Proceedings of the 2022 Winter Simulation Conference
B. Feng, G. Pedrielli, Y. Peng, S. Shashaani, E. Song, C.G. Corlu, L.H. Lee, E.P. Chew, T. Roeder, and P. Lendermann, eds.

COVID-19 SUPPLY CHAIN PLANNING: A SIMULATION-OPTIMIZATION APPROACH

Samaneh Maghoulan
Hande Musdal Ondemir
Mohammad Dehghanimohammadabadi

Mechanical and Industrial Engineering Department
Northeastern University
360 Huntington Ave
Boston, MA 02115, USA

ABSTRACT

Healthcare providers' preparedness and response plans are crucial to effectively cope with infectious disease outbreaks such as COVID-19. These plans need to provide strategic and operational actionable insights to guarantee the availability of essential resources when needed. This study uses a simulation-optimization approach to (i) determine an optimal replenishment policy to restock personal protective equipment (PPE) items, and (ii) determine proactive demand planning for critical resources such as the number of beds, and ventilators. This model leverages a Simio-MATLAB integration to complete simulation and optimization tasks.

1 INTRODUCTION

Due to the lack of an appropriate preparedness and response plans, many healthcare providers in the USA experienced a severe shortage of personal protective equipment (PPE) during the COVID-19 pandemic (Dai et al. 2020). Inadequate PPE threatens the safety of frontline medical staff and negatively impacts quality of care. The level of preparedness to combat unprecedented outbreaks directly depends on proactive planning, strategic thinking, and demand forecasts. Outbreak preparedness alleviates the stress of the situation and eliminates poor choices made in haste. One of these critical decisions is to plan resources efficiently and timely (Petrović 2020).The resources range from staffing needs (nurses, physicians, etc.), the number of beds, essential equipment such as ventilators and ventilator accessories, or even PPE items such as face masks, gloves, eye protection, and gowns.

An effective preparedness plan provides strategic and operational insights and ensures the availability of critical resources when needed. Simulation is a great tool to capture real-life systems' complexities and uncertainties, and study multiple what-if scenarios. During outbreaks, simulation becomes a critical tool to study infectious diseases and understand the dynamics of the outbreak process, the impact of disease and population properties, and the potential effect of interventions (Eriksson et al. 2009). This study aims to demonstrate the simulation modeling capabilities to support healthcare providers to make informed decisions and improve hospital preparedness. Therefore, this work's contributions are:

- Highlight the importance of simulation modeling for disease outbreak preparedness during a pandemic and post-pandemic situations.
- Use simulation-optimization to determine the best replenishment policy to restock PPE items.
- Analyze the healthcare resource requirements in different pandemic situations such as pandemic severity, effective social distance impacts, and vaccinations plans.

978-1-6654-7661-4/22/$31.00 ©2022 IEEE

This study is accomplished using Simio, a well-known and powerful simulation software. Different optimization platforms such as metaheuristics (coded in MATLAB and linked with Simio) as well as OptQuest are used to perform optimization.

The rest of this paper is organized as follows: A summary of the related works is provided in Section 2. Simulation modeling details and the healthcare center operations are described in Section 3. In Section 4, two experimental analyses are conducted to demonstrate the applicability of simulation modeling for outbreak preparedness. This work is concluded in Section 5 followed by some future extension insights.

2 BACKGROUND AND RELATED WORKS

Simulation has proven to be a useful tool to assist hospitals with their preparedness plans and is used in the past during outbreaks such as poliovirus (Moulsdale et al. 2014), influenza (Beeler et al. 2016), and Ebola (Delaney et al. 2016). Due to its vast capabilities, simulation has been used to support different decision-making problems related to pandemic preparedness. These problems include resource allocations, staffing, disease spread modeling, vaccination plans, and even training and educational needs. Interested readers can refer to (Currie et al. 2020) to gain more insights.

One of the main advantages of simulation is to analyse supply chain of healthcare systems. To study the impacts of epidemic outbreaks (COVID-19) on the supply chain performance, (Ivanov 2020) used anyLogistix simulation and optimization software. (Goodarzian et al. 2021) applied multiple metaheuristic algorithms to solve the sustainable medical supply chain network model. They considered three factors including economic, environmental, and social effects to address sustainability of the system during the COVID-19 pandemic. To mitigate the risk of drug shortage due to manufacturing problems, lack of infrastructure, and immediate reaction mechanisms, (Tirkolaee et al. 2022) used anyLogistix optimization and simulation software.

One of the important preparedness elements during pandemics is adequate staffing to manage infected patients and infections of surrounding patients, staff members, as well as the local community (Meng et al. 2020). (Beeler et al. 2016) used discrete-event simulation (DES) to determine staffing levels at mass immunization clinics (MICs) based on several factors of concern to public health authorities such as: total vaccination volume, patient wait times, operating costs, and intra-facility influenza transmission risk. In another study, reviewed some ideas for limiting staff shortages and creating surge capacity in acute care settings, and strategies for sustainability that can help hospitals maintain adequate staffing throughout their pandemic response. (Beeler et al. 2011) developed a DES model to estimate the expected number of infections resulting from disease transmission and considering various factors like crowdedness, staffing levels, and the percentage of infectious individuals entering the health care facilities. (Lu et al. 2020) used Arena, a discrete event simulation package, to create a computer simulation model and evaluate bed utilization as well as the corresponding supply needs during a pandemic situation in individual hospitals. Using data-driven approaches, they made an adaptive model to control policies that can be utilized for regional forecast targeting a specific hospital's catchment area.

Due to the importance of simulation modeling to address Covid-19 related problems, many researchers contributed to the Winter Simulation Conference in last two years. currie2020simulation developed an optimization-based, data-driven hospital load balancing model to find a trade-off between short transport times for patients that are not high acuity while avoiding hospital overloading. Authors used a simulation model to conduct experiments tailored for New York City's EMS system. To evaluate the impact of COVID-19 restrictions on airport operations, (Schultz et al. 2021) simulated an airport environment. Findings and lessons learned from this study are applied to a real airport to improve operators in redesigning airport terminals and managing passenger flows. (Neuner et al. 2021) used a simulation-based approach to analyze the treatment of patients accessing the ED of an Italian hospital.

This study aims to take advantage of simulation modeling to help with disease outbreak preparedness and response. The applied simulation model will be used as a decision support tool to estimate the capacities and quantities needed for care delivery to the infected population.

3 SIMULATION-OPTIMIZATION APPROACH

Simulation is a perfect tool to test multiple what-if scenarios based on different outbreak circumstances and draw managerial insights correspondingly. Simio is a powerful tool to build and run data-driven simulation models which enable its users to apply user-defined parameters and data-tables inputs (Dehghanimohammadabadi and Kabadayi 2020). By taking advantage of these features, this study aims to model the demand uncertainty and assess the capacity of critical resources for a hospital to cope with unprecedented conditions. The applied simulation model in this study was initially presented in 2020 Simio Webinar (Simio, LLC. 2020) and then enhanced by Simio (Simio, LLC. 2021). This model consists of three interconnected processes, (i) the infectious disease spread, (ii) the hospital operations and resource allocation, and (iii) Re-ordering PPE items. These processes are explained as follows.

3.1 Process 1: Infectious Disease Spread

This process is designed to estimate the daily number of infected people and identify the expected number of daily hospitalizations based on the demographic characteristics of the community. Multiple factors are used to develop this process:

- **Contagion Factor (*R*0 or R-naught):** Indicates how contagious/infectious a disease is. This factor determines the expected number of secondary cases produced by an infection in a susceptible population.
- **Social Distancing Factor (*SDF*):** A numerical parameter ranging between 0 (no effectiveness) and 1 (total effectiveness).
- **Contagion Duration (*CD*)**: The contagious period for asymptomatic and non-hospitalized people which is typically 1 to 14 days.
- **Hospital's Service Area Population (P_0):** Population of the area that the hospital provides the service.
- **Reported Cases (C_0):** Initial number of cases in the population.
  Based on the provided factors, this process determines the Daily Number of Infectious Cases of a given day (D_t) based on Equation 1:

$$D_t = (P_0 - \sum_{i=0}^{t-1} c_i).R0.(1 - SDF) \tag{1}$$

where $P_0 - \sum_{i=0}^{t-1} c_i$ calculates the non-infected population (current healthy population) who might get infected by the disease. The multiplication of $R0$ and healthy population determines the number of people who will catch the disease from an infected person. $R0$ is important to spread an infectious disease because if it is greater than 1, the infection will probably keep spreading, and if it is less than 1, the outbreak will likely peter out (Yong 2020).

Then, $(1 - SDF)$ term implies the effectiveness of social distancing (also referred to as *physical distancing*) in a community. During lockdowns and full quarantine situations $(SDF = 1)$ the rate of transmission gets reduced and therefore, the number of cases in any given time will eventually decline. During the re-opening phase, social distancing is an effective means of containing the spread of COVID-19, but only if we all participate (Pedersen and Favero 2020). As a result, in a well-practiced community with social distancing appropriately in place, the spread of the virus can get reduced excessively. For instance, SDF of 0.5 effectively halves the effect of Contagion Factor ($R0$) based on the Equation 1. It needs to be noted that, *SDF* determines the effectiveness of social distancing in a community and should not be interpreted as a percentage of people practicing it.

As shown in Figure 1, the designed process starts on simulation model's *Run Initialization* to calculate the number of infected cases according to Equation 1. This process starts with an *assign* step to initialize

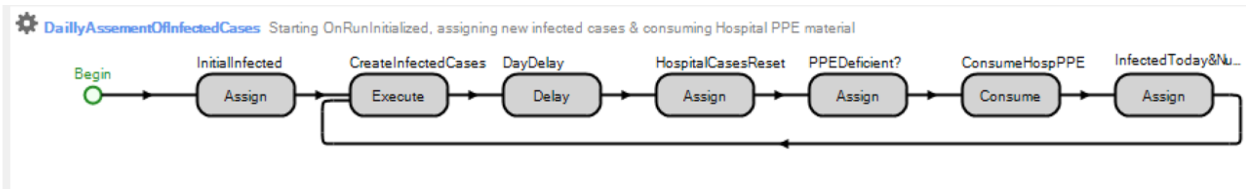


Figure 1: Daily assessment of infected cases process in Simio.

InfectedToday, *HealthyCurrentTotal*, *InfectedCurrentTotal* variables. Then, a loop begins to calculate cases on a daily basis. In this loop, there is a *execute* step to called *Tracking Infected Cases* process which adds newly infected cases and tracks whether they are hospitalized or not (Figure 2). Next, is a *Delay* step which delays the process for 24 hours to generate cases on a daily basis. The subsequent steps determine whether there is a deficit for PPE stocks (*assign* steps), and how many PPE items will be consumed on a given day (*consume* step). This cycle repeats on a daily basis until simulation reaches to its end (run length).

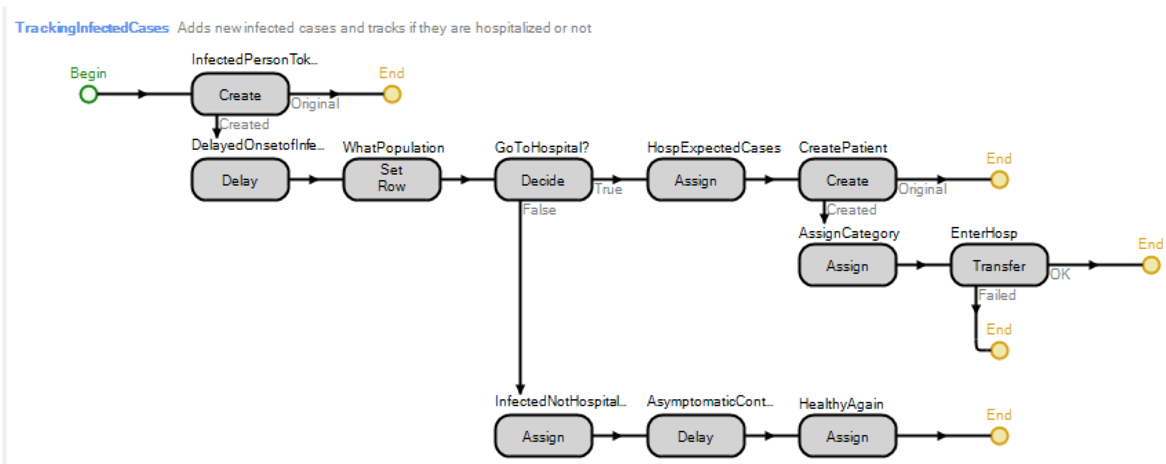


Figure 2: Tracking infected cases process in Simio.

3.2 Process 2: Hospital Operations and Resource Allocation

Among infectious cases, there are some that require hospitalization. The hospitalized cases enter the model as a *Patient Entity* and will follow the procedures illustrated in Figure 3. This is the second important process in the model which (1) simulates patients' arrival, (2) assigns a bed to a new patient, (3) checks whether a ventilator is needed, (4) calculates the number of PPEs used by the patient, and finally (5) discharges the patient from the hospital-based on its assigned length of stay. The patient arrival rate for each day is directly determined by the Process 1 explained in Section 3.1.

The implementation details of this process are shown in Figure 4. This process determines whether a hospitalized patient requires a ventilator based on patient's age. If an ventilator is required and it is available, then the *Seize* step will occupy one unit of that for the patient. Otherwise, *VentDeficientCount* variable will be incremented by 1 to account for ventilator unavailability. Also, in case a ventilator is not needed, token will delay the patient for the length of stay (without using the ventilator).

The defined variables in Processes 1 and 2, provide measures for the number of times a critical resource was not available. This includes a deficit in beds, ventilators, and PPE items. The ultimate goal is to plan properly that all resources be available when needed to avoid facing deficit for the entire simulation run. A comprehensive experimental analyse is conducted in Section 4 to analyse this furthermore.

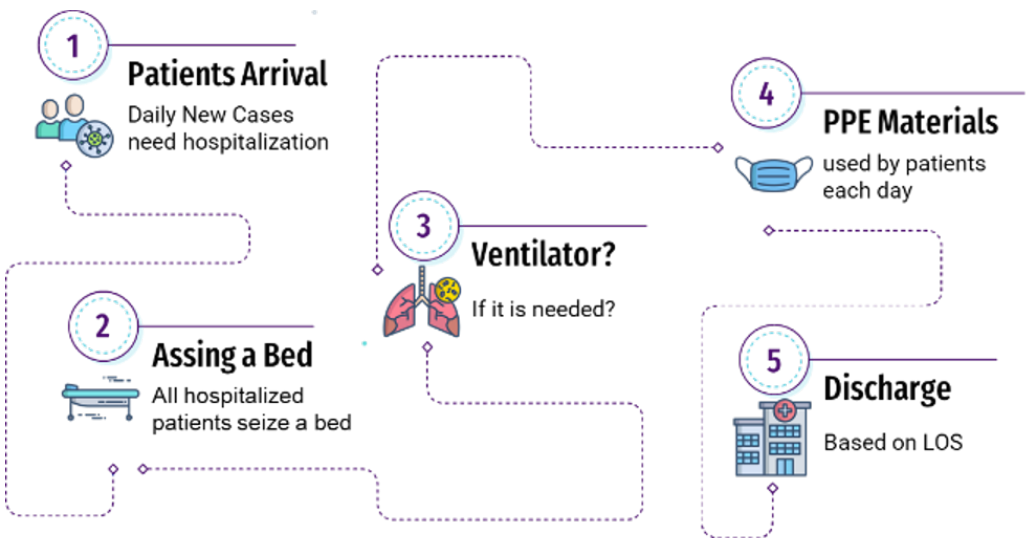


Figure 3: Hospital operations and resource allocation process.

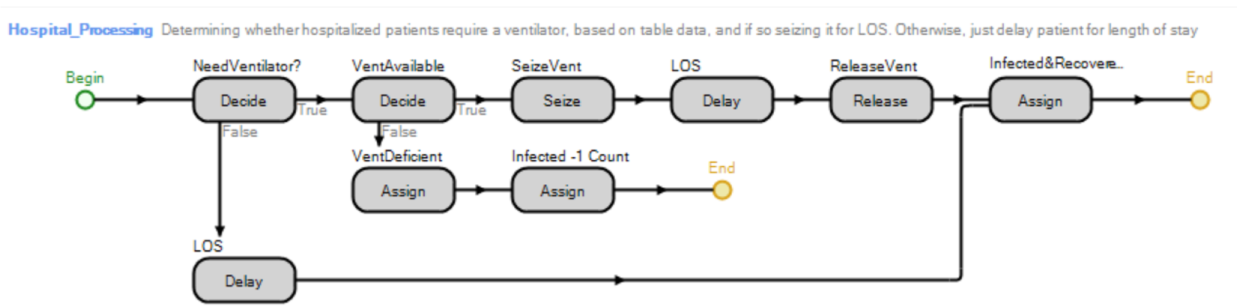


Figure 4: Hospital operation process in Simio.

3.3 Process 3: Re ordering PPEs

During pandemics, donning and doffing of personal protective equipment (PPE) is essential (Murray, Heather and Purdy, Eve 2020) both for staff and patients. The rampant nature of COVID-19 has caused a shortage of PPE in high demand areas (Ahmed et al. 2020). Therefore, it is critical for a hospital to have a robust replenishment policy to ensure PPE items are available for both its patients and staff.

To model the demand/supply trade-off of the PPE items in the simulation environment, a process is defined based on a (s,S) inventory policy. As depicted in Figure 5, in this policy, an order is placed when the inventory level drops to the reorder point (s) or lower. This way the inventory can be replenished to level S (order up to level or upper stock) (Helal et al. 2021). The order will be delivered based on the defined lead time for each item. Table 1 lists the *order lead time* and *consumption rate* of each of the PPE items in this study. To implement this inventory policy in Simio, the *PPE re-order* process (Figure 6) is triggered to *Produce* the required PPE item after some delay based on its lead time distribution defined in Table 1.

3.4 Simulation Model Parameters and Data-table Inputs

The simulation model used in this study is a data-driven model and is developed based on multiple data-table inputs. These tables include information regarding the patients' age groups, population mix, hospitalization

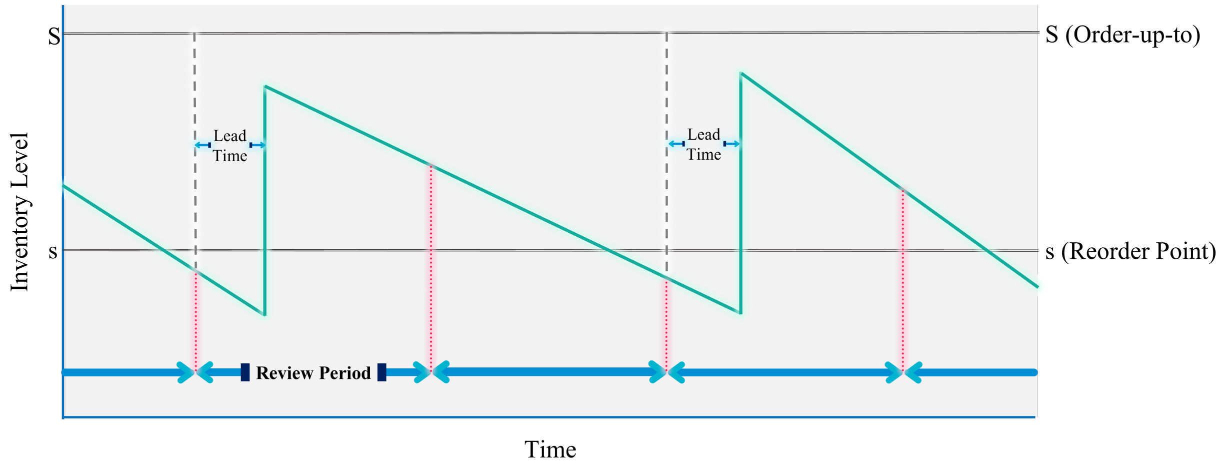


Figure 5: (S,s) inventory policy.

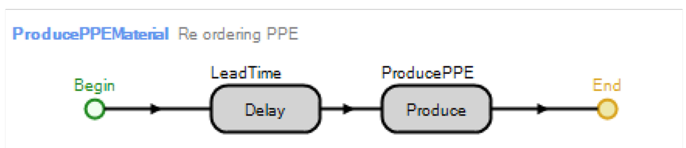


Figure 6: PPE re-ordering process in Simio.

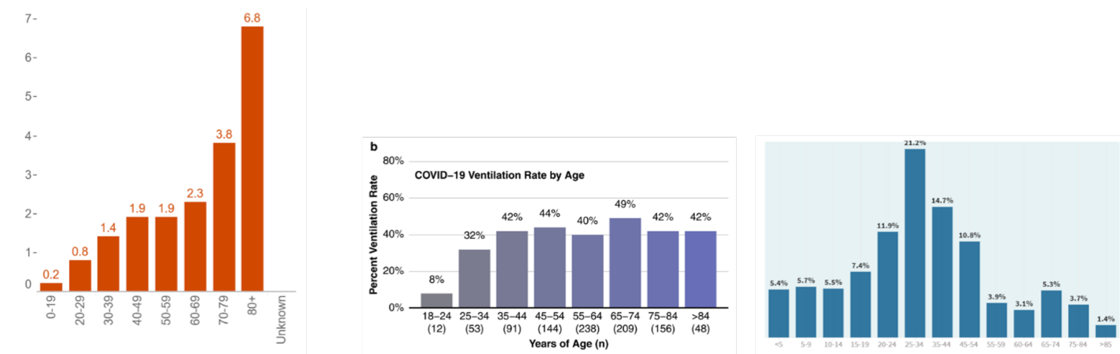
Table 1: PPE supplies.

Items	Order Lead time	Patient use per day
Masks	Triangular(1,1,4)	1
Gloves	Uniform(2,4)	4
Gowns	Uniform(4,7)	1

rates, and ventilation probability (the likelihood of requiring ventilator for different age groups). To construct these tables, multiple data sources are used based on a regional hospital in Boston, MA, area. This data is imported into Simio using its data-table function capabilities and are listed as below:

- Age Groups Hospitalization Rate: from Massachusetts department of public health (Figure 7-a)
- Age Groups Ventilator Needs: from a study conducted by (Nicholson et al. 2021). (Figure 7-b)
- Age Groups population mix of city of Boston (Figure 7-c)

The important simulation model parameters are listed in Table 2. It needs to be noted that these values are subject to change depending on the hospital capacity and the disease's characteristics. In the next section, an experimental analysis is provided to study how changing the Contagion Factor and Social Distancing Factor can impact the supply needs of the PPE items. The other factors are remained the same throughout the study, however, interested readers can extend the scope of the experiment and analyse the effect of other parameterization combinations.



(a) (b) (c)

Figure 7: Demographic data and hospitalization needs, (a) age groups hospitalization rate - August 2020 (Mass.gov 2021) (b) age groups ventilator needs (Nicholson et al. 2021), (c) Age groups population mix of city of Boston. (worldpopulationreview 2021)

Table 2: Simulation model parameters.

Variable Parameters	Initial Values	Fixed Parameters	Values
Contagion Factor	2	Reported Cases	50
Beds Capacity	100	Service Area Population	25,000
Ventilator Capacity	50	Contagion Duration	Uniform(1,14)
Social Distancing Factor	0.35	Hospital Stay Length	Triangular(1,7,20)

4 EXPERIMENTAL RESULTS

To provide a holistic view of levels of preparedness in the hospital, two experiments with multiple scenarios are conducted. Each of these experiments is discussed below supported with its corresponding analytical results. In both experiments, the replication size is set to 30 and the simulation run length is 20 weeks.

4.1 Experiment 1: Replenishment Policy for PPE items

In the first experiment, a simulation-optimization (SO) model is used to determine the best replenishment policy for the PPE items. Each patient consumes a different number of PPE items per day (Table 1). These items include masks, gloves, and gowns and the simulation model uses a continuous review reorder point s/reorder quantity S replenishment policy to re-stock them. Therefore, determining the optimal values of s and S is critical to minimize the inventory cost without facing any shortage. Due to the stochastic nature of the hospital operations, a combined simulation-optimization (SO) approach is needed to tackle this problem.

The applied SO model in this study is an integration of MATLAB and Simio. MATLAB is a powerful computational software which is a perfect tool to apply different optimization algorithms. As depicted in Figure 8, this connection is made by a Simio API that links the optimization algorithm in MATLAB with Simio to configure the simulation parameters (controls), and find the optimal or near-to-optimal values. The coded optimization algorithm in this work is Particle Swarm Optimization (PSO) and has been successfully used in many SO studies such as (Dehghanimohammadabadi and Keyser 2017) and (Dehghanimohammadabadi, Rezaeiahari, and Keyser 2017).The objective of this optimization model is to determine the best (s,S) policy for each PPE item (mask, gloves, and mask) and satisfy demands during the planning horizon. In other words, the optimizer needs to determine the best value for each parameter to reduce re-ordering costs and simultaneously ensure there is no deficit for all PPE items.

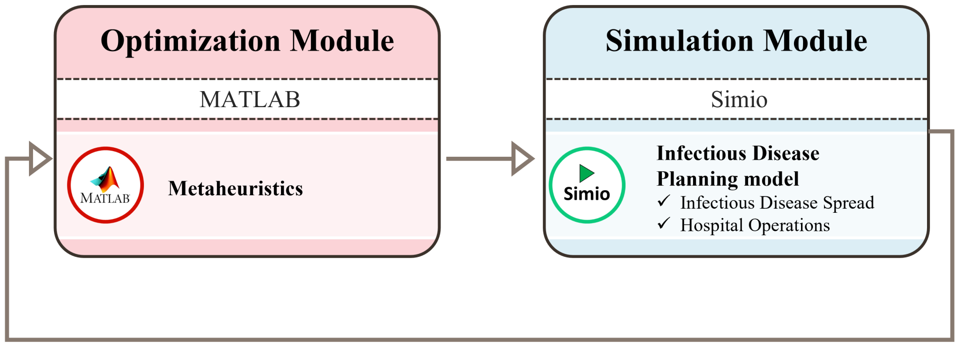


Figure 8: Simulation-optimization framework using MATLAB-Simio.

The optimization results are tabulated in Table 3. These results suggest high reorder quantity for gloves and gowns due to their long lead times, while masks can be re-ordered in small quantities with more frequencies. This provides an insight to the healthcare facility managers to understand how to set their PPE items replenishment policies to support hospital operations. This experiments considered a 20-weeks horizon, therefore, there might be a need to refresh these results depending on the pandemic situations. Figure 9 represents the replenishment curves for all PPE items provided by Simio. It is clear that gowns and gloves are re-stocked in long intervals while masks are ordered more frequently in a smaller order size.

Table 3: Simulation-optimization results.

Items	Reorder Point (s)	Reorder Quantity (S)
Masks	500	250
Gloves	2,100	2,750
Gowns	1,000	2,000

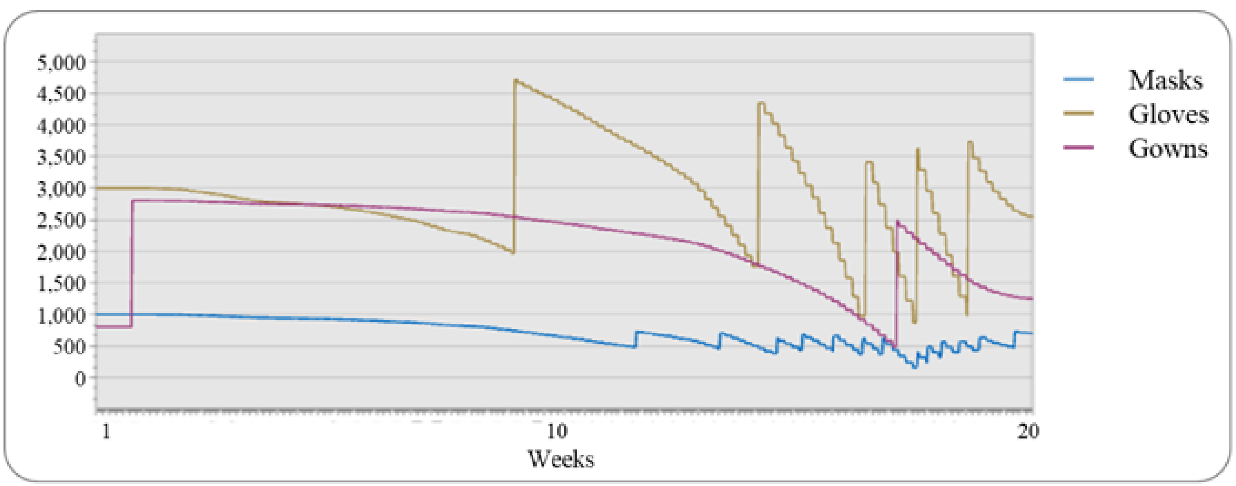


Figure 9: Hospital PPE items inventory replenishment results.

4.2 Experiment 2: Critical Resource Planning

This experiment focuses on capacity planning of critical resources such as bed and ventilators in a hospital during pandemics. Three different scenarios are considered in this section to analyze the impact of (i) Contagion Factor, (ii) Social Distancing Factor, and (iii) Vaccination Plans. To optimize each scenario, OptQuest (an embedded optimizer in Simio) is used. The experimental design and the corresponding values for each scenario are listed in Table 4 and results are discussed as follows.

Table 4: Experiment scenarios.

Scenarios	Parameter	Levels
1	Contagion Factor (R0)	2.0, 2.5, 3.0
2	Social Distancing Factor (SDF)	0.30, 0.35, 0.40
3	Vaccination Plans	Vaccination, No vaccination

4.2.1 Scenario 1- Contagion Factor Analysis

Contagion Factor (R_0) indicates how contagious a disease is and shows how many individuals will catch the disease from an infected person on average. This scenario analyses the impact of R0 on the different levels of preparedness and resource availability on the hospital. For each experiment, OptQuest tries to find the minimum number of required resources (beds and ventilators) to ensure there is at least one available when needed. As expected, by increasing the Contagion Factor, more resources are required (10). In the best-case scenario ($R_0 = 2$), the hospital needs 114 beds and 56 ventilators to serve its patients; while this demand increases to 117 beds and 80 ventilators when the disease contagious rate is set to 3. This helps healthcare decision-makers to identify the best and the worst-case scenarios and be prepared for unexpected situations.

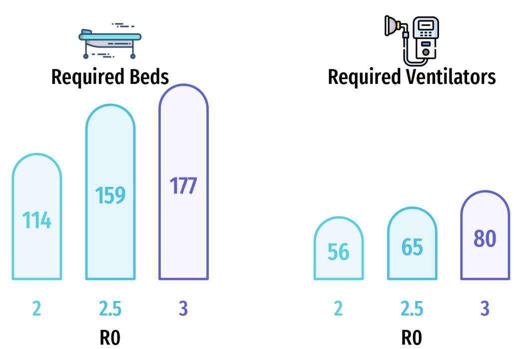


Figure 10: Contagion factor analysis results.

4.2.2 Scenario 2- Social Distancing Factor (SDF) Analysis

Social distancing practices can effectively control the disease transmission and prevent an infected person from infecting a healthy person from infecting a healthy person by way of droplets and viral particles (Wu, Jianqing and Zha, Ping 2020). Effective social distancing requires people to wear masks and keep a safe space between themselves and others who are not from their household (11-a). Therefore, an experiment is conducted to understand the effectiveness of social distancing practices to remove the burden from a healthcare system. According to Equation 1, increasing the awareness of social distancing in a community can hugely reduce the disease transmission, and therefore lower down the number of infected cases. As shown in Figure 11-b, by slightly changing the SDF factor from 0.3 to 0.4, the healthcare facility receives a smaller number of patients and dramatically reduces the required number of resources (beds and ventilators). This highlights the importance of people awareness in following physical distancing protocols to ensure their safety and help to alleviate the burden placed on healthcare facilities.

Figure 11: (a) Social distancing effectiveness, (b) Social Distancing Factor analysis results.

4.2.3 Scenario 3- Vaccination Plans

As of now, many states started vaccinating their resistance, which in return can immune the community and eliminate the disease eventually. During this phase, healthcare planners need to analyze multiple resource allocation plans. Certain age groups (i.e., people aged 65 years and older) get prioritized to receive their vaccine due to their high risk of hospitalization, illness, and death from Covid-19. To model this, the hospitalization rate for the people aged 65 years and older is set to zero. This will reduce the number of patient arrivals and therefore releases a large number of resources to the hospital. As shown in Figure 12, by vaccinating elderly people, the number of required beds reduces to 90 (21% decrease from 114) with 45 ventilators (20% decrease from 56).

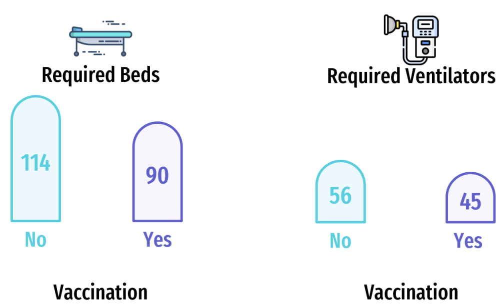


Figure 12: Vaccination plan results.

5 CONCLUSION AND FUTURE WORKS

This study shows the applicability of simulation modeling as a decision support system to help healthcare managers to combat unprecedented outbreaks such as Covid-19. In this study, simulation was used to model two important processes in an outbreak, (i) the disease transition model, and (ii) hospital operations. Within the first model, the area population of the hospital, as well as the contagion rate of disease and social distancing effectiveness, are studied. This process estimates the daily number of infected individuals and identifies the expected number of daily hospitalizations based on the demographic characteristics of the community. These characteristics include age group data and their corresponding hospitalization rate. Utilizing these data, this process simulates the disease transition model and generates the number of daily arrivals for the hospital. The second process simulates the hospital operations and helps to determine the required resources needed during patients' stay. These include beds, ventilators (if needed), and PPE items.

Based on the developed simulation model, two experiments are conducted to 1) determine the best replenishment policy for PPE items, and 2) analyze the impact of multiple factors on the Covid-19 spread and its impact on hospital resources demand. The results of these experiments were intuitive and provided clear insights for the healthcare managers to understand the criticality of the required resources. This tool enables healthcare planners to explore scenarios based on elements inside and outside their control and increase hospital preparedness. In addition, this decision support system can help a healthcare facility to gradually transit to past pandemic situations as the vaccination plans settle down in their community.

This work can be extended in numerous ways. Currently, Contagion Factor is assumed to be constant among all age groups which is reasonable at the early stages of a pandemic. This factor can be adjusted for different age groups by receiving more observations and collecting more data. Another extension of this work is to analyze staffing needs such as nurses, and physicians, in different phases of a pandemic.

REFERENCES

Ahmed, J., F. Malik, T. B. Arif, Z. Majid, M. A. Chaudhary, J. Ahmad, M. Malik, T. M. Khan, and M. Khalid. 2020. "Availability of Personal Protective Equipment (PPE) among US and Pakistani Doctors in COVID-19 Pandemic". *Cureus* 12(6).

Beeler, M., D. Aleman, and M. Carter. 2016. "A Simulation Case study to Improve Staffing Decisions at Mass Immunization Clinics for Pandemic Influenza". In *Operational Research for Emergency Planning in Healthcare: Volume 1*, 190–223.

Beeler, M. F., D. M. Aleman, and M. W. Carter. 2011. "Estimation and Management of Pandemic Influenza Transmission Risk at Mass Immunization Clinics". In *Proceedings of the 2011 Winter Simulation Conference (WSC)*, edited by S. Jain, R. R. Creasey, J. Himmelspach, P. K. White, and M. C. Fu, 1117–1124. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Currie, C. S., J. W. Fowler, K. Kotiadis, T. Monks, B. S. Onggo, D. A. Robertson, and A. A. Tako. 2020. "How Simulation Modelling Can Help Reduce the Impact of COVID-19". *Journal of Simulation* 14(2):83–97.

Dai, T., G. Bai, and G. F. Anderson. 2020. "PPE Supply Chain Needs Data Transparency and Stress Testing". *Journal of General Internal Medicine* 35(9).

Dehghanimohammadabadi, M., and N. Kabadayi. 2020. "A two-stage AHP Multi-objective Simulation Optimization Approach in Healthcare". *International Journal of the Analytic Hierarchy Process* 12(1).

Dehghanimohammadabadi, M., and T. K. Keyser. 2017. "Intelligent Simulation: Integration of SIMIO and MATLAB to Deploy Decision Support Systems to Simulation Environment". *Simulation Modelling Practice and Theory* 71:45–60.

Dehghanimohammadabadi, M., M. Rezaeiahari, and T. K. Keyser. 2017. "Simheuristic of Patient Scheduling Using a Table-experiment Approach—Simio and MATLAB Integration Application". In *Proceedings of the 2017 Winter Simulation Conference*, edited by V. W. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer, and E. H. Page, 2929–2939. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Delaney, H. M., P. F. Lucero, R. C. Maves, J. V. Lawler, J. K. Maddry, K. A. Biever, S. G. Womble, R. V. Coffman, and C. K. Murray. 2016. "Ebola Virus Disease Simulation Case Series: Patient with Ebola Virus Disease in The Prodromal Phase of Illness (Scenario 1), the "Wet" Gastrointestinal Phase of Illness (Scenario 2), and the Late, Critically Ill Phase of Disease (Scenario 3)". *Simulation in Healthcare* 11(2):106–116.

Eriksson, H., M. Morin, J. Ekberg, J. Jenvald, and T. Timpka. 2009. "Assumptions management in simulation of infectious disease outbreaks". In *AMIA Annual Symposium Proceedings*, Volume 2009, 173. Rockville, Maryland: American Medical Informatics Association.

Goodarzian, F., A. A. Taleizadeh, P. Ghasemi, and A. Abraham. 2021. "An Integrated Sustainable Medical Supply Chain Network During COVID-19". *Engineering Applications of Artificial Intelligence* 100:104188.

Helal, M. A., A. Bensoussan, V. Ramakrishna, and S. P. Sethi. 2021. "A Mathematical Method for Optimal Inventory Policies with Backlog Sales". *International Journal for Traffic & Transport Engineering* 11(2).

Ivanov, D. 2020. "Predicting the Impacts of Epidemic Outbreaks on Global Supply Chains: A Simulation-Based Analysis on The Coronavirus Outbreak (COVID-19/SARS-Cov-2) Case". *Transportation Research Part E: Logistics and Transportation Review* 136:101922.

Lu, Y., Y. Guan, J. Fishe, T. Hogan, and X. Zhong. 2020. "Hospital Beds and Personal Protective Equipment Planning for COVID-19 Pandemic: A computer Simulation Approach". *Research Square* 1(1):1–10.

Mass.gov 2021. "Massachusetts COVID-19 Response Reporting". https://www.mass.gov/info-details/covid-19-response-reporting, accessed September 20th, 2021.

Meng, M., S. Zhang, C.-J. Zhai, and D.-C. Chen. 2020. "Rapidly Organize Redeployed Medical Staff in Coronavirus Disease 2019 Pandemic: What We Should Do". *Chinese Medical Journal* 133(18):2143–2145.

Moulsdale, H. J., N. Khetsuriani, S. Deshevoi, R. Butler, J. Simpson, and D. Salisbury. 2014. "Simulation Exercises to Strengthen Polio Outbreak Preparedness: Experience of the World Health Organization European Region". *The Journal of Infectious Diseases* 210(suppl_1):S208–S215.

Murray, Heather and Purdy, Eve 2020. "How We Are Using Simulation to Help Our Hospital Prepare for COVID-19". https://cmajblogs.com/how-we-are-using-simulation-to-help-our-hospital-prepare-for-covid-19, accessed April 24th, 2021.

Neuner, C., P. Bocciarelli, and A. D'Ambrogio. 2021. "BPMN-based Simulation Analysis of The COVID-19 Impact on Emergency Departments: A Case Study in Italy". In *Proceedings of the 2021 Winter Simulation Conference*, edited by S. Kim, B. Feng, K. Smith, S. Masoud, Z. Zheng, C. Szabo, and M. Loper, 1–12. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Nicholson, C. J., L. Wooster, H. H. Sigurslid, R. H. Li, W. Jiang, W. Tian, C. L. L. Cardenas, and R. Malhotra. 2021. "Estimating Risk of Mechanical Ventilation and In-Hospital Mortality Among Adult COVID-19 Patients Admitted to Mass General Brigham: The VICE and DICE scores". *EClinicalMedicine* 33:100765.

Pedersen, M. J., and N. Favero. 2020. "Social Distancing During The COVID-19 Pandemic: Who Are the Present and Future Noncompliers?". *Public Administration Review* 80(5):805–814.

Petrović, N. 2020. "Simulation Environment for Optimal Resource Planning During COVID-19 Crisis". In *2020 55th International Scientific Conference on Information, Communication and Energy Systems and Technologies (ICEST)*, 23–26. Institute of Electrical and Electronics Engineers, Inc.

Schultz, M., M. Luo, D. Lubig, M. M. Mota, and P. Scala. 2021. "COVID-19-Related Challenges for New Normality in Airport Terminal Operations". In *Proceedings of the 2021 Winter Simulation Conference*, edited by S. Kim, B. Feng, K. Smith, S. Masoud, Z. Zheng, C. Szabo, and M. Loper, 1–12. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Simio, LLC. 2020. "Redefining your Business Planning Strategy | Simio". https://www.simio.com/resources/webinar/2020-05-07-Simio-Webinar.php, accessed April 27th, 2022.

Simio, LLC. 2021. "Covid-19: Infectious Disease Sample Model". https://www.simio.com/applications/healthcare-simulation-software/Covid-19.php, accessed April 27th, 2022.

Tirkolaee, E. B., A. Goli, P. Ghasemi, and F. Goodarzian. 2022. "Designing a Sustainable Closed-Loop Supply Chain Network of Face Masks During the COVID-19 Pandemic: Pareto-Based Algorithms". *Journal of Cleaner Production* 333:130056.

worldpopulationreview 2021. "Boston, Massachusetts Population 2021 Demographics". https://worldpopulationreview.com/us-cities/boston-ma-population, accessed September 20th, 2021.

Wu, Jianqing and Zha, Ping 2020. "Mask Is a Double-edged Sword in the Fight Against COVID-19 Pandemic". https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3563851, accessed April 27th, 2022.

Yong, Ed 2020, January. "The Deceptively Simple Number Sparking Coronavirus Fears". https://www.theatlantic.com/science/archive/2020/01/how-fast-and-far-will-new-coronavirus-spread/605632/, accessed Feb 1st, 2022.

AUTHOR BIOGRAPHIES

SAMANEH MAGHOULAN is master student of Industrial Engineering at Northeastern University, Boston, MA, USA. Her research interest is in simulation modeling with healthcare applications. Her email address is maghoulan.s@northeastern.edu

HANDE MUSDAL ONDEMIR is Assistant Teaching Professor in the Department of Mechanical and Industrial at Northeastern University, Boston, MA, USA. She earned her Ph.D. in Industrial Engineering and MS in Operations Research from Northeastern University, and a B.S. in Industrial Engineering from Yildiz Technical University in Turkey. Her research interests includes operations research, mathematical modeling and optimization, simulation, multi-criteria decision making, computer programming, and applied statistics. Her email address is h.musdal@northeastern.edu.

MOHAMMAD DEHGHANIMOHAMMADABADI Associate Teaching Professor of Mechanical and Industrial engineering, Northeastern University, Boston, MA, USA. His research is mainly focused on developing and generalizing simulation and optimization frameworks in different disciplines. This article is part of his initiatives to develop a framework to integrate Discrete Event Simulation with Reinforcement Learning. His e-mail address is m.dehghani@northeastern.edu