2020). Given that a majority of the infected people act as asymptomatic carriers of the virus, the impact on the healthcare providers and on other patients is exacerbated (World Health Organization 2020a; Day 2020). A February 2020 case study observed that one patient potentially exposed 41 healthcare workers to the SARS-CoV-2 virus, forcing the hospital to quarantine these providers (Ng et al. 2020).

Although various effective actions, including increasing the production of ventilators, testing kits, and setting up temporary hospital facilities, have been adopted to thwart the damage, one of the critical issues faced is the physician shortage (MedPage Today 2020). Currently, physicians from different specialties, retired physicians, and early-graduated medical students are all contributing to the workforce (Time 2020).

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Along with the physician shortage, another concern is the lack of availability of personal protective equipment (PPE) for healthcare workers (World Health Organization 2020d). Recently, by late March, the U.S Surgeon General declared a formal advisory urging hospitals to cancel elective surgeries to restrict the spreading of the SARS-CoV-2 virus within facilities and to reduce the use of medical resources and PPEs needed to manage a potential surge of COVID-19 cases (American College of Surgeons 2020).

A recent study that investigated the delaying of elective surgery to accommodate more COVID-19 patients in hospitals observed that more than 50% of all elective surgical cases have the potential to cause significant harm to patients if canceled (Stahel 2020). Along with these non-canceled elective surgeries, there are a set of urgent, life-threatening surgeries that need to be performed right away. This requires hospital operating rooms to continue providing surgical care but under a higher risk due to a lack of PPE availability and the risk of a patient being an asymptomatic carrier. Although the entire surgical team are exposed to this risk, the case of anesthesiologists requires special attention. As anesthesiologists specialize in emergent airway management, acute and intensive care, and perioperative anesthesia, they perform complex procedures including tracheal intubation, which involves inserting a tube through the patient's airway (Kharasch and Jiang 2020). Their close contact with a patient's airway places them at higher risk as there is a potential of exposure to respiratory droplets from the patients (Chen et al. 2020; Zhang et al. 2020a). Moreover, the American Society of Anesthesiologists estimated that about more than one-third of its members are more than 55 years old, which was categorized as the high-risk age group for COVID-19 (Wong 2020).

The use of agent-based modeling (ABM) has gained popularity in healthcare operations management literature and particularly, in the infectious disease prevention and control domain (Barnes et al. 2013). Capable of modeling and simulating the actions of various autonomous individuals including physicians, nurses, and patients, jointly with the interactions among them, ABM-based approaches have provided additional insights with more realistic models for disease spread and assessment of various health service operations (Tracy et al. 2018; Perez and Dragicevic 2009; Khalil et al. 2012; Crooks and Hailegiorgis 2014; Chumachenko et al. 2018)

We highlight several ABM-based approaches in the infectious disease control literature. Utilizing an ABM, (Barnes et al. 2010) investigated the performance of various infection control measures such as hand-hygiene, patient screening, and, patient isolation, to control the transmission of Methicillin-resistant Staphylococcus aureus (MRSA) spread within a hospital. They showed that increasing hand-hygiene compliance is more effective than hiring additional healthcare workers to minimize MRSA transmission, and hand-hygiene compliance must still be supplemented with other measures to effectively prevent transmission. Aleman et al. (2011) developed an ABM simulation for a pandemic outbreak scenario. Capturing nonhomogeneous transmission and infection rates, their model serves as a decision support tool, predicting disease spread during a pandemic, generating a map of the estimated disease spread area within the geography of interests, and assessing the relative effectiveness of various mitigation strategies to control the disease. Finally, Codella et al. (2015) used ABM to capture both the natural progression of Clostridium Difficile in patients and its transmission in a midsized hospital among patients, healthcare workers, and visitors. The authors used their model to evaluate the effectiveness of vancomycin administration, hand hygiene, isolation, and disinfection with bleach, and they demonstrated the impact of these strategies on asymptomatic colonization rates and patient length of stay durations.

Researchers have used various modeling techniques to estimate the spread and number of deaths (Jung et al. 2020; Russell et al. 2020), hospital bed and PPE requirements as a result of the SARS-CoV-2 virus (Zhang et al. 2020b; Moghadas et al. 2020). In our research, we address the impact of the anesthesia team staffing schedule on the likelihood of individual providers becoming infected and the ability of the team to continue providing care to their patients. We use an ABM-based approach to test staffing policies that illustrate the infection spread within the anesthesiology department of the largest healthcare provider in Upstate South Carolina. The department operates across several facilities with a number of workforce deployment options across these facilities.

2 DATA AND ASSUMPTIONS

Data used in this study was derived from PRISMA Health Upstate. Table 1 below represents the anesthesiologist requirement and staff grouping in each PRISMA Health facility. Additionally, the anesthesiologist-to-anesthesiologist interaction per hour, anesthesiologist-to-patient interaction per day, testing frequency per week, and quarantine period were derived from discussions with the PRISMA Health Department of Anesthesiology. Currently, with the limited availability of testing kits, the anesthesiologists are tested only once in a week, and according to current PRISMA Health policy, those tested positive for COVID-19 are sent to a mandatory quarantine period of 14 days.

Table 1: PRISMA health facilities and anesthesiologist requirement.

Facility	Shift and anesthesiologist requirement
Facility 1	21 (3 groups of seven anesthesiologists)
Facility 2	6 (2 groups of three anesthesiologists)
Facility 3	6 (2 groups of three anesthesiologists)
Facility 4	6 (2 groups of three anesthesiologists)
Facility 5	2 (1 group of two anesthesiologists)
Facility 6	2 (1 group of two anesthesiologists)

Further, data pertinent to the COVID-19 transmission probabilities, incubation time, asymptomatic probability, recovery period, and mortality rate were obtained from publicly available reports and literature. From the data obtained from the initial 38,000 COVID-19 cases in China, it was observed that the transmission rate was 1% - 5% among people in close contact with infected patients (The Hospitalist 2020). However, the rate of spread to family members and others in close contact fell to 1% - 3% with isolation and social distancing. In our ABM model, anesthesiologists are infected from patient interactions based on a combination of the frequency of patient interactions and the likelihood of infection from a single interaction. The transmission rate above is not calculated in this same manner. Based on discussions with the PRISMA Health stakeholders and current population infectivity in the area, we calibrated these values to convert this to a value more appropriately reflecting current infectious spread. Another factor is that the research is intended to illustrate the effects of infectivity originating from patients and infectivity originating from infected colleagues. Physician-to-physician transmissions may be more prevalent as the same level of caution may not be taken among colleagues. We chose to test two levels of patient transmission. In the first case, we utilize the calibrated value of .05%, and in the second case, we assume a 0% transmission from patients.

The incubation period is defined as the time from exposure to the virus until the first symptoms are developed (Centers for Disease Control and Prevention 2020b). In the case of COVID-19, the initial reports from the World Health Organization (WHO) and China's national health commission reported the incubation period between 2-10 days and 10-14 days, respectively (World Health Organization 2020b; Al Jazeera 2020). A recent report from the Centers for Disease Control and Prevention (CDC) announced that the incubation period could be between 2-14 days (Centers for Disease Control and Prevention 2020c). Further, the mean incubation period was derived based on the data from two studies that investigated 425 and 1,099 COVID-19 cases (Guan et al. 2020; Li et al. 2020). The asymptomatic probability of COVID-19 cases was obtained from a recent WHO report and a study that investigated the new cases of COVID-19 infections in China (World Health Organization 2020c; Day 2020).

During the quarantine period, most of the infected population recovers from the disease; however, some will perish (Wu and McGoogan 2020). Although the mortality rate of COVID-19 is low compared to Middle East Respiratory Syndrome (MERS) and Severe Acute Respiratory Syndrome (SARS), the current WHO report has increased the mortality rate to 3.4% from the initial estimate of 2% (World Health Organization 2020a). However, in this study, based on the mortality rates in the state of South Carolina and discussions with PRISMA Health stakeholders, we assumed a 2% mortality rate among care providers.

For anesthesiologists re-entering the health system after the mandatory quarantine period, the probability of getting infected for a second time and the period of immunity to the virus is yet to be understood fully. However, initial assumptions and observations from animal testing assume that people recovering from SARS-CoV-2 will develop relatively robust immunity for at least a few months (Bao et al. 2020). Conversely, recent observations from South Korea, where people contracted SARS-CoV-2 a second time and a non-peer-reviewed study reported the lack of development of the antibody responses to SARS-CoV-2 in recovered individuals, forces the researchers to make reasonable assumptions regarding the immunity period while modeling (Wu et al. 2020). In this study, we consider two scenarios: one where all anesthesiologists develop an immunity to the virus for more than three months, and the other where they have an immunity period of only fourteen days based on data from South Korea (NPR 2020). Table 2 lists the parameters considered in the model.

Table 2: Model parameters and values.

Parameters	Values
Anesthesiologist transmission rate	0.3%
Number of interactions between anesthesiologists	3 per hour
Patient transmission rate	0 or 0.05%
Number of anesthesiologist and patient interaction	13 per day
Incubation period	Triangular (2, 4, 14) days
Asymptomatic probability	78%
Workforce testing frequency	1 per week
Quarantine period	14 days
Mortality rate	2%
Immunity period	>90 days or 14 days

3 SIMULATION MODEL

In this paper, we created a simulation model in AnyLogic using agent-based modeling (ABM). This provided the flexibility to consider each anesthesiologist as a unique agent with specific parameters and attributes, interacting with other anesthesiologists working in the same hospital. Additionally, this allowed the flexibility to model each hospital as an agent with further segregation into groups within each hospital. Moreover, the capability to track the current state (in terms of Susceptible-Exposed-Infected-Recovered, or SEIR) of each physician made this the best option to model the rapidly spreading COVID-19.

Figure 1 depicts the anesthesiologist state chart, which illustrates the states where an anesthesiologist can be at any given point of time. By default, all anesthesiologists are placed in the susceptible pool (yellow box). We employ two options to initiate infection in anesthesiologists: (a) by randomly exposing an anesthesiologist, or (b) by assuming anesthesiologists were already infected. In option (a), the randomly exposed anesthesiologist is immediately moved to the exposed state and will stay in that state (without infecting others) based on an incubation period. In option (b), the anesthesiologist is directly placed into the infectious state (white box). After model initialization, anesthesiologists are infected by a patient or by another anesthesiologist based on the corresponding contact rates and transmission probabilities.

In the infectious state, the anesthesiologist interacts with another anesthesiologist in the same facility based on the contact rate. On initialization, we connected a certain number of anesthesiologists to a hospital resulting in forming a bidirectional connection where each anesthesiologist is linked to a hospital and each hospital is connected to a certain number of anesthesiologists based on the hospital requirement. Further, within each hospital, we created groups that represent the various shifts available as the anesthesiologist will only interact with colleagues present during the same shift.

The anesthesiologist-to-anesthesiologist interaction is initiated by a message from a separate hospital state chart. Upon receiving the message from the anesthesiologist, the linked hospital will iterate and find other anesthesiologists working on the same shift in the same hospital and forward the message to one of them. Forwarding the message triggers the physician state chart, and the anesthesiologist either transits to the exposed state or stays in the susceptible state based on the probability of transmission.

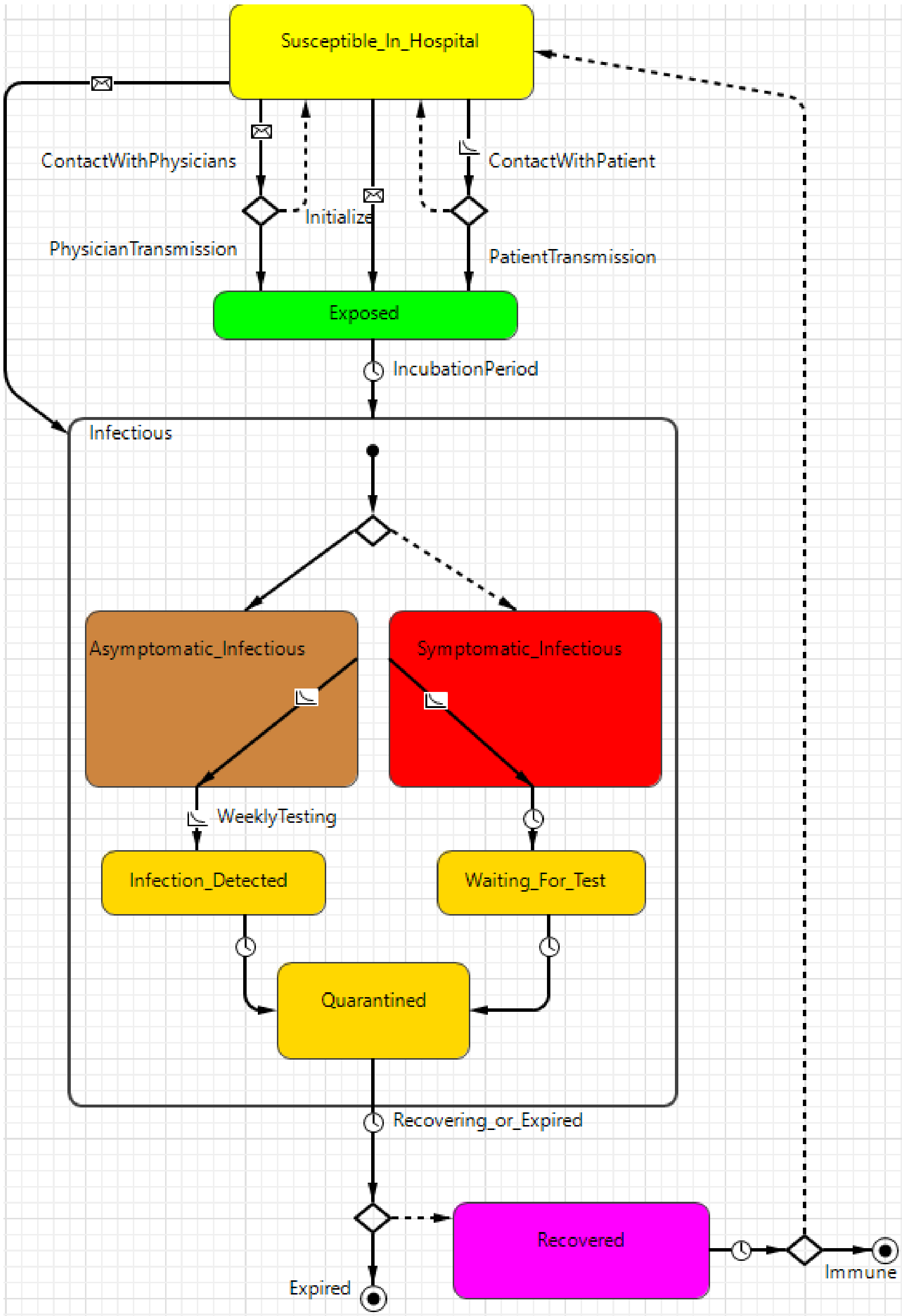

Figure 1: Anesthesiologist state chart.

An infected anesthesiologist can be either in the asymptomatic or symptomatic state based on the associated probability. In the symptomatic state, the anesthesiologist exhibiting symptoms is sent for testing the next day and stays home for the quarantine period as reported in Table 2. However, for anesthesiologists in the asymptomatic state, which represents the majority of COVID-19 cases, the anesthesiologist is sent for testing based on the testing frequency adopted by the hospital. Similar to the symptomatic case, an anesthesiologist tested positive is then quarantined for 14 days. After the mandatory quarantine period, the vast majority of the anesthesiologists reenter the health system, whereas a few of them moves to the final state based on the mortality rate. Upon reentering the system, based on the scenario, the anesthesiologists either have a possibility of getting infected for the second time after the immunity period of 14 days, or they develop immunity toward COVID-19 that lasts for more than 90 days.

We do not model individual patient infectivity levels in the simulation model, and the patient transmission probability is incorporated as a rate accounted for the risk of infection transmission across all patients being served by the anesthesia team. This approach was adopted as it does not affect the efficacy of the model to replicate the anesthesiologist interaction within the hospital.

4 STAFF SCHEDULING POLICIES

In pursuit of the best policy to limit the infection spread within the anesthesia department, we considered three different staff scheduling policies. Each policy allowed a different level of intermixing of anesthesiologists between different hospitals. The baseline policy was the current policy adopted by the Department of Anesthesiology of PRISMA Health Upstate. Further, within each policy, we considered various scenarios that had a different number of infected anesthesiologists on initialization. The following metrics were selected as the performance metrics to evaluate each policy based on expert opinions from the PRISMA Health Dept. of Anesthesiology stakeholders.

- Average number of infected anesthesiologists/day
- Total number of anesthesiologists infected
- Average number of anesthesiologists missing work

4.1 Inter-Hospital Mixing (Baseline policy)

Under this policy, an anesthesiologist is allowed to work in any facility. However, anesthesiologists sign onto this schedule and work at the same facility for a week, with the option to switch facilities or groups within a hospital every week. This implies that an anesthesiologist working at facility 1 can work at facility 2 or switch groups within facility 1 after each week. It provides the most flexibility in how the staffing schedule is set. In this model, these decisions are generated randomly, as there's no particular preference among the employees. In Figure 2, the possible shift options for an anesthesiologist under this policy are represented by dashed lines (inter-hospital) and bold lines (inter-group) interactions.

4.2 Inter-Group Mixing

In this policy, we restrict the anesthesiologist interaction by limiting the shift options to those available within a facility. Here an anesthesiologist is allowed to switch groups within the same hospital but cannot sign up for a shift in a different facility. In Figure 2, the possible shift options for an anesthesiologist under this policy are represented by bold lines (inter-group) interactions.

4.3 No Mixing

In this policy, we further restrict the anesthesiologist interaction by segregating the anesthesiologists into predefined groups within a single hospital. They can only bid for that particular shift. In Figure 2, each predefined group is represented as circles, either as subgroups within the facilities 1-4 or as a single group at smaller facilities 5 and 6.

All of the policies were developed based on discussions with the PRISMA Health stakeholders to ensure each policy is realistic and applicable in any health system with multiple campuses. Due to the uncertainty in specific parameters in the model, it is imperative that we run multiple scenarios. We chose to vary the patient transmission rate, immunity period, and the number of anesthesiologists infected at each facility on initialization. The first two parameters were selected due to the lack of available information and variability observed in the currently available data. The third parameter was chosen to capture the impact of spread across each facility under the three policies. Moreover, we wanted to test the policies under multiple potential scenarios to better inform and assist the stakeholders in decision making. We provide our results in the next section and compare the results from each policy under each scenario.

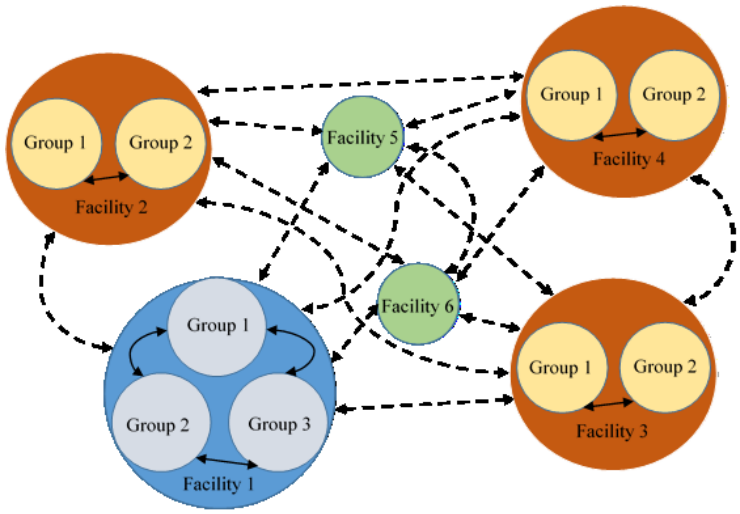

Figure 2: Anesthesiologist inter-hospital (dashed lines) and inter-group (bold lines) interaction.

5 RESULTS

In addition to varying the patient transmission rate and immunity period, we also tested five scenarios for the number of anesthesiologists infected at each facility on initialization. This resulted in 20 simulated scenarios under each shift staffing policy for a time horizon of 90 days and 500 replications. We present the results in five tables where each table represents a different scenario based on number of anesthesiologists infected at each facility at initialization. Within each table, we present four cases:

Case 1: Once recovered, then immune for 90 days; patient transmission rate is 0%.
Case 2: Once recovered, then immune for only 14 days; patient transmission rate is 0%.
Case 3: Once recovered, then immune for 90 days; patient transmission rate is 0.05%.
Case 4: Once recovered, then immune for only 14 days; patient transmission rate is 0.05%.

In the first scenario, we present the results where one anesthesiologist from each group at facility 1 is infected initially. Facility 1 staffs the highest number of anesthesiologists. Hence, the scenario in Table 3 represents a high-risk scenario where the potential for infection spread within the department is high.

Table 3: Results – three anesthesiologists infected at initialization (groups 1, 2, 3 at facility 1).

	Inter-Hospital Mixing			**Inter-Group Mixing**			**No Mixing**		
Case	Avg # infected	Total # infected	# not working	Avg # infected	Total # infected	# not working	Avg # infected	Total # infected	# not working
1	4.0 (.11)	16.2 (.50)	3.1 (.08)	3.1 (.06)	11.1 (.24)	2.3 (.04)	2.4 (.05)	7.9 (.18)	1.8 (.03)
2	4.7 (.14)	20.7 (.70)	3.4 (.10)	3.4 (.08)	13.8 (.40)	2.6 (.06)	2.4 (.05)	8.3 (.22)	1.9 (.03)
3	7.4 (.05)	32.7 (.17)	5.5 (.04)	6.6 (.05)	29.9 (.18)	4.9 (.04)	6.1 (.05)	28.1 (.18)	4.6 (.03)
4	9.3 (.09)	48.2 (.37)	6.8 (.06)	8.4 (.08)	43.3 (.32)	6.2 (.05)	7.5 (.07)	38.5 (.29)	5.5 (.05)

From Table 3, we observed that compared to the baseline inter-hospital mixing policy, both restricted policies demonstrate marked improvements. Under a no mixing policy, in the absence of the patient transmission rate (cases 1 and 2), the average number of anesthesiologists missing work and the average number infected was reduced by more than 40%. In cases 3 and 4, these numbers were reduced to around 16% with a no mixing policy, but still outperforming the baseline inter-hospital mixing policy. A similar pattern can be observed for the total number of anesthesiologists infected. For cases 1 and 2, the total number infected decreased by more than 50%, and for cases 3 and 4 by 15%. Although the inter-group policy did not exhibit as much improvement as the no mixing policy, it followed a similar pattern where the average number of anesthesiologists missing work and the average number infected was reduced by 25% for cases 1 and 2 and reduced by 10% for cases 3 and 4. Similarly, the total number of anesthesiologists infected decreased by 30% for cases 1 and 2, and by around 10% for cases 3 and 4.

Tables 4-7 provide additional results that change the initial anesthesiologists infected, first reducing the number infected at facility 1, and then allowing the first infection to begin at a different facility.

Table 4: Results – two anesthesiologists infected at initialization (groups 1, 2 at facility 1).

	Inter-Hospital Mixing			**Inter-Group Mixing**			**No Mixing**		
Case	Avg # infected	Total # infected	# not working	Avg # infected	Total # infected	# not working	Avg # infected	Total # infected	# not working
1	3.3 (.11)	14.0 (.53)	2.5 (.08)	2.4 (.07)	9.1 (.30)	1.8 (.05)	1.6 (.03)	5.3 (.15)	1.2 (.02)
2	3.6 (.13)	16.7 (.67)	2.7 (.09)	2.8 (.09)	11.8 (.43)	2.1 (.06)	1.6 (.04)	5.6 (.18)	1.3 (.03)
3	7.1 (.05)	33.1 (.17)	5.4 (.03)	6.6 (.05)	30.8 (.17)	4.9 (.03)	6.0 (.05)	28.7 (.18)	4.4 (.03)
4	9.0 (.08)	47.6 (.36)	6.6 (.05)	8.1 (.07)	43.3 (.31)	5.9 (.04)	7.2 (.06)	37.9 (.28)	5.2 (.04)

Table 5: Results – one anesthesiologist infected at initialization (facility 1).

	Inter-Hospital Mixing			**Inter-Group Mixing**			**No Mixing**		
Case	Avg # infected	Total # infected	# not working	Avg # infected	Total # infected	# not working	Avg # infected	Total # infected	# not working
1	1.9 (.10)	8.1 (.48)	1.4 (.07)	1.5 (.07)	5.9 (.31)	1.1 (.04)	0.8 (.02)	2.6 (.11)	0.6 (.01)
2	1.9 (.11)	8.9 (.58)	1.4 (.07)	2.0 (.10)	7.8 (.44)	1.2 (.06)	0.8 (.03)	2.8 (.13)	0.6 (.02)
3	6.9 (.06)	33.5 (.19)	5.1 (.04)	6.4 (.05)	31.4 (.18)	4.8 (.03)	5.9 (.05)	29.1 (.19)	4.3 (.03)
4	8.5 (.08)	46.5 (.35)	6.2 (.05)	7.5 (.07)	41.4 (.33)	5.5 (.05)	6.7 (.07)	36.5 (.30)	4.9 (.04)

Table 6: Results – one anesthesiologist infected at initialization (facility 2, 3, or 4).

	Inter-Hospital Mixing			**Inter-Group Mixing**			**No Mixing**		
Case	Avg # infected	Total # infected	# not working	Avg # infected	Total # infected	# not working	Avg # infected	Total # infected	# not working
1	1.5 (.10)	6.5 (.45)	1.1 (.06)	0.6 (.02)	1.6 (.07)	0.4 (01)	0.5 (.01)	1.1 (.04)	0.4 (.01)
2	1.6 (.10)	6.9 (.52)	1.1 (.07)	0.6 (.02)	1.7 (.09)	0.4 (.01)	0.4 (.01)	0.9 (.04)	0.3 (.00)
3	7.0 (.06)	33.6 (.19)	5.2 (.04)	6.4 (.05)	31.4 (.18)	4.7 (.03)	5.9 (.05)	29.2 (.20)	4.3 (.03)
4	8.3 (.08)	45.9 (.33)	6.1 (.06)	7.5 (.07)	41.3 (.33)	5.5 (.05)	6.6 (.06)	36.2 (.30)	4.8 (.04)

Table 7: Results – one anesthesiologist infected at initialization (facility 5 or 6).

	Inter-Hospital Mixing			**Inter-Group Mixing**			**No Mixing**		
Case	Avg # infected	Total # infected	# not working	Avg # infected	Total # infected	# not working	Avg # infected	Total # infected	# not working
1	1.1 (.07)	4.6 (.39)	0.8 (.05)	0.3 (.00)	0.5 (.02)	0.3 (.00)	0.3 (.00)	0.5 (.02)	0.3 (.00)
2	1.2 (.10)	5.1 (.48)	0.8 (.06)	0.3 (.00)	0.5 (.02)	0.3 (.00)	0.3 (.00)	0.5 (.02)	0.3 (.01)
3	6.8 (.06)	33.2 (.20)	5.1 (.04)	6.5 (.05)	32.0 (.18)	4.8 (.03)	5.9 (.05)	29.6 (.20)	4.3 (.04)
4	8.3 (.08)	45.8 (.37)	6.1 (.05)	7.5 (.07)	41.1 (.32)	5.5 (.05)	6.7 (.06)	36.4 (.28)	4.8 (.04)

Across all scenarios tested, the results consistently demonstrate that a no mixing shift policy outperforms either an inter-group or inter-hospital mixing shift policy, with the inter-hospital mixing policy always resulting in the highest levels of infection spread. Another important observation from these tests was the impact of the patient transmission rate (cases 1, 2 vs. cases 3, 4). Under all the scenarios, comparing policy 3 to the baseline, the decrease in the average number of anesthesiologists infected, the total number infected, and the average number missing work was more than 40% in the absence of patient transmission rate. Although the decreases in the performance metrics were not as prominent in the presence of patient transmission rate as was observed in its absence, they were still significant.

To better illustrate the effect of each policy, Figure 3 depicts the current number of anesthesiologists not working by day over the three-month simulation. The plotted values are the average over 500 replications for two cases where 3 providers are infected at initialization.

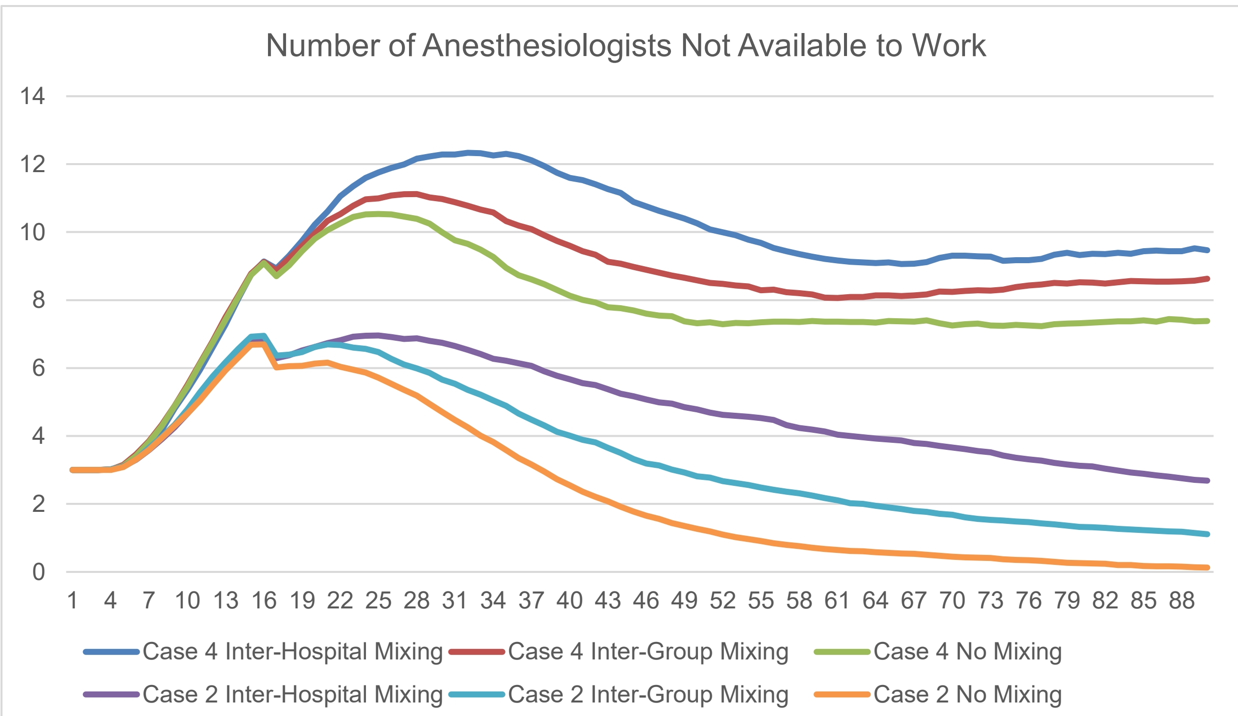

Figure 3: Number of anesthesiologists not available to work (3 providers infected at initialization).

Further, to comprehend the number of anesthesiologist deaths under each policy, we calculated the average number of fatalities where 3 providers are infected at initialization, as represented in Table 8.

Table 8: Mortality – three anesthesiologists infected at initialization (groups 1, 2, 3 at facility 1).

	Inter-Hospital Mixing	**Inter-Group Mixing**	**No Mixing**
Case	Average # dead	Average # dead	Average # dead
1	0.38 (.03)	0.22 (.02)	0.18 (.02)
2	0.45 (.03)	0.35 (.03)	0.25 (.02)
3	0.67 (.04)	0.60 (.05)	0.52 (.03)
4	0.79 (.04)	0.71 (.04)	0.63 (.03)

It can be observed that the average number of deaths for all the cases is less than one, which can be primarily attributed to the low mortality rate of COVID-19 and the low numbers of anesthesiologists in the department. Although the average number of deaths is minimal, it should be noted that the numbers decreased for all the cases when comparing policy 3 to the baseline policy. Additionally, it can be observed that in the absence of patient transmission, there was a minimum decrease of 45%, and in the presence of patient transmission, there was a decrease of 20%.

Finally, these results are based on a set of assumptions concerning infectivity, frequency of testing, precautionary measures taken by staff, and initial infection conditions. Additional tests are being conducted to determine the effects of these parameters. Given any scenario where infectivity parameters increase among the anesthesia providers, the no mixing policy is expected to provide more significant benefits than what has been presented here. There is still much to be explored in this area of research.

6 CONCLUSIONS AND FUTURE WORK

Protecting the healthcare workers during a pandemic is very crucial, and all health systems should be prepared with an alternative to their regular staffing/scheduling to maximize the availability of their staff. Especially among high-risk small population groups like anesthesiologists that manage surgical patients, critical care (intensive care unit) patients, and assist with intubation for non-surgical patients' absence of multiple providers could paralyze the hospital. As such, hospital administrators closely monitor the number of anesthesiologists available to work, and both on a hospital or system-level, the number of anesthesiologists available establishes the foundation of staffing models to approve elective surgeries as volume increases. In this research, we developed an agent-based simulation model and tested various policies that investigated the risk of the infection spread and the number of anesthesiologists available to work. We observed that segregating the anesthesiologists into groups and assigning them a particular shift within a facility can reduce the number of anesthesiologists not available for work by 14% and infected by 13%. Furthermore, we observed that this segregation could reduce the number of deaths by 20%.

The proposed model could help the hospital administrators adjust staffing models based on population prevalence and hospital prevalence of disease and better manage elective surgical volume increases. Further, this model could assist in creating lower-fidelity analytic models such as a (static) stochastic optimization model with endogenous uncertainty (Ryu and Jiang 2019), which captures the interdependence between the risk of infection and staffing/scheduling decision making. Integrated with an appropriate model for characterizing the underlying stochastic processes, this stochastic optimization model can also be further extended to a Markov decision process model (Broyles et al. 2011), which prescribes optimal staffing and scheduling in a dynamic setting.

Moreover, public health experts warn that the effects of COVID-19 on healthcare systems will be experienced over the long term, as surges are expected (BBC News 2020). Thus, the effective implementation of the ideas presented in this paper requires additional considerations regarding the evolution of population health through the stages of the pandemic and the resulting demand for anesthesiologists for COVID-19 cases. Constrained Markov decision models can be used to strategically allocate anesthesiologists to mitigate infection risk while maintaining minimum requirements imposed by population health dynamics.

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AUTHOR BIOGRAPHIES

VISHNUNARAYAN GIRISHAN PRABHU is a PhD student in the Department of Industrial Engineering at Clemson University. His research interests include applying predictive analytics techniques in healthcare. His email address is vgirish@clemson.edu.

KEVIN TAAFFE is the Harriet and Jerry Professor of Industrial Engineering at Clemson University. His research interests include the application of simulation and optimization in healthcare, production, and transportation logistics. Dr. Taaffe focuses on healthcare logistics problems that range from patient flow to operating room scheduling. His email address is taaffe@clemson.edu.

WILLIAM HAND is the Vice Chairman of Academics in the Department of Anesthesiology and Perioperative Medicine at Prisma Health and an Assistant Professor at the USC School of Medicine. He specializes in studying the application of dynamic physiologic parameters, simulation-based perioperative crisis management. His email address is William.Hand@prismahealth.org.

ÇAĞLAR ÇAĞLAYAN is an Assistant Professor in the Department of Industrial Engineering at Clemson University. He specializes in studying clinical decision-making under uncertainty problems. His email address is ccaglay@clemson.edu.

TUGCE ISIK is an Assistant Professor in the Department of Industrial Engineering at Clemson University. She specializes in operations planning and control, queueing networks, and Markov decision processes. Her email address is tisik@clemson.edu.

YONGJIA SONG is an Assistant Professor in the Department of Industrial Engineering at Clemson University. He specializes in stochastic optimization and its applications in health care, and energy systems. His email address is yongjis@clemson.edu.