

Overcoming a Pandemic:

How Engineering and Modeling Techniques Are Used to Inform a Health System From Preparation to Recovery from the COVID-19 Pandemic

Tze Chiam, PhD and Mia Papas, PhD

Value Institute, ChristianaCare

Abstract

COVID-19, a novel disease that spreads across the globe, has posed multiple challenges to the healthcare systems around the world. Due to the lack of understanding of the spread and management of this disease, one major challenge is for healthcare systems to anticipate the volumes and needs of patients infected with the disease. In order to provide insights into optimal allocation of resources from preparing ChristianaCare for the pandemic to the recovery of the healthcare system, industrial engineering and predictive modeling approaches are used. This paper discusses five interrelated studies that utilize various techniques to inform multiple aspects of the healthcare system in order to be better prepared for the pandemic.

Introduction

As COVID-19 is a novel disease, the lack of understanding of its pathogenesis resulted in limited insight into its management.¹ The rampant spread of COVID-19 resulted in drastic increases of patients seeking medical care, both in the intensive care units as well as in the general medical units. Based on the transmission rates of COVID-19 observed in other countries such as China and Italy, it is believed that the US healthcare system will not be sufficiently equipped to provide care for all patients,^{2,3} due to the potential shortages of critical hospital resources such as hospital beds and ventilators.

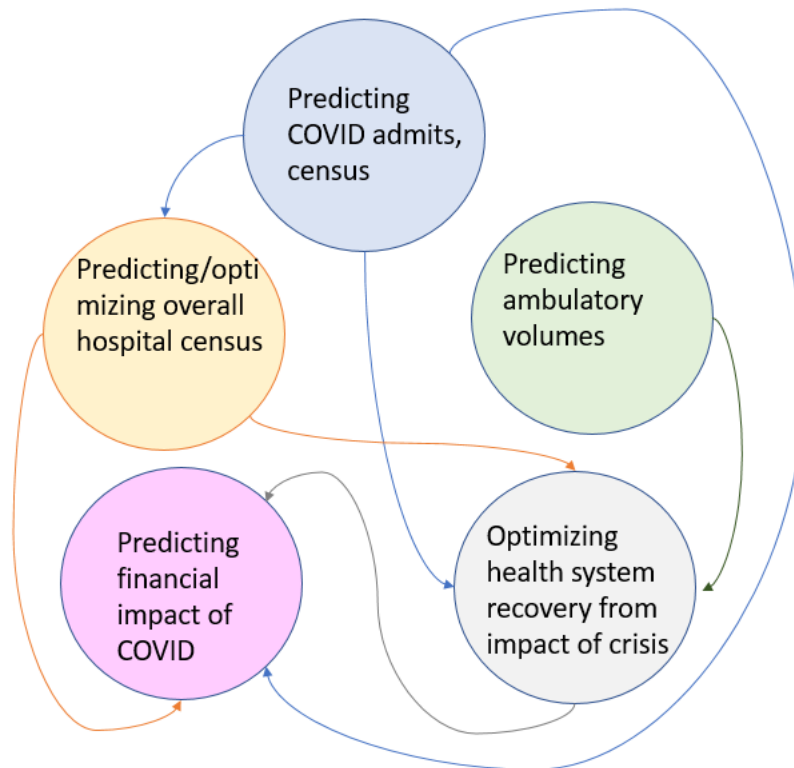
In order to provide insight into resource requirements for healthcare systems, several research groups and commercial companies have developed models to predict the COVID-19 patient admissions, inpatient census, and ventilator needs.⁴⁻⁶

The models developed rely on an epidemiologic compartmental model known as the SIR model, with compartments representing those individuals who transition through stages of being susceptible (S), infective (I), and recovered (R). While these models provide a foundation for understanding disease spread in general, due to the specificity of this disease to specific communities, there is a need to customize predictions based on characteristics local to the hospital catchment area. As a result, building upon the model by Becker and Chivers,⁴ we developed a model to predict COVID-19 daily patient admit volumes and daily census based on ChristianaCare catchment area characteristics and to allow for flexibility in specifying model parameters based on local assumptions and needs.

As the healthcare system is a complex system with many components having dynamic, non-linear relationships with one another,⁷ it is crucial to examine each component of the healthcare system separately and understand the impact of the pandemic on each subsystem. In order to provide such insights, the Value Institute at ChristianaCare engaged in various investigations utilizing industrial engineering and quantitative modeling approaches. Figure 1 illustrates the

inter-connectedness among five investigations conducted toward understanding impact of the pandemic to ChristianaCare.

Figure 1: Inter-connectedness of COVID-related investigations toward a complete understanding of pandemic impact to ChristianaCare



Epidemiologic SIR model for predicting COVID-19 inpatient volumes

As the pandemic began to spread, epidemiologists across the globe began developing models to simulate the spread of the coronavirus in order to not only predict mortality and morbidity, but also the number of hospitalized cases, ICU bed and ventilator needs. Epidemiologists and data scientists worked together to make the coding freely available to scientists around the world. These models utilize a traditional epidemiologic SIR framework that attempts to understand spread through how an individual transitions through three states: a susceptible (S) state to the virus, a infectious state (I), and then finally recovery (R) or death. Such SIR framework has been used to understand other the spread of other diseases such as dengue fever and SARS.⁸

Given the novel COVID-19 disease, many assumptions needed to be made to compute the probabilities that feed these models. First, every individual starts out as being susceptible since there is no evidence of any natural immunity to this virus. Then assumptions are made regarding rate of infection in the population, which changes as mitigation efforts such as school closures, quarantine, and isolation are introduced. And finally, it assumes that once an individual recovers, the individual is no longer susceptible to contracting the virus again. Given these assumptions and the fact that many of them depend upon the characteristics of the local population, a collaboration between the scientists at the Biden School at the University of Delaware and the

Value Institute was started to develop a Delaware-specific predictive model utilizing Python coding language that allows for the customization of the prediction. This customization predicts COVID-19 admissions and hospital census based on the demographics of individuals who reside within the catchment area of ChristianaCare, within the framework of the epidemiologic SIR model.

This model was developed to predict the daily admit volumes and census of COVID-19 patients in the ICU and non-ICU units, as well as the number of ventilators needed. Eight-day predictions from this model are shared with hospital administrators daily to inform decisions such as beds and ventilator resources allocation, as well as staffing decisions. As an example, Table 1 demonstrates the predictions produced from the model for the week of June 15, 2020.

Table 1. Predictions of new admissions and hospitalized census for ChristianaCare for the week of June 15, 2020

	Bed Needs	ICU Beds	Ventilators
6/15			
New Admits	10 (10, 11)	3 (3, 3)	1 (1, 1)
Total COVID patients	54 (53, 57)	23 (22, 24)	10 (10, 10)
CHRISTIANA			
New Admits	7	2	1
Total COVID patients	36	15	7
WILMINGTON			
New Admits	3	1	0
Total COVID patients	18	8	3
6/16			
New Admits	11 (10, 12)	3 (3, 4)	1 (1, 1)
Total COVID patients	57 (55, 61)	24 (23, 25)	10 (10, 11)
CHRISTIANA			
New Admits	7	2	1
Total COVID patients	38	16	7
WILMINGTON			
New Admits	4	1	0
Total COVID patients	19	8	3
6/17			
New Admits	11 (10, 13)	3 (3, 4)	1 (1, 2)
Total COVID patients	60 (56, 65)	25 (24, 27)	11 (11, 12)
CHRISTIANA			
New Admits	7	2	1
Total COVID patients	40	17	7
WILMINGTON			
New Admits	4	1	0
Total COVID patients	20	8	4
6/18			
New Admits	12 (11, 13)	4 (3, 4)	1 (1, 2)
Total COVID patients	63 (58, 69)	26 (25, 28)	12 (11, 12)
CHRISTIANA			

New Admits	8	3	1
Total COVID patients	42	17	8
WILMINGTON			
New Admits	4	1	0
Total COVID patients	21	9	4
6/19			
New Admits	12 (11, 14)	4 (3, 4)	1 (1, 2)
Total COVID patients	66 (60, 74)	28 (26, 30)	12 (11, 13)
CHRISTIANA			
New Admits	8	3	1
Total COVID patients	44	19	8
WILMINGTON			
New Admits	4	1	0
Total COVID patients	22	9	4
6/20			
New Admits	13 (11, 15)	4 (3, 5)	2 (1, 2)
Total COVID patients	69 (62,78)	29 (27, 32)	13 (12, 14)
CHRISTIANA			
New Admits	9	3	1
Total COVID patients	46	19	9
WILMINGTON			
New Admits	4	1	0
Total COVID patients	23	10	4
6/21			
New Admits	14 (12, 16)	4 (3, 5)	2 (1, 2)
Total COVID patients	73 (64, 83)	31 (28, 34)	13 (12, 15)
CHRISTIANA			
New Admits	9	3	1
Total COVID patients	49	21	9
WILMINGTON			
New Admits	5	1	1
Total COVID patients	24	10	4

Discrete-event simulation for predicting overall inpatient volumes

A discrete-event simulation (DES) model using Arena Simulation was developed to predict inpatient ICU and non-ICU census as well as overall ventilator needs by COVID-19 and non-COVID-19 patients across the health system.

Due to the flexibility of DES, as well as the improved computing speed and memory in modern computers, DES has been increasingly used in healthcare services for problems of increasing size and complexity.⁹ Used in many healthcare settings including healthcare systems operations, disease progression modeling, screening modeling, and health behavior modeling,¹⁰ discrete-event simulation is a class of computer simulation model that utilizes time distributions and process flow derived from the actual system to mimic its behavior.

In this model, patients are broadly categorized into:

- COVID-19 patients requiring ICU care,
- COVID-19 patients requiring ICU care and ventilators,
- COVID-19 patients requiring non-ICU care;
- non-COVID-19 patients requiring ICU care,
- non-COVID-19 patients requiring ICU care and ventilators,
- non-COVID-19 patients requiring non-ICU care,
- non-COVID-19 patients requiring non-ICU care and ventilators.

Each category of patient has its own stochastic properties such as length-of-stay and percent distribution of patients needing ICU level-of-care and/or ventilators. The stochastics associated with rate of arrivals of each patient category was obtained through retrospective data.

The predictions obtained through DES provided hospital administrators an eight-day window for short-term decision-making on resources allocation (Table 2). This model continues to be updated and refined as we observe new trends from the previous study and non-COVID patient volumes through statistical analysis.

Table 2. Projected Total Patient Census (COVID and non-COVID) for the week of June 15, 2020

	Total Beds	ICU Beds	Total Ventilators
6/15			
CHRISTIANA	629 (551, 706)	66 (51, 84)	45 (35, 54)
WILMINGTON	159 (136, 194)	10 (6, 16)	7 (2, 14)
6/16			
CHRISTIANA	626 (536, 702)	67 (48, 84)	44 (33, 54)
WILMINGTON	153 (124, 184)	10 (6, 15)	7 (2, 14)
6/17			
CHRISTIANA	626 (557, 704)	65 (45, 81)	44 (36, 55)
WILMINGTON	151 (121, 185)	10 (6, 17)	7 (1, 14)
6/18			
CHRISTIANA	634 (582, 730)	68 (52, 90)	45 (33, 59)
WILMINGTON	157 (131, 187)	11 (6, 18)	7 (2, 13)
6/19			
CHRISTIANA	638 (594, 746)	71 (58, 89)	47 (33, 59)
WILMINGTON	151 (136, 193)	11 (6, 18)	8 (2, 13)
6/20			
CHRISTIANA	630 (594, 720)	71 (57, 91)	49 (34, 67)
WILMINGTON	150 (130, 191)	12 (7, 17)	8 (2, 17)
6/21			
CHRISTIANA	629 (575, 689)	72 (54, 93)	48 (33, 64)
WILMINGTON	146 (129, 176)	12 (8, 17)	8 (2, 12)

Markov model for predicting financial impact to hospital

Due to the unknown impact on hospital finances by the COVID-19 patient population, we developed a Markov model to capture the changes in patients' health states and levels of care during their hospital stay, as well as the associated charges with each transition. This model is constructed based on a preliminary dataset consisting of all COVID-19 patients hospitalized at ChristianaCare hospitals.

Consisting of a defined state space with discrete states, a Markov model is a stochastic representation of the probable transitions of a system from one state to another. The transition between two consecutive states is governed by transition probabilities obtained through analysis of retrospective data.¹¹ As a highly versatile model, the Markov model (and its variance) has been used in a wide range of applications, including cost-effectiveness of a healthcare case management program,¹² disease burden,¹³ and evaluation of economic value of cancer treatment.¹⁴

Utilizing the Markov model, incorporating predicted COVID-19 patient volumes from the first study above, we predicted the charges for the COVID-19 inpatients assuming future discharged COVID-19 patients would follow similar transitions and probabilities represented in the Markov model developed. The predicted volumes and charges are shared with the Finance department at ChristianaCare to inform financial decision-making.

ARIMA model for predicting ambulatory visit volumes

As many health systems in the country utilize various tools to predict COVID-19 inpatient volumes, there is limited research on tools to predict outpatient volumes. At ChristianaCare, COVID-19 outpatient visits include previously hospitalized patients who recovered from COVID-19, and COVID-19 patients needing healthcare but with conditions not meeting criteria to be hospitalized. Some of these patients can be seen virtually while some need to be seen in-person. In this study, we developed an ARIMA model to predict COVID-19 volumes based on three locations that had the highest retrospective visit volumes. These three ambulatory locations also belong to ChristianaCare.

ARIMA (Auto Regressive Integrated Moving Average) model is a class of time-series model that utilizes a pattern of growth, rate of change of growth, as well as noise between consecutive time points based on retrospective data, in order to make predictions.¹⁵ It has been used in various industries including healthcare. Some healthcare applications include forecasting volumes of cases of epidemic disease,^{16,17} and hospital daily outpatient visits.¹⁸

As all three locations of interest provide healthcare to non-COVID-19 patients as well, we developed an ARIMA model to predict non-COVID-19 volumes at the same locations as they will continue to provide care to all patients during the pandemic and beyond. Results from these models are provided weekly to clinical and operational leads for decision-making on resources allocation at the locations of interest.

Human factors principles for health system recovery

The COVID-19 pandemic has caused outpatient practices to conduct a majority of outpatient consultation appointments through telemedicine instead of on-site visits. In order to resume on-site visits for select patient populations, there is a need for re-designing workflow and physical

spaces to allow for social distancing in order to prevent the spread of COVID-19,¹⁹ while optimizing providers' efficiency. In order to accomplish these goals, human factors engineering principles are needed to re-design the clinical systems.

Human factors engineering is a discipline concerned with how humans interact with elements within their environment or system in order to optimize safety and performance. Healthcare is a complex sociotechnical system with complex interactions between humans, humans and technology, humans and artifacts, and humans and tools. Human factors engineering principles have been increasingly used in healthcare in the recent years²⁰ from infection prevention²¹ to work system analysis.²²

In this on-going study, human factors engineering principles will be applied to areas in the outpatient care center such as check-in areas, waiting rooms, exam rooms, and collaborative clinical workspaces. Principles such as mistake proofing that aim to “make the right thing to do the easy thing to do” and “make the wrong things to do the hard things to do” will be employed to ensure an efficient and safe place for both the caregivers and patients. Heuristic evaluations and usability tests with end-users, where relevant, will be used in case of any new technology needed for the design of clinic recovery.

Conclusion

The use of engineering and predictive modeling techniques in healthcare has been increasingly popular in recent years. As the COVID-19 pandemic is unprecedented, various challenges to the healthcare system ensue, from planning for capacity and finance prior to the onset of the pandemic at the hospital, to re-designing physical spaces for resuming operations as close to normalcy as possible.

In order to overcome such challenges, we leveraged industrial engineering and predictive modeling techniques to provide insight for the healthcare system to make data-driven and evidence-based decisions, including resources allocation in the inpatient and outpatient settings, as well as financial decisions.

Limitations

Due to the lack of data and knowledge on the pathogenesis of COVID-19, as well as the challenge of predicting human behavior that will impact the spread of the disease, such techniques and models are developed and used based on current knowledge available in the literature as well as direct observations in the health system.

As more knowledge is gained regarding the disease, including seasonality effects, the models described in this paper will be further refined to continue provide insight for on-going decision support for the health system.

Acknowledgements

SIR Model Project team: Best, E., Bianco, F., Chiam, T., Dobler, G., Fawcett, M., Liu, W., Hicks, L., Papas, M., Singleton, E., Tunguhan, J., Subedi, K., Zhang, Y.

DES Model Project team: Chiam, T., Fawcett, M., Kessler, J., Zupick, N.

Markov Model Project team: Chiam, T., Gbadebo, A., Jarrold, K., Jurkovitz, C., Papas, M., Poole, C., Voli, M., Zhang, Z.

ARIMA Model Project team: Bollinger, M., Chiam, T., Harrison, C., Li, R., Jarrold, K., Jurkovitz, C., Kerzner, R., Laughery, J., Ndura, K., Papas, M., Teal, C.

Human Factors Project team: Alders, V., Jarrold, K., Mount-Campbell, A.

References

1. Cao, W., & Li, T. (2020, May). COVID-19: Towards understanding of pathogenesis. *Cell Research*, 30(5), 367–369. [PubMed https://doi.org/10.1038/s41422-020-0327-4](https://doi.org/10.1038/s41422-020-0327-4)
2. Li, R., Rivers, C., Tan, Q., Murray, M. B., Toner, E., & Lipsitch, M. (2020, May 1). estimated demand for us hospital inpatient and intensive care unit beds for patients with COVID-19 based on comparisons with Wuhan and Guangzhou, China. *JAMA Network Open*, 3(5), e208297. [PubMed https://doi.org/10.1001/jamanetworkopen.2020.8297](https://doi.org/10.1001/jamanetworkopen.2020.8297)
3. The Institute for Health Metrics and Evaluation. (2020). New COVID-19 forecasts: US hospitals could be overwhelmed in the second week of April by demand for ICU beds, and US deaths could total 81,000 by July. Retrieved from <http://www.healthdata.org/news-release/new-covid-19-forecasts-us-hospitals-could-be-overwhelmed-second-week-april-demand-icu>
4. Becker, M., & Chivers, C. (2020). Announcing CHIME, A tool for COVID-19 capacity planning. *Predictive Healthcare*. Retrieved from <http://predictivehealthcare.pennmedicine.org/2020/03/14/announcing-chime.html>
5. Abir, M., Nelson, C., Chan, E., Al-Ibrahim, H., Cutter, C., Patel, K., & Bogart, A. (2020). RAND critical care surge response tool: an excel-based model for helping hospitals respond to the COVID-19 crisis. Retrieved from: <https://doi.org/10.7249/TLA164-1>
6. Qventus. (2020). Localized COVID-19 model and scenario planner. Retrieved from <https://qventus.com/covid-19-model/>
7. Lipsitch, L. A. (2012, July 18). Understanding health care as a complex system: The foundation for unintended consequences. *JAMA*, 308(3), 243–244. [PubMed https://doi.org/10.1001/jama.2012.7551](https://doi.org/10.1001/jama.2012.7551)
8. Rodrigues, H. S. (2016). *Application of SIR epidemiological model: new trends*. Retrieved from <http://arxiv.org/abs/1611.02565>
9. Allen, M., Spencer, A., Gibson, A., Matthews, J., Allwood, A., Prosser, S., & Pitt, M. (2015). Right cot, right place, right time: improving the design and organisation of neonatal care networks – a computer simulation study. In *Health Services and Delivery Research* (Vol. 3, pp. 1–128). <https://doi.org/10.3310/hsdr03200>
10. Zhang, X. (2018, September 4). Application of discrete event simulation in health care: A systematic review. *BMC Health Services Research*, 18(1), 687. [PubMed https://doi.org/10.1186/s12913-018-3456-4](https://doi.org/10.1186/s12913-018-3456-4)
11. Sonnenberg, F. A., & Beck, J. R. (1993, October-December). Markov models in medical decision making: A practical guide. *Med Decis Making*, 13(4), 322–338. [PubMed https://doi.org/10.1177/0272989X9301300409](https://doi.org/10.1177/0272989X9301300409)

12. van Voorst, H., & Arnold, A. E. R. (2020, June). Cost and health effects of case management compared with outpatient clinic follow-up in a Dutch heart failure cohort. *ESC Heart Failure*, 7(3), 1136–1144. [PubMed https://doi.org/10.1002/ehf2.12692](https://doi.org/10.1002/ehf2.12692)
13. Estes, C., Chan, H. L. Y., Chien, R. N., Chuang, W. L., Fung, J., Goh, G. B. B., . . . Razavi, H. (2020, April). Modelling NAFLD disease burden in four Asian regions-2019-2030. *Alimentary Pharmacology & Therapeutics*, 51(8), 801–811. [PubMed https://doi.org/10.1111/apt.15673](https://doi.org/10.1111/apt.15673)
14. Bullement, A., Cranmer, H. L., & Shields, G. E. (2019, December). A review of recent decision-analytic models used to evaluate the economic value of cancer treatments. *Applied Health Economics and Health Policy*, 17(6), 771–780. [PubMed https://doi.org/10.1007/s40258-019-00513-3](https://doi.org/10.1007/s40258-019-00513-3)
15. Abugaber, D. (n.d.). Chapter 23: Using ARIMA for time series analysis. Retrieved from https://ademos.people.uic.edu/Chapter23.html#1_what_is_arima
16. Pan, Y., Zhang, M., Chen, Z., Zhou, M., & Zhang, Z. (2016). An ARIMA based model for forecasting the patient number of epidemic disease. *2016 13th International Conference on Service Systems and Service Management, ICSSSM 2016*. <https://doi.org/10.1109/ICSSSM.2016.7538560>
17. Tandon, H., Ranjan, P., Chakraborty, T., & Suhag, V. (2020). *Coronavirus (COVID-19): ARIMA based time-series analysis to forecast near future*. Retrieved from <http://arxiv.org/abs/2004.07859>
18. Luo, L., Luo, L., Zhang, X., & He, X. (2017, July 10). Hospital daily outpatient visits forecasting using a combinatorial model based on ARIMA and SES models. *BMC Health Services Research*, 17(1), 469. [PubMed https://doi.org/10.1186/s12913-017-2407-9](https://doi.org/10.1186/s12913-017-2407-9)
19. Centers for Disease Control and Prevention. (2020). Social distancing. Retrieved from <https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/social-distancing.html>
20. Waterson, P., & Catchpole, K. (2016, July). Human factors in healthcare: Welcome progress, but still scratching the surface. *BMJ Quality & Safety*, 25(7), 480–484. [PubMed https://doi.org/10.1136/bmjqs-2015-005074](https://doi.org/10.1136/bmjqs-2015-005074)
21. Jacob, J. T., Herwaldt, L. A., & Durso, F. T., & the CDC Prevention Epicenters Program. (2018, August). Preventing healthcare-associated infections through human factors engineering. *Current Opinion in Infectious Diseases*, 31(4), 353–358. [PubMed https://doi.org/10.1097/QCO.0000000000000463](https://doi.org/10.1097/QCO.0000000000000463)
22. Heiden, S. M., Holden, R. J., Alder, C. A., Bodke, K., & Boustani, M. (2017, October). Human factors in mental healthcare: A work system analysis of a community-based program for older adults with depression and dementia. *Applied Ergonomics*, 64, 27–40. [PubMed https://doi.org/10.1016/j.apergo.2017.05.002](https://doi.org/10.1016/j.apergo.2017.05.002)