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Hospital Beds Planning and Admission Control Policies for COVID-19 Pandemic: A Hybrid Computer Simulation Approach

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***Abstract*— Health care systems are at the front line to fight the COVID-19 pandemic. Emergent questions for each hospital are how many general ward and intensive care unit beds are needed, and additionally, how to optimally allocate these resources during demand surge to effectively save lives. However, hospital pandemic preparedness has been hampered by a lack of sufficiently specific planning guidelines. In this paper, we developed a hybrid computer simulation approach, with a system dynamic model to predict COVID-19 cases and a discrete-event simulation to evaluate hospital bed utilization and subsequently determine bed allocations. Two control policies, the type-dependent admission control policy and the early step-down policy, based on patient risk profiling, were proposed to lower the overall death rate of the patient population in need of intensive care. The model was validated using historical patient census data from the University of Florida Health Jacksonville, Jacksonville, FL. The allocation of hospital beds to low-risk and high-risk arrival patients to achieve the goal of reducing the death 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.**

***Index Terms*— COVID-19, hospital pandemic planning, hybrid computer simulation, admission control.**

I. INTRODUCTION

The COVID-19 pandemic challenge is unprecedented. In the early stage of the outbreak, the US's healthcare system was severely strained, 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 the outbreak. An important follow-up question is how to optimally allocate these scarce resources to achieve the goal of reducing the case fatality rate and helping a maximum number of patients to recover. This study aimed to address the above questions using a computer simulation approach.

The pandemic of COVID-19 could overwhelm hospitals, but a planning guidance that accounts for the complex and dynamic interrelationships between hospital operating factors 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. In addition, the relationship is governed by a stochastic process rather than being deterministic. There are inherent uncertainties in patient demand, length of stay, and day-to-day hospital operations. These factors are instrumental in accurately predicting and evaluating system performance.

To guide hospital operations, a method that allows for the control of system performance, accounting for operational bottlenecks and the complex and dynamic nature of the system is desired. Discrete-event simulation (DES) has been a popular and effective decision-support tool for the optimal allocation of limited healthcare resources to strike the balance between minimizing healthcare delivery costs and increasing patient satisfaction [5]–[7]. Emerging applications of DES addressing the COVID-19 pandemic hospital planning problems can be found in [8]–[12]. The review of how simulation modeling can help reduce the impact of COVID-19 was presented in [13]. In these works, the regional disease-spread feature and the heterogeneity in patient pathways were not sufficiently accounted for when modeling the system. For instance, the hospitalization and death rates differ drastically across different age groups, and the age distribution of a population is region-specific. In addition, the patient demand is not stationary and could vary significantly in different phases of the pandemic. Therefore, we propose a hybrid simulation approach to modelling the COVID patient arrival process using system dynamics, and feeding it into a DES that models the operations of a hospital unit in time. The Susceptible-Exposed-Infectious-Recovered (SEIR) model is a type of system dynamics models that has been widely used in predicting infectious disease transmission like severe acute respiratory syndrome (SARS) [14], H1N1 influenza [15], and MERS-CoV [16], where S, E, I, R represent the number of susceptible, exposed, infectious and recovered people separately at a particular time. A data-driven SEIR model is trained using the data of the catchment area of the target hospital.

To allocate scarce resources to individual patients given the bed capacity constraints, we further propose to categorize patients into different types based on the potential consequence, if they cannot be treated timely in the ICU [17]. By categorizing the hospitalization population into high-risk and low-risk groups, we analyzed the effect of implementing control policies including a type-dependent admission control policy, and an early ICU step-down policy based on

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patient types. Region-specific population characteristics are incorporated to support decision making. The optimal control policy to lower the overall death rate of the patient population is identified for different degree of resource shortage, and a rigorous early step-down policy shows greater potential in surging resource demands.

The efforts of this study are organized as follows. Model conceptualization and development, as well as the numerical experiment settings are included in Section II. In Section III, the results from model validation and sensitivity analysis are presented, including the bed capacity decisions and the control policy comparison. Finally, the effectiveness of the control policies, the limitations of the current study, and the future research directions are discussed in Section IV.

II. METHODS

A hybrid computer simulation model was developed to evaluate the hospital preparedness and provide resource allocation decision support. The simulation model was initially validated using data from the University of Florida (UF) Health Jacksonville, Jacksonville, FL, and was tested under a spectrum of scenarios (e.g., different intervention policies and disease characteristics). In the following, we describe how the simulation inputs were calibrated based on carefully researching the clinical evidence, and introduce the conceptualized patient flow in a typical hospital COVID unit.

A. Input analysis

The daily COVID hospitalizations are not time-homogeneous and are closely related to the number of people infected. 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. The range of epidemiological variables, including hospitalization rate, hospitalizations that require ICU stay, denoted as ICU rate, hospital length of stay by unit type (ICU and ward), and case fatality rate (death rate) were determined by review of the literature and expert consensus of the team. In particular, the patient age distribution, hospitalization rate, ICU rate, and death rate were obtained from UF Health Jacksonville and the Florida Department of Health (FDOH) [18]. Based on the difference in these event rates, patients were broadly categorized into a high-risk group and a low-risk group. This was inspired by the multi-principal allocation framework for prioritizing which patients should receive ventilators when a shortage occurs [17]. In our study, the high-risk group contains patients 65 years old and above. Among the hospitalization population, the death rate of this age group exceeded 20%. The below 65-year-old group is regarded as of low-risk, with the death rate being under 11% on average after hospitalization. Similarly, there was a salient difference in ICU rates and average lengths of stay between the two groups. It is worth noting that other criteria can be used to classify patients and our choice was based on the goal of controlling the overall death rate. The hospital lengths of stay by unit type (ICU and ward) were obtained from UF Health Jacksonville and the CDC [19]. We present Table I below to summarize the basic setting. The total number of existing beds, and potential surge beds for use in the COVID unit were provided by the hospital. Currently, 35 beds are reserved for the COVID unit of UF Health Jacksonville. The market share of the hospital is assumed to be 15%. The group-wise event rates (and lengths of stay) in Table I were calculated by taking the weighted average of event rates (and lengths of stay) of each specified age stratum, for the low-risk and high-risk groups, respectively. The hospital related parameters were obtained from different healthcare provides in their regions, while the disease characteristics can be gradually updated as more instances collected and research conducted for certain new pandemic.

TABLE I
DISEASE AND PROCESS VARIABLES USED IN THE SIMULATION

Variables	Value (SD*)		Reference
	Type 1 patient	Type 2 patient	
Hospitalization rate	6%	6%	[18], [20], [21]
Hospital market share	15%	15%	-
Population percentage (among hospitalization)	50%	50%	[22]
ICU rate	35%	23%	[4], [18], [23]
Case fatality rate (among hospitalization)	43%	9%	[4], [18]
Average time spent in an ICU bed (day)	9.30 (5.86)	8.90 (5.58)	[2], [19]
Average time spent in hospital (day) for ICU patient	13.30 (8.37)	12.90 (8.09)	[19]
Average time spent in hospital (day) for ward patient	6.80 (4.48)	4.00 (2.40)	[19], [24]

B. SEIR model development

We let $S(t)$, $E(t)$, $I(t)$, and $R(t)$ represent the population at each state and each time t, P (resp. Q) be the expected number of cases directly generated by one infectious (resp. exposed) case in a population where all individuals are susceptible to infection. Furthermore, R_0 represents the basic reproductive number, and the effective R_0 equals to $P+Q$; N represents the total population in the area (i.e., $N = S(t) + E(t) + I(t) + R(t)$); L represents the incubation period, D represents the infectious period, and V represents the serial interval, which equals to $L + D$. COVID-19 has its own feature and the transmission rates and increments/decrements of the population at each stage are represented in the following equations:

$$\frac{dS(t)}{dt} = -\frac{PS(t)I(t)}{ND} - \frac{QS(t)E(t)}{NL} \quad (1a)$$

$$\frac{dE(t)}{dt} = \frac{PS(t)I(t)}{ND} + \frac{QS(t)E(t)}{NL} - \frac{E(t)}{L} \quad (1b)$$

$$\frac{dI(t)}{dt} = \frac{E(t)}{L} - \frac{I(t)}{D} \quad (1c)$$

$$\frac{dR(t)}{dt} = \frac{I(t)}{D} \quad (1d)$$

The total population N for our work is 1.56 million, based on the metro Jacksonville area [25]. For the parameters, P and Q are obtained by linearizing the model by assuming

*SD: Standard deviation

no depletion of susceptible [14], and considering the proportion of secondary cases infected by asymptomatic and symptomatic cases [26]. The serial interval is 7.5 days and the incubation period is 5.2 days, according to [27]. The values of the parameters were fine tuned by minimizing the prediction error given the historical daily COVID cases from the FDOH dashboard data [18]. For planning purposes, the future patient arrival is simulated based on the SEIR model. The hospitalization demand is proportional to the new case generated according to the hospital market share and the hospitalization rate.

C. DES model conceptualization

A DES model based on the general patient flow in hospital COVID units was developed using commercial simulation software, Arena®. The scope of the system and the patient flow is described as follows. Patients arriving at the hospital will be triaged first. Mild patients will be directly discharged after administering the treatment, which is out of the scope of this study. Severe patients, based on their level of severity will be admitted to an ICU (critical condition) or a ward (non-critical, e.g., do not need ventilators). In the model, type 1 (high risk) patients have a higher chance to be admitted to an ICU with a rate of 35%, and that of type 2 (low risk) patients is only 23%. Patients in wards, depending on their types being 1 or 2, will stay an average of 6.80 days with a standard deviation of 4.48 days, i.e., 6.80 (4.48) days, or 4.00 (2.40) days, and will be discharged. Patients in ICUs with critical conditions (stage 1) will be stabilized and transferred to a ward (stage 2). The total length of stay for ICU patients are 13.30 (8.37) and 12.90 (8.09) days with their average time in the ICU as 9.30 (5.86) and 8.90 (5.58) days, for type 1 and type 2 patients, respectively.

When the ICU is full or exceeding its surge capacity (typically 20% more than the normal bed allocation), new arrivals have to be rejected. These patients might be transferred to another hospital or sent home. Here we consider an admission control policy: when the ICU bed occupancy is below the normal bed allocation, all new arrivals will be admitted. When the ICU bed occupancy is above the normal bed allocation but below the surge capacity, only high-risk patients are admitted. The goal is to make room for a future critical condition patient. We denote this as a type-dependent admission control policy, and the corresponding patient flow is illustrated in Fig 1. Besides, as shown in Fig 2, we consider the early step-down of a patient from the ICU to make room for an incoming critical condition patient. If a new arrival is of type 1 and the ICU is at its surge capacity, then, we will search for a current ICU patient who is of type 2 and has stayed for the number of days which is more than the mean number of mechanical ventilation usage days in ICUs [19]. If there exists a patient that qualifies both criteria, he or she will be stepped down to a ward. This is denoted as an early step-down policy. If a patient is rejected or stepped down due to capacity constraints, their health outcome will be affected. Generally, ICU refusal or delay of ICU care would result in a higher death rate [28]. To penalize this, their death rate will be adjusted by multiplying a factor of 1.5, or 1.2, if a patient is rejected or stepped down early, respectively. The condition of patient transfer between hospital units can also be accommodated by adjusting the penalty factors.

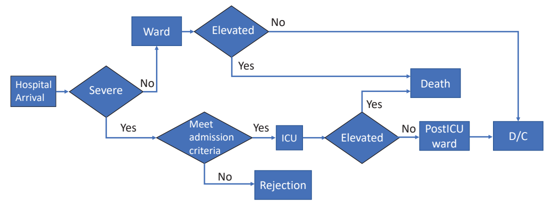

Fig. 1. Patient flow in the hospital COVID unit under the admission control policy

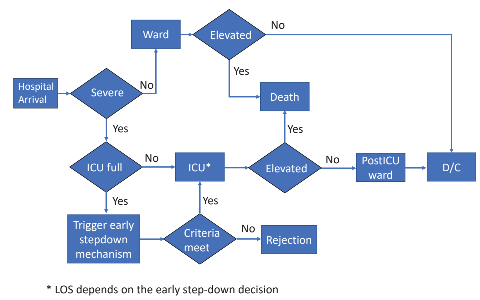

Fig. 2. Patient flow in the hospital COVID unit under the early step-down policy

D. Model validation

The validity of the model was tested against different assumptions, the forecast arrival by the SEIR model was compared with the historical COVID cases from FDOH, and the historical census data were used to compare with the DES model outputs. The real hospital patient census in the COVID unit (ward and ICU) during March 23rd – May 11th, 2020 were provided by UF Health Jacksonville. The bed capacity was set as 10 for the ICU and 25 for general wards. Other parameters were set based on Table I.

E. Sensitivity analysis

With a fixed bed capacity, we constructed several scenarios to highlight particular aspects of the type-dependent admission control policy and the early step-down policy. As we allow the ratio of high-risk to low-risk patients in the population to vary from 1:4, 1:1, to 4:1, the objective was then to determine the appropriate policy that suits the problem setting and patient mix. The resultant overall death rate of the patient population was used as the performance metrics. The admission control policy was tested in four scenarios. The first three correspond to three ICU bed buffer ranges,60%-120%, 80%-120%, and 100%-120% of the normal bed capacity. If the current bed occupancy is below the lower bound of the range, both types of patients can be admitted; if the current bed occupancy is within this range, only type 1 patient could be admitted. The fourth case (base case) allows the admission of all types of patients, including types 1 and 2, until the ICU surge capacity (120% of the normal bed capacity) is reached.

Next, we considered five variations for the early step-down policy, including the base case which does not allow any early step-down. The other four scenarios were tuned by two key parameters. The first parameter is the patient type that is eligible for early step-down. It has two choices, type 2 patients only, or all types are eligible. The second parameter is the minimum ICU days a patient has stayed in order to be eligible for early step-down. The number of days was set as two days and six days, corresponding to the minimum and the mean usage days of mechanical ventilation in ICUs [19]. In addition, the early step-down death rate penalty factor is set to 1.2 and 1.1, for a minimum of two-and six-day ICU stay before step-down, respectively.

For all the sensitivity analysis, the patient arrival was simulated to reflect the peak of the outbreak since the onset in the metro Jacksonville area and the state of Florida, resulting in the surging demand for hospital resources.

III. Results

A. Validation results

We ran the model for 200 replications for all the simulation studies to ensure a narrow confidence interval (CI). We first present the case study of UF Health Jacksonville to validate our model. Historical data showed that the average ward census was 6.53 patients/day and the average ICU census was 2.38 patients/day in the COVID unit during March 23rd – May 11th, 2020. Our simulation yielded the average census of 6.17 ± 0.38 (the number following ± refers to the halfwidth of 95% CI), and 2.26 ± 0.14, for ward and ICU, respectively, suggesting that the model can well capture the system dynamics. We validate that the patient censuses in the ICU and the ward conform to the real data, and these factors are directly relevant to determining the number of beds.

B. Control policy analysis

With the setting of 10 ICU beds and 25 ward beds, we varied the hospitalization rate from 6%, 8% to 10%, and changed the high-risk to low-risk population ratio from 1:4, 1:1, to 4:1. Different control strategies were compared. If the current bed capacity results in moderate robustness against demand variation, i.e., only a few rejections are observed, the type-dependent admission policy can well accommodate the temporary bed shortage. However, it cannot handle the case where there is a consistent deficiency in bed capacity. The early step-down policy, meanwhile, is more effective to handle the case of a severe bed shortage. We present the major observations in Table II to evaluate the effectiveness of the proposed methods. Without an admission control policy, with 6% hospitalization rate, the rejection rate in the hospital is 6.18 ± 0.87%, and the overall death rate is 24.94 ± 1.59%. By allowing only the high-risk group to enter the ICU when the bed occupancy is in its buffer range, the rejection rate increases, but the overall death rate decreases. With the ICU buffer ranging between 60%-120%, 80%-120%, and 100%-120% of its normal capacity, the rejection rates are 9.81 ± 1.00%, 8.91 ± 1.03%, and 7.63 ± 1.02%, and the overall death rates are 24.12 ± 1.55%, 24.24 ± 1.54%, and 24.11 ± 1.55%. Among the 237 severe patients coming to the hospital, the total death (including death from rejection cases and hospitalization cases) decreased from 27 ± 2.55 (baseline) to 26 ± 2.64, 26 ± 2.59, and 25 ± 2.60, respectively.

TABLE II

Simulation outputs for control policy analysis

Case Index*	1	2	3	4
ICU Utilization	40.35%	36.42%	38.13%	39.58%
(95% CI)	(± 4.00%)	(± 3.60%)	(± 3.70%)	(± 3.90%)
Ward Utilization	36.53%	35.87%	35.71%	36.03%
(95% CI)	(± 3.70%)	(± 3.60%)	(± 3.60%)	(± 3.60%)
Rejection Count	9	12	12	11
(95% CI)	(± 1.38)	(± 1.55)	(± 1.58)	(± 1.53)
Hospital Death Count	23	23	23	23
(95% CI)	(± 2.46)	(± 2.60)	(± 2.55)	(± 2.55)
Rejection Death Count	4	3	3	3
(95% CI)	(± 1.66)	(± 0.43)	(± 0.46)	(± 0.53)
Total Death Count	27	26	26	25
(95% CI)	(± 2.55)	(± 2.64)	(± 2.59)	(± 2.60)
Total Discharged Count	97	99	99	98
(95% CI)	(± 10.54)	(± 10.67)	(± 10.71)	(± 2.60)
Overall Death Rate	24.94%	24.12%	24.24%	24.11%
(95% CI)	(± 1.59%)	(± 1.55%)	(± 1.54%)	(± 1.55%)

Case Index*	5	6	7	8	9
ICU Utilization	61.30%	60.23%	60.39%	60.34%	60.17%
(95% CI)	(± 5.30%)	(± 5.20%)	(± 5.20%)	(± 5.20%)	(± 5.20%)
Ward Utilization	44.16%	45.06%	44.68%	45.14%	44.93%
(95% CI)	(± 4.50%)	(± 4.70%)	(± 4.60%)	(± 4.70%)	(± 4.60%)
Rejection Count	28	11	19	0	10
(95% CI)	(± 3.48)	(± 1.95)	(± 2.50)	(± 0.00)	(± 1.46)
Early Step-down Count	0	17	8	28	17
(95% CI)	(± 0.00)	(± 2.28)	(± 1.13)	(± 3.51)	(± 2.10)
Hospital Death Count	33	39	35	42	38
(95% CI)	(± 6.27)	(± 4.02)	(± 3.56)	(± 4.38)	(± 3.89)
Rejection Death Count	16	6	11	0	6
(95% CI)	(± 2.04)	(± 1.15)	(± 1.47)	(± 0.00)	(± 0.90)
Total Death Count	49	45	46	42	44
(95% CI)	(± 6.59)	(± 4.18)	(± 3.85)	(± 4.38)	(± 3.99)
Total Discharged Count	118	114	115	110	113
(95% CI)	(± 12.20	(± 11.84)	(± 11.92)	(± 11.32)	(± 11.62)
Overall Death Rate	37.85%	36.97%	37.29%	36.29%	36.69%
(95% CI)	(± 2.02%)	(± 2.01%)	(± 2.02%)	(± 1.99%)	(± 2.00%)

For the early step-down policy, the policy effects are more salient in a high demand setting. To illustrate, the hospitalization rate was selected at 8%, and the high-risk to low-risk group population ratio was set at 4:1. In the base case, the rejection rate, death rate, and total death cases are 17.62 ± 1.74%, 37.85 ± 2.02%, and 49 ± 6.59. When the early step-down policy is applied, if only the low-risk group was eligible to step-down after two (or six) days' ICU care, the rejection rate is lowered to 6.88 ± 1.12% (or 12.64 ± 1.36%), the death rate decreases to 36.97± 2.01% (or 37.29 ± 2.02%), and total death number drops to 45 ± 4.18 (or 46 ± 3.85). When no patient categorization was implemented in the early step-down process, the rejection rate, death rate,

*Case index is explained below:

Cases 1-4: Base case (no admission control), and admission control with ICU buffer ranging 60%-120%, 80%-120%, 100%-120% of its normal capacity, at 6% hospitalization rate and 1:1 high-risk and low-risk group population ratio.

Cases 5-9: Base case (no early step-down), early step-down for low-risk group patients after 2 days and 6 days ICU stay, and early step-down for all types patients after 2 days and 6 days ICU stay, at 8% hospitalization rate and 4:1 high-risk and low-risk group population ratio.

and total deaths are 0.01 ± 0.001% (or 6.87 ± 0.88%), 36.29 ± 1.99% (or 36.67 ± 2.00%), 42 ± 4.38 or 44 ± 3.99, for two (or six) days' stay in the ICU.

IV. Discussion and Conclusion

A. Control policy comparison

The type-dependent admission control policy slightly lowered the overall death rate of hospital system during peak days, at the cost of an increased rejection rate. When the hospitalization rate was 6% or 8%, the 100%-120% ICU buffer range yielded the lowest death rate and moderate bed utilization, among the three ICU buffer range choices. If the hospitalization rate was raised to 10%, the lowest death rate and bed utilization results came from the 60%-120% buffer range setting. Meanwhile, the 100%-120% setting had a comparable death rate and higher ICU bed utilization outcomes. By rejecting the low-risk group to ensure that high-risk patients have access to the ICU, the 100%-120% of ICU buffer setting would be the most appropriate one to balance the bed utilization and overall death rate.

The early step-down policy greatly decreased the rejection rate by allowing the high-risk group to have a higher priority accessing the ICU and other equipment (e.g., ventilators). The overall death rate was also lowered, where the decreased numbers of deaths due to rejection were partially compensated by the increased number of hospital deaths. The sensitivity analysis indicated that, the setting which allows low-risk patients to step-down after six days in ICU was less effective in reducing the death rate and the total number of deaths. This is potentially because six days can already be sufficient for some low-risk patients and there is not an effective reduction in their ICU stay. Therefore, when hospital resource shortage occurs, we would recommend employing a more aggressive step-down policy, i.e., letting low-risk patients step-down after two days' ICU care, or allowing all types of patients to step-down early after staying between two to six days in the ICU. It should be noted that the single-cut threshold is adopted for a first-step analysis. To implement this policy, the clinicians should come up with a patient-specific step-down plan based on individual patients' diagnoses. By monitoring and updating the composition of the patient mix, the hospital system could adjust the early step-down strategies accordingly. When more low-risk patients are expected to come to the hospital and the resources are not highly utilized, letting only low-risk group patients to step-down after a relatively shortened but sufficient ICU stay would suffice to control the overall death rate, and maintain relatively high patient satisfaction. If more high-risk patients are expected to show up, it would be more efficient to allow all types of ICU patients to step-down at their earliest possible dates to save more lives.

By considering the total rejection, total death and total discharged number of patients in Table 2, we use a normalized reward index to include these three factors, and compare the results with this single metric. The reward index includes large negative penalty for death cases, relative smaller negative penalty for patient rejections, and a positive reward for discharged cases. The reward values were obtained for each test scenario, then, normalized based on the mean and standard deviation for all sensitivity test scenarios per each control policy. The normalized results are shown in Fig 3 for cases 1-4 in the admission control policy, and cases 5-9 of the early step-down policy, where cases 1 and 5 are the base cases for each policy respectively. From cases 1-4 in Fig 3, we can tell that the 60%-120% ICU bed buffer range has negative reward, which comes from the inefficient bed utilization and more rejections due to this. And the 100%-120% buffer range admission control policy can give the highest positive reward to handle the conditions of beginning of peak days. When resources shortage continues and more severe patients need hospitalization, the Fig 3's cases 5-9 give the guidance of early step-down policy choices to accommodate. Case 8 represents allowing all patients to early step-down after 2-day ICU care, which is the most aggressive step-down policy, and gives the largest positive reward in the urgent shortage scenario.

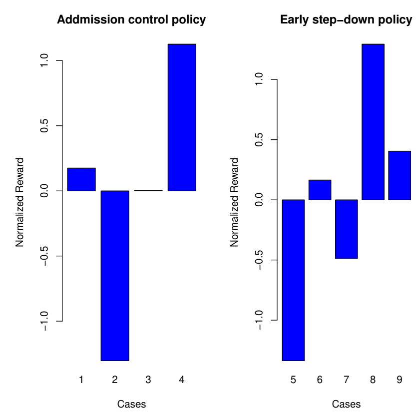

Fig. 3. Normalized reward index for the control policy simulation

Comparing the two control policies, the early step-down policy had a better performance in minimizing the total number of deaths, especially when the bed shortage is significant. This can represent the scenario of surging demand for hospital resources, or represent an area where the resources are not sufficiently available, e.g., developing countries. Besides, different early step-down policies had comparable effects with small variances in the overall death rate. This is good to note as in reality, the days that qualify for early step-down can be in a range and it can be implied that such flexibility would not be detrimental to the effectiveness of the policy. In addition, although we did not exercise the extensive exploration, the parameters in this simulation model can be tuned to cater to any real hospital setting. Take the death rate penalty factor for example, instead of using the 1.1, 1.2, and 1.5 multipliers assumed in this study, these values could be adjusted with continuously updated hospital data. The effectiveness of the control policies will be more salient as the ratio of death due to rejection goes higher. Overall, we expect this decision support tool to provide adaptive suggestions to accommodate various potential ICU settings and hospital planning situations.

B. Limitations and future work

Our hybrid simulation model provides a timely decision support tool for pandemic planning. By integrating the DES planning tool with a predictive SEIR model, the projection of hospital congestion and delay in treatment can be analyzed ahead of time, which can grant a lead time for mitigating medical resource shortage. This united framework will also enable us to refine the SEIR model parameters based on the simulation output and its alignment with real-world data, achieving the best predictability to inform the optimal decision to combat the pandemic. For future work, this hybrid simulation model can be implemented to investigate the planning of other limited healthcare resources (e.g., mechanical ventilation and ECMO) with appropriate adjustments.

In our simulation model, we focused mainly on the ICU bed utilization, and simplified the general ward bed planning and the patient flow in the ward. There is a need to capture the overall patient flow in the hospital to determine how many beds should be reserved to the COVID unit and distributed to wards and ICUs. To achieve this, we also need to estimate the occupancy of hospital beds due to non-COVID patients, and the non-COVID patient arrival process cannot be handled by the SEIR model.

When classifying the high-risk and low-risk groups, only age was used. The control policies can be enhanced by considering more clinical characteristics and risk factors, like preexisting lung problems or heart diseases, for patient categorization. With a mechanism that allows for precise patient risk-based grouping, the simulation tool has the potential to improve the decision making and achieve a better overall care performance for managing COVID-19 patients.

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