Hospital beds and personal protective equipment planning for COVID-19 pandemic: A computer simulation approach

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Method Article

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Abstract

Health care systems are at the frontline to fight the COVID-19 pandemic. An emergent question for each hospital is how many general ward and intensive care unit beds are needed and how much personal protective equipment to be purchased. However, hospital pandemic preparedness has been hampered by a lack of sufficiently specific planning guidelines. In this paper, we developed a computer simulation approach to evaluating bed utilizations and the corresponding supply needs based on the operational considerations and constraints in individual hospitals. We built a data-driven SEIR model which is adaptive to control policies and can be utilized for regional forecast targeting a specific hospital's catchment area. The forecast model was integrated into a discrete-event simulation which modeled the patient flow and the interaction with hospital resources. We tested the simulation model outputs against patient census data from UF Health Jacksonville, Jacksonville, FL. Simulation results were consistent with the observation that the hospital has ample bed resources to accommodate the regional COVID patients. After validation, the model was used to predict future bed utilizations given a spectrum of possible scenarios to advise bed planning and stockpiling decisions. Lastly, how to optimally allocate hospital resources to achieve the goal of reducing the case fatality rate while helping a maximum number of patients to recover was discussed. This decision support tool is tailored to a given hospital setting of interest and is generalizable to other hospitals to tackle the pandemic planning challenge.

Introduction

The COVID-19 pandemic challenge is unprecedented. The outbreak of this disease in the US severely strains the nation's health care system, with the demand for beds and some specialized equipment needed to treat patients and protect staff far exceeding supply [1-4]. An emergent question for each hospital is how many general ward and intensive care unit (ICU) beds are needed at the peak of outbreak and how much personal protective equipment (PPE) to be purchased for hospital staff. An important follow-up question is how to optimally allocate hospital resources to achieve the goal of reducing the case fatality rate and helping a maximum number of patients to recover.

The pandemic of COVID-19 could overwhelm hospitals but planning guidance that accounts for the dynamic interrelationships between planning elements is lacking. This is due to the differences among hospitals and between various pandemic scenarios (e.g., COVID-19 differs from Ebola and SARS in various aspects). Consequently, it is difficult to provide guidance based on historical experience, and the case-specific findings might not be broadly applicable to all hospitals. Moreover, the complex and dynamic interrelationships between the elements in hospital pandemic planning must be taken into consideration. For instance, changing bed or ventilator capacity affects staffing, PPE, and pharmaceutical needs and vice versa. In addition, there are uncertainties inherent in the patient demand, length of stay, and hospital operations, so the relationship is governed by a stochastic process rather than deterministic. These factors are instrumental to accurately predicting and evaluating the system performance. Furthermore, the existing method to increase surge capacity does not account for operational bottlenecks and the dynamic nature of the system and the feedback loop – the decision can subsequently influence the projection of demands and system dynamics. Therefore, we are motivated to develop simulation-based decision-making tools that could address the above challenges in an integrated fashion.

A discrete-event simulation (DES) models the operation of a system (a hospital unit herein) as a sequence of events (e.g., patient arrival and departure) in time. DES has been a popular and effective decision-making tool for the optimal allocation of scarce health care resources to strike the balance between minimizing health care delivery costs and increasing patient satisfaction. DES of health care systems and performance modeling in health care using DES were extensively reviewed in [5-7]. Emerging applications of DES addressing the COVID-19 pandemic hospital planning problems can be found in [8-10]. The review of how simulation modeling can help reduce the impact of COVID-19 was presented in [11]. However, most of the DES work on COVID-19 did not account for the highly dynamic and regional-specific disease spread nature and the impact of interventions (e.g., social distancing orders) on infection control. Our work innovatively incorporates COVID-19 case forecasting into the DES for hospital planning. In particular, the input of patient arrivals is modeled by a tailored compartmental model – a data-driven SEIR model [12]. This model is adaptive to control policies and can be utilized for regional forecast targeting a specific hospital's catchment area. The input patient arrival drives the DES, which models the patient flow and the interaction with hospital resources. Such an integrated framework can be used to evaluate bed utilizations and the corresponding supply needs based on the operational considerations and constraints in hospitals. The computer simulation model is validated using data from UF Health Jacksonville, Jacksonville, FL, and can be used to test a spectrum of scenarios (e.g., different intervention policies and disease characteristics) to evaluate the hospital preparedness and provide surge capacity decision support.

Methods

We develop an analytical tool using computer simulation techniques to address hospital pandemic planning problems. In the following, we calibrate the simulation inputs based on carefully researching the clinical evidence, and develop a DES model of the patient flow in the COVID unit. Finally, we use real world data to validate the simulation model.

Input analysis

The daily COVID hospitalizations are not time-homogeneous and cannot be modeled as a simple Poisson process. For planning purposes, the future patient arrival is obtained from a data-driven SEIR model. The traditional SEIR model describes a stochastic process with four states, representing the susceptible, exposed, infectious and recovered population, denoted as and . The challenges reside in calibrating the control parameters that govern the system dynamics, e.g., how fast the exposed population migrates to the infectious population. In this study, we use historical data [13] to train the model parameters and dynamically adjust the basic reproduction number, , the factor that dictates the doubling time of infectious cases. Before any interventions, we numerically get the optimal and optimal (the day of the first community-spread case) by minimizing the mean squared error of the reported infectious-population and the infectious-population generated by our SEIR model. To detect the change of with stay-at-home orders in place, we conduct curve-fitting using the time series estimate of of several European countries including Italy, Spain and Germany. These countries have implemented the order early enough to provide sufficient observations for model calibration. After the lockdown order is released, will change gradually according to the fitted time series curve. In this way, we are able to predict the disease spread down to the county level and will help individual hospitals to understand the future demand given regional-specific situations.

The range of epidemiologic variables, e.g., hospitalization rate, hospitalizations that require ICU stay, denoted as ICU rate, hospital length of stay by unit type (ICU vs ward), and case fatality rate are determined by review of the literature and expert consensus of the team. We provide a table (Table 1) below to summarize the basic setting. The total number of existing beds, and potential surge beds for use in ward and ICU are provided by the hospital. Currently, 35 beds are reserved for the COVID unit of UF Health Jacksonville.

Model conceptualization

A DES model based on the general patient flow in hospital COVID units is developed using a commercial simulation software Arena®. Patients arriving at the hospital will be triaged first. Mild patients will be directly discharged after administering the treatment. Severe patients, based on their level of severity will be admitted to ICU (critical condition) or ward (non-critical, e.g., do not need ventilators). Due to the dynamic progression of diseases, patients' condition can elevate and they need to be admitted to ICU from ward. Patients in ICU experience the critical condition (stage 1) and then are stabilized (stage 2). ICU patients can be stepped down to ward when necessary (e.g., to make room for a critical condition patient). If not treated promptly, patients developing severe complications will die (see Figure 1).

Model validation

The validity of the model was tested against different assumptions, and the historical census data were used to compare with the model outputs. In particular, we focused on the catchment area of UF Health Jacksonville. It is a metropolitan area with 1.5 million people, covering five counties: Baker, Clay, Duval, Nassau, and St. Johns, Florida. Daily confirmed COVID cases in these counties were obtained from the Florida Department of Health (FDOH) website [17]. The historical case data were used as the patient arrival input to replace the SEIR model prediction for validation purposes. The real hospital patient census in the COVID unit (ward and ICU) were provided by UF Health Jacksonville. The bed capacity was set as 10 for the ICU and 25 for general wards. Other parameters were the same as those in Table 1.

Sensitivity analysis

We constructed several scenarios each intended to highlight some particular aspect of the disease profile characteristics (Table 2) and investigated the resulting supply implications. In particular, we varied the range of market size from 5%, 10%, and 15%, representing different patient diversions to the hospital. The hospitalization rates were set as 15%, 20%, and 25%; the ICU rates among the hospitalized patients were set as 15%, 25%, and 40%, representing different levels of severity of the disease. This yields a total of 27 scenarios. The bed capacity was set as 10 for the ICU and 25 for general wards. The patient arrival was simulated based on the SEIR model's prediction of 100 days' infected cases (March 18th to August 1st) of the metro Jacksonville area.

Results

We ran the model for 200 replications for all the simulation studies to ensure a narrow confidence interval. The outputs directly generated from the model include but not limited to the daily patient census by bed type (ICU and ward), number of deaths, and number of rejections due to capacity limitation. Such outputs are fundamental to clinical and operational decisions. We first present the case study of UF Health Jacksonville to validate our model. Historical data showed that the average ward census is 6.53 patients/day and the average ICU census is

2.38 patients/day in the COVID unit during March 23rd – May 11th. Our simulation yielded the average census of 6.17 with a 95% confidence interval (CI) (5.78-6.55), and 2.26 (95% CI 2.12-2.40), for ward and ICU, respectively, suggesting that the model can well capture the system dynamics.

Figures 2 and 3 display the real daily confirmed cases from March 18th to May 18th obtained from FDOH (blue dash line) and the real hospital COVID patient census (March 23rd – May 11th) in general wards and the ICU provided by UF Health Jacksonville (black solid line) for comparison. It can be seen that the hospitalization rate is not consistent per each batch of the cases and there is a visible delay comparing the timing of the burst of hospitalizations to the peak of case increments. It can be inferred that some infected patients might not be admitted immediately after being diagnosed. Figures 4 and 5 illustrate the outputs of the ward and ICU bed utilization (the average and the 95% CI across 200 replications, denoted by a dashed line, a dash-dotted line, and a dotted line, respectively) and the corresponding historical census data (black solid line). The simulation outputs displayed here are the average over two hundred of sample paths and thus are continuous variables. Since the hospitalization rate is set as a constant in the model, the simulation outputs are smoother and less volatile, in contrast to the real data. However, the average census is similar (reflected by the area under the curve), the estimate of which is important for PPE planning. In addition, our simulation outputs suggest that there is no patient rejection, which means the maximum demand has yet exceeded the capacity cap. The real data also articulate that the hospital currently has allocated sufficient bed resources to the COVID unit.

We examined different scenarios that reflect low-to-high level impacts to normal operations and observed the following (see Table S1 in the Supplementary Material). When the ICU rate increases, there are more busy ICU beds, and fewer busy ward beds. The number of total rejections decreases, and the number of total deaths increases. When the market share or the hospitalization rate increases, there are more patients hospitalized, resulting in more busy ICU and ward beds, and the numbers of total rejections and deaths increase. Overall, the ICU and ward beds are sparsely occupied over the simulated duration (March 18th to August 1st). We can infer that the current setting (a total of 35 beds in the COVID unit) is not necessary especially given the anticipated suppression of the outbreak. In addition, it can be noticed that in some high-impact scenarios, there are several patients rejected due to capacity limitation. The hospital can strategically add/remove some beds in the COVID unit to accommodate the dynamic patient demand. Furthermore, for cases with a large number of rejections, an early-stepdown mechanism can be considered to reduce rejections and deaths.

Based on patient census, PPE needs can be calculated following the Assistant Secretary for Preparedness and Response (ASPR) protocol [18]. We only include the essential supplies and the formulas to calculate PPE needs (including gloves, shoe covers, gowns, N95s, face shields, headcovers, and surgical masks) are obtained from the ASPR official website, and the staffing standard of various diseases (Ebola, MERS and SARS, and Pandemic Influenza) are used as the reference for our analysis. The PPE needs of the COVID unit for the monthly planning horizon are presented in Table 3. In the table, March and April supplies are based on historical data and May- July supplies are based on the SEIR model prediction as simulation inputs. Here we consider the effect of economy reopen and thus the prediction is rather conservative – the hospital is recommended to order the amount similar to that of April to prepare for a second wave of outbreak as the government lifts the lockdown. The prediction can be updated after observing the impact of economy reopen on infection control to adjust the planning decision.

Discussion And Conclusion

In summary, this computer simulation tool can give guidance on how many supplies to stockpile and provide ways to increase surge capacity in an efficient and effective fashion. The following can be done in future research. To accommodate surge capacity and determine how many beds should be reserved to the COVID unit and distributed to ward and ICU, one needs to estimate the occupancy of hospital beds due to non-COVID patients to project the number of available beds and categorize their availability based on clinical use (e.g., has a mechanic ventilator or not). The model can be expanded to capture the overall patient flow in the hospital. Then, it can be used to test the bed allocation to minimize adverse outcomes based on constraints identified in the hospital. Second, the model can be strengthened to examine whether to discharge a patient before they have fully recovered in order to create a bed for another sicker patient, and how many elective surgeries to be cancelled to make room for potential COVID patients. To explore the interrelationship between the system capacity and the patient outcomes, the model's logic can be enhanced to accommodate various assumptions. For instance, if a patient is in need of hospitalization, but no bed is available, the model will assign a higher fatality rate to that patient comparing to a population average. Thus, the in-hospital fatality rate is linked to the magnitude of bed shortages. Since the magnitude of shortages is related to the magnitude of the patient surge, which, in turn, is a function of the basic reproduction number influenced by hospital preparedness, the output of the simulation model can introduce a feedback loop. The projection of the hospital congestion and delay in treatment can be analyzed to understand the adverse outcomes due to medical resource shortage. It will enable us to learn the critical SEIR model parameters adaptively and closely align the prediction with the most recent information and consequently, achieving the best predictability to inform the optimal decision to combat the pandemic. Currently, the model is validated using data from one urban academic hospital in an area that has had much less burden of COVID disease than other urban areas (e.g., compared to NYC or Atlanta). The market share is 15% and it encompasses an underserved and mostly minority population and a population that does not travel much, which contributes to the limitations.

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Tables

Table 1 Disease and process variables used in the simulation

	Value (SD*)	Reference
Hospitalization rate	20%	[13-14]
ICU rate	40%	[4,15]
Hospital market share	15%	-
Average time spent in an ICU bed (day)	8 (1)	[2]
Average time spent in hospital (day)	12 (5)	[16]
Case fatality rate	1.6%	[4]

*SD: Standard deviation

Table 2 Ranges of disease and process variables used in the sensitivity analysis

	Low end of range	Medium of range	High end of range
Hospitalization rate	15%	20%	25%
ICU rate	15%	25%	40%
Hospital market share	5%	10%	15%

Table 3 PPE planning for May – July 2020

	Glove	Shoe Cover	Gown	N95	Face Shield	Head cover	Surgical Mask
March 2020	600	252	126	45	45	45	45
April 2020	2400	1008	504	180	180	180	180
May 2020	1600	672	336	120	120	120	120
June 2020	2400	1008	504	180	180	180	180
July 2020	2400	1008	504	180	180	180	180

Declarations

The authors declare no competing interests.

Figures

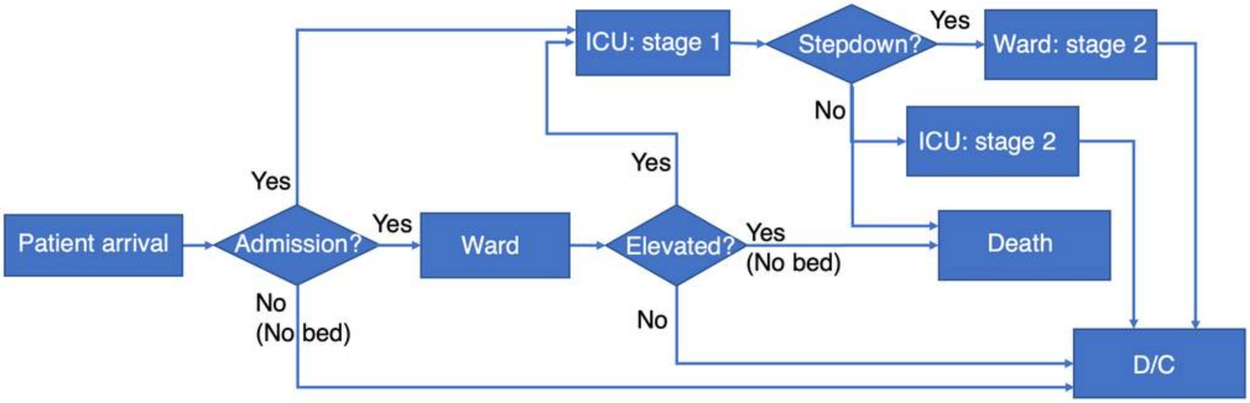

Figure 1

Patient flow in the hospital COVID unit.

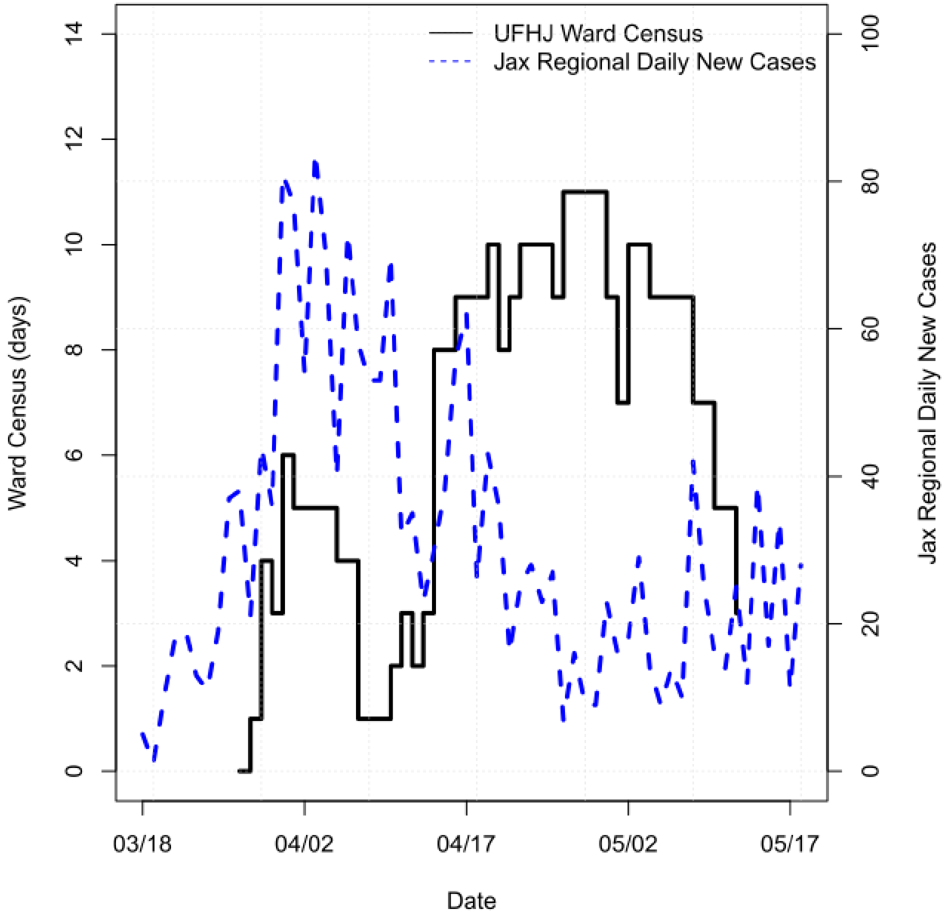

Figure 2

Historical confirmed COVID cases of the metro Jacksonville area and daily ward census in the COVID unit of UF Health Jacksonville.

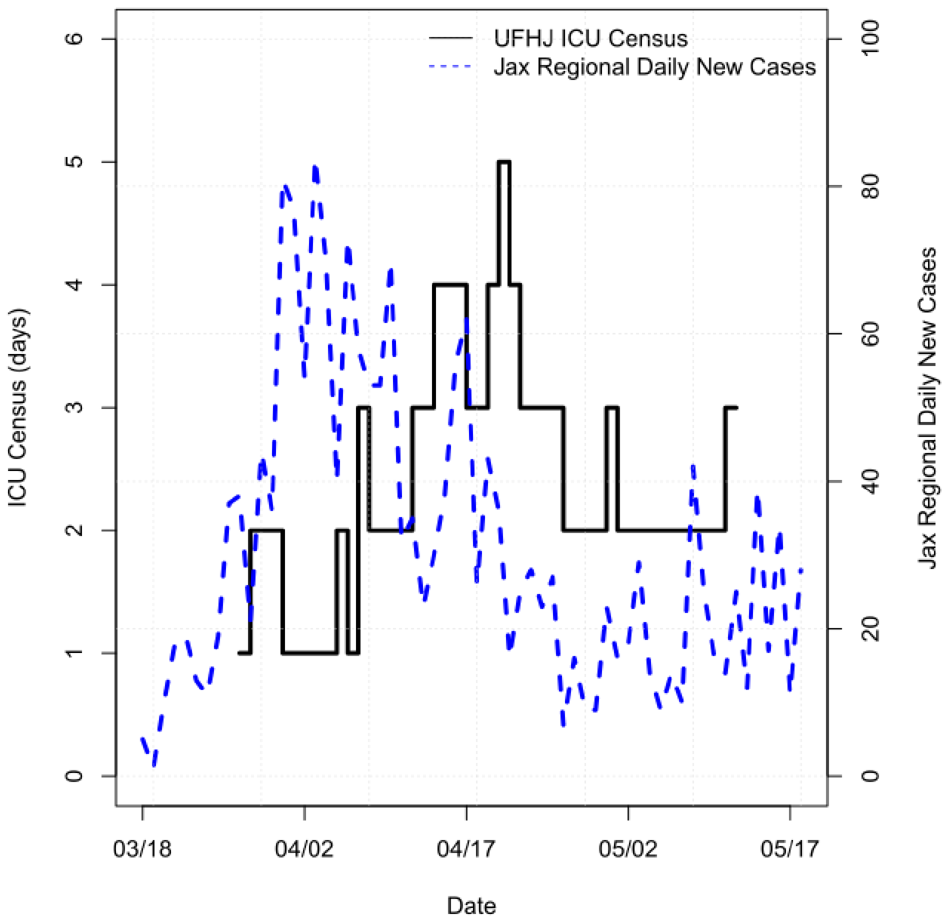

Figure 3

Historical confirmed COVID cases of the metro Jacksonville area and daily ICU census in the COVID unit of UF Health Jacksonville.

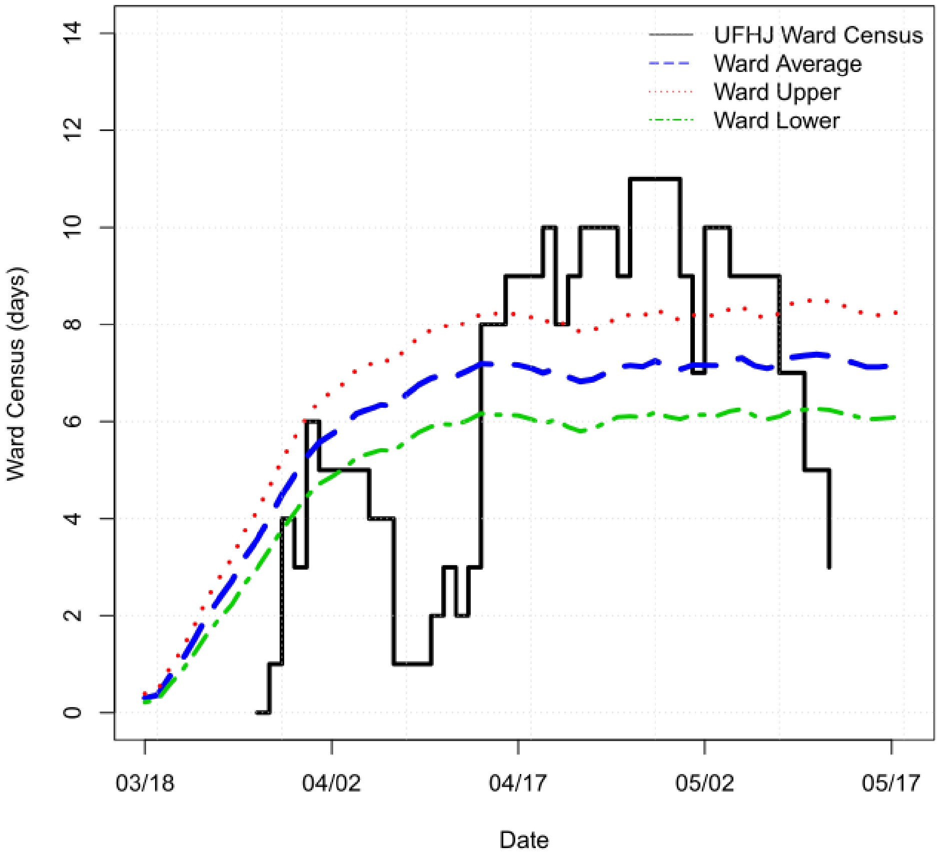

Figure 4

Average daily ward census in the COVID unit obtained from the simulation model.

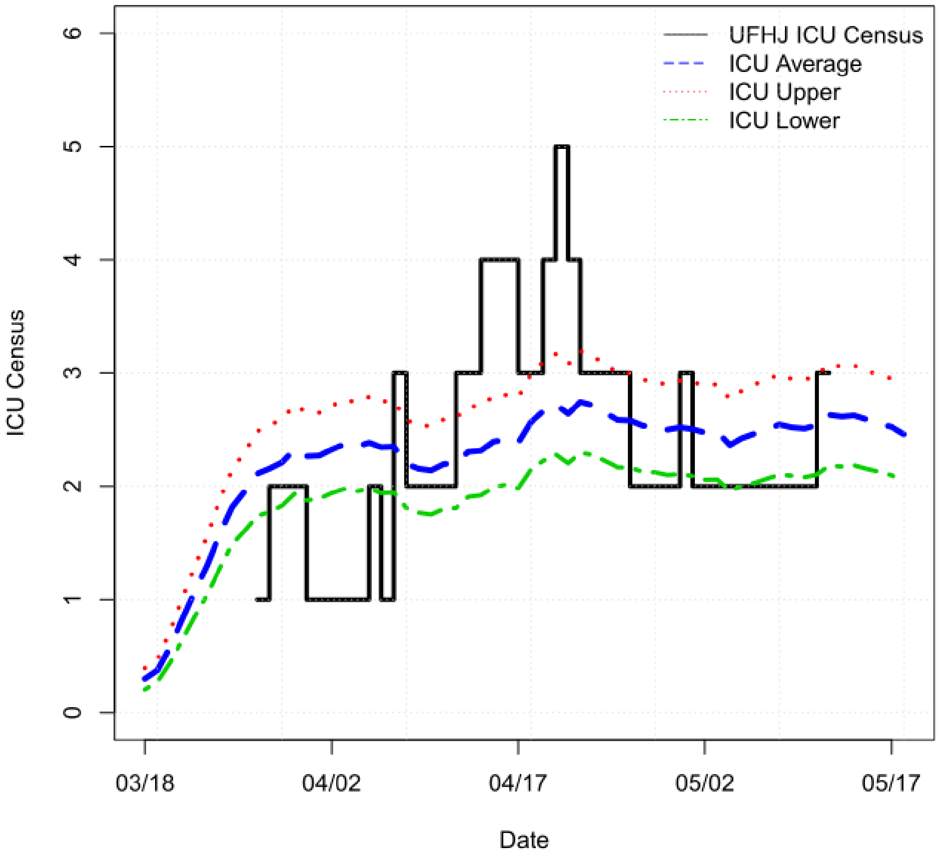

Figure 5

Average daily ICU census in the COVID unit obtained from the simulation model.

Supplementary Files

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- SupplementaryMaterial.docx