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ASSESSING STRAIN ON HOSPITAL CAPACITY DURING A LOCALIZED EPIDEMIC USING A CALIBRATED HOSPITALIZATION MICROSIMULATION

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ABSTRACT

The ability of healthcare systems to provide patient care can become disrupted and overwhelmed during a major epidemic or pandemic. We adapted an existing hospitalization microsimulation of North Carolina to assess the impact of a localized epidemic of a fictitious pathogen on inpatient hospital bed availability in the same locale. As area hospital beds reach capacity, agents are turned away and seek treatment at different hospital locations. We explore how variability in the duration and severity of an epidemic affects hospital capacity in different North Carolina counties. We analyze various epidemic scenarios and provide insights into how many days counties and hospitals would have to prepare for a surge in capacity.

1 INTRODUCTION

During a major epidemic or pandemic, hospital operations can be disrupted and capacity to provide patient care can become overwhelmed (World Health Organization 2014; Banach et al. 2017; Hick et al. 2020). As evident with the current coronavirus disease 2019 (COVID-19) pandemic, even advanced health systems can be stretched beyond capacity, resulting in worst-case scenarios for rationing of care in some locations (Cavallo et al. 2020). Preparedness planning to anticipate and address these scenarios can help mitigate poor patient outcomes (Cavallo et al. 2020). Modeling infectious diseases and the need for hospitzliation caused from the spread of viruses can be used to help leaders better prepare for and respond to public health crises (Rivers et al. 2019). Several simulation tools have previously been developed to assist planners in making bed related decisions (Devapriya et al. 2015; Toerper et al. 2018), but these tools do not allow planners to see when and where capacity will be reached for all hospitals within a region or US state.

We sought to adapt a previously built agent-based model, developed to evaluate interventions that prevent healthcare-associated infections, to assess the strain on hospital capacity during an epidemic for all licensed hospitals in North Carolina (NC). This model simulates patient movement among healthcare facilities, including short-term acute care hospitals (STACHs), long-term acute care hospitals (LTACHs), nursing homes, and the community in a regional healthcare network in NC (Rhea et al. 2019). The underlying microsimulationl of agent movement in the model, which can also incorporate agent disease states for various healthcare-associated infections, was calibrated using multiple data sources (Jones et al. 2019). Subsequently, the model was expanded from a regional healthcare network model to a North Carolina statewide model in which agent admissions, transfers, and discharges for 112 STACHs, 10 LTACHs, and 421 nursing homes are simulated daily (Hilscher et al. 2019). We incorporated healthcare facility-specific details (e.g., number of beds, admission rates) into model calibration with agent movement informed by age, presence of comorbidities, and North Carolina home county.

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1.1 Community Movement

Agents in the model have daily probabilities of moving from the community to one of several healthcare facility nodes. This movement was calibrated to match yearly totals of agent movement by agent demographics (Jones et al. 2019). Within a calendar year, we expect over 900,000 admissions to the 112 short-term acute care facilities from agents that live in North Carolina and are currently within the community node (UNC Sheps Center Data 2017). Some large counties can expect to account for over 50,000 hospital admissions annually, while other small counties will have no more than 200-300 admissions for an entire year. While the quantity of admissions is drastically different for each county, we use this simulation to test the impact that similar epidemics could have on counties of all sizes. Table 1 below shows example daily probabilities of agent movement for one county. The probability in this table is the daily probability that an agent from County X would go to any modeled healthcare facility (i.e., STACH, LTACH, nursing home). The five columns that follow represent that probability that if an agent was selected to go to a healthcare facility, that agent would go to one of the five different healthcare facility types. In this example, H1, H2, and H3 represent three different types of hospitals deidentified by health system affiliation and size.

Table 1: Example of community movement probabilities for county X.

County	Age	Probability	H1	H2	H3	LTACH	NH
X	<50	0.000173	0.207	0.188	0.605	0.0	0.0
X	50 <65	0.000246	0.207	0.188	0.605	0.0	0.0
X	65+	0.000784	0.160	0.145	0.468	0	.227

Note that in our microsimulation, agents cannot move directly from the community to LTACHs, and that community to nursing home movement represents 15% of all community movement.

1.2 Hospital Movement and Assumptions

Each agent admitted to a hospital is assigned a unique length of stay based on hospital-specific distributions, with an average length of stay of 5 days. The statewide model includes 21,463 beds (NC Department of Health and Human Services 2018). During a typical model run, once steady state is reach (about 50 days), approximately 60% of all hospital beds are occupied.

We make a few additional simplifying assumptions, including that the fictitious pathogen effects agents of all ages at the same rate and that the epidemic did not impact the following parameters in the model:

- average length of stay at healthcare facilities
- proportion of agents seeking an intensive-care unit (ICU)
- all-cause mortality
- the proportion of agents leaving the community and seeking nursing home care

Each of these assumptions could be revisited and adjusted using available data from example epidemics or pandemics.

As the modeled epidemic grows towards its peak, more agents will be admitted to hospitals. Details of how the epidemic effects admissions are in section 2.1. If a hospital reaches capacity, agents are turned away and seek treatment at a different hospital location. Upon being turned away from the first hospital, agents attempt their *next choice* hospital. This next choice represents the hospital that an agent would have gone to if the agent was a transfer from the original hospital they were assigned to. The second choice hospital is selected based on a combination of the agent's home county and the first hospital. If this second hospital is full, an agent will try any hospital in their surrounding area, which consists of all hospitals that had discharge data for someone from the agents home county. Finally, if all of these hospitals are full, the agent is considered completely turned away and would need to seek treatment somewhere else. We do not simulate this additional search for another hospital.

2 The Epidemic

On top of the underlying microsimulation, we included a fictitious epidemic to increase the number of hospitalizations occurring. The disease attacks all agents equally and will increase an agents probability of needing hospitalization. Agents cannot die from the disease, and they are assigned a length of stay from the same distribution used for normal agents. Although we did not include any of the following in our epidemic, the model is capable of:

- Assigning disease to agents based on age, gender, or other demographics.
- Including unique length of stat distributions by disease.
- Modeling ICU vs. non-ICU bed needs.
- Including disease mortality.

Since this epidemic is fictitious, the results are not to be used and only serve to show the type of analysis capable of the model. Including a fake mortality rate of $x\%$, would only contribute to the epidemic being fictitious. For this reason, we did not include varying disease rates by demographic, LOS distributions, ICU and non-ICU bed assignments, or disease mortality.

2.1 The Epidemic Curve

Figure 1 provides an example of the fictitious epidemic curve. The curve shows the increased likelihood of agents moving from the community to a facility for an outbreak lasting 30 days with a maximum increased likelihood of 100%. The characteristics of this curve could be adjusted to reflect specific epidemic curves.

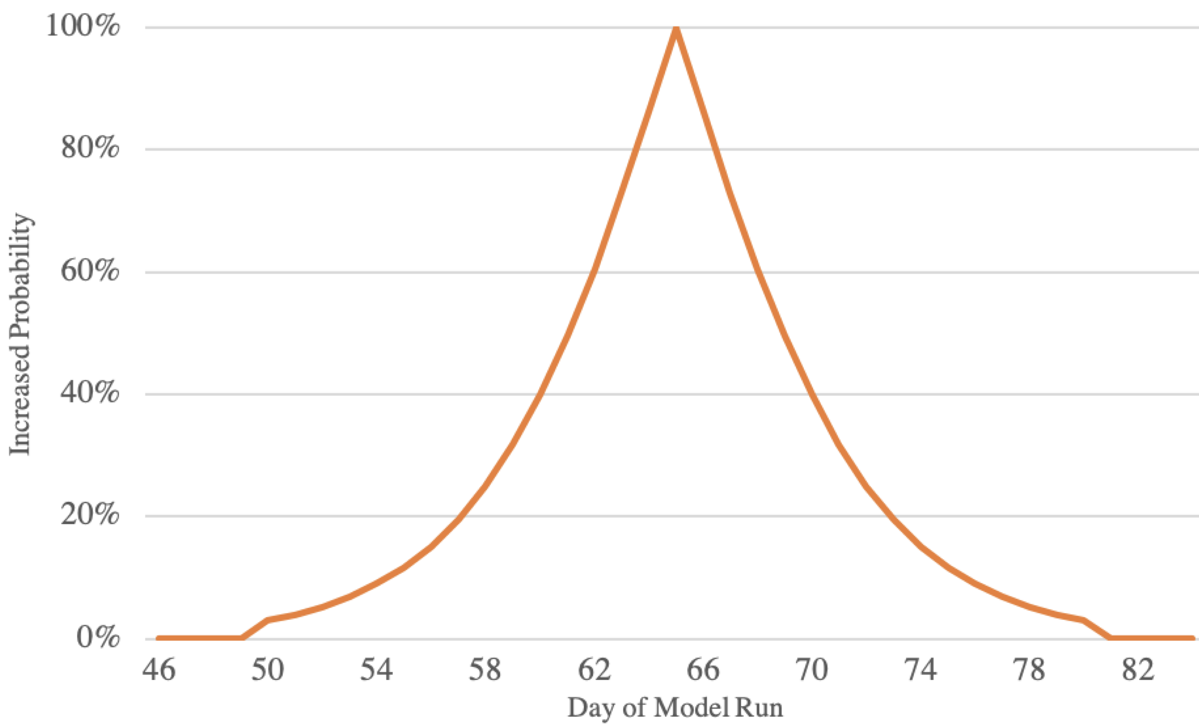

Figure 1: Increase in daily probability based on example epidemic.

By examining the curve, we see that agents are twice as likely to need healthcare on day 65 (the midpoint of the outbreak) than they would be before the outbreak began. For the fictitious epidemic, we used a variation of the sigmoid function,

$$\frac{1}{1+e^{-x}},$$

to calculate this increase in probability. The function was scaled to the current day in the epidemic until the midpoint in Equation (1), and then scaled back down until the epidemic finished in Equation (2).

$$X = -5+10*(d/l) \tag{1}$$
$$X = -5+10*(l-d/l) \tag{2}$$

where d was the current day of the epidemic, l was the total length of the epidemic. Note that this equation was arbitrarily chosen so that $-5 < X < 5$, and that the values of 5 and 10 in this equation are not related to the severity values chosen for model runs. This will result in an increased probability ranging from 0% to 100%. The value of X is then plugged into Equation (3).

$$m = \frac{\frac{1}{1+e^{-X}}}{.5} * s \tag{3}$$

where s is the severity, and m is the calculated multiplier that was used to increase the daily probability.

2.2 Scenarios

We created different epidemic scenarios and tested the impact of each scenario on all 100 NC counties. For each scenario, an epidemic begins in a single county on day 50 of the model run, as the microsimulation generally takes about 50 days to ramp-up to a steady-state. The epidemic only effects the probabilities of community transition for the single county specified for each model run. Agents within these communities all have daily probabilities of transferring from the community to one of the other healthcare facility nodes (section 1.1). The epidemic increases this probability based on the length of the outbreak and the severity. Probabilities will increase until the epidemic reaches its midpoint and then begin to decrease as the epidemic progresses.

For our model runs, we included scenarios where the disease caused by the epidemic pathogen resulted in an increase in hospital-seeking behavior of agents, by multiples of 2, 5, and 10. We also looked at two different epidemic durations, 60 days (two months) and 180 days (six months), resulting in six different epidemic scenarios. Again, each scenario was tested for each county, creating a total of 600 total model runs. As the underlying patient movement is well calibrated (Jones et al. 2019), and patient admissions are steady throughout the year, we did not run sensitivity analysis for each combination. Rather, we ran sensitivity in the original calibration and expect similar stability here.

3 AVAILABLE ANALYSIS

Microsimulations allow us to explore various types of analysis. We can look at capacity for individual hospitals, capacity for all hospitals connected to individual counties, the number of patients turned away from their first-choice hospital, and the number of patients completely turned away, among other variables. To begin looking at the available types of analysis, we will explore a single scenario. The epidemic for the following analysis last for 180 days and has a severity of 5, indicating that on day 140 of the model, agents are 5x as likely to need hospitalization as on a normal day. We will show the results for the impact of this epidemic on County X, an urban county in North Carolina.

3.1 Hospital Capacity by Day

Figure 2 shows the hospital capacity for the four hospitals that agents from County X typically go to based on historical data (UNC Sheps Center Data 2017).

Figure 2: Hospital capacity by day for hospitals connected to county X.

The hospital names are masked, but the order of the hospitals IDs are based on how many patients from County X typically go to each hospital, with Hospital 1 being the first choice hospital for County X (the hospital that receives the most patients from the specific county in a given year). As seen in Figure 2 it takes about 70 days before Hospital 1 becomes full, and agents are turned away. On day 70, agents would be less than 2.5x as likely to go to a hospital than on a normal day, which is well short of the epidemic's peak of 5.0x. Also notice that on day 50, Hospital 3 was only at about 35% capacity. Shortly after the peak of the epidemic, this hospital surpassed 70% capacity, doubling the number of patients in the hospital.

3.2 Agents Turned Away

County X is not the only county that relies on Hospital 1 for patient care. For example, there are 6 counties that rely on Hospital 1. Hospitals 2, 3, and 4 will also take-in patients from additional counties. If an epidemic occurs in County X, it will have ripple effects on the availability of care for agents from other counties as well. At the peak of the epidemic, over 30 agents were turned away from Hospital 1 (which has 400 hospital beds) as seen in Figure 3.

When an agent is turned away, they first seek treatment at hospitals that their first-choice hospital would transfer to. For this scenario, there were two hospitals that saw a significant increase in patients once agents started getting turned away. In Figure 4 below, both hospitals are in the same network as Hospital 1. At the peak of the epidemic, they are both hovering at 100% capacity.

4 OVERALL RESULTS

Of the 600 total model runs (3 severities x 2 epidemic lengths x 100 counties), 540 provided viable results. In order to be viable for analysis, the county in the scenario most start with at least 5 people in a single hospital location. This decision was made to keep hospitals out of the analysis that would not largely be affected by an epidemic occurring within a county. There were 10 counties, each with populations of less than 20,000, that did not meet our specifications.

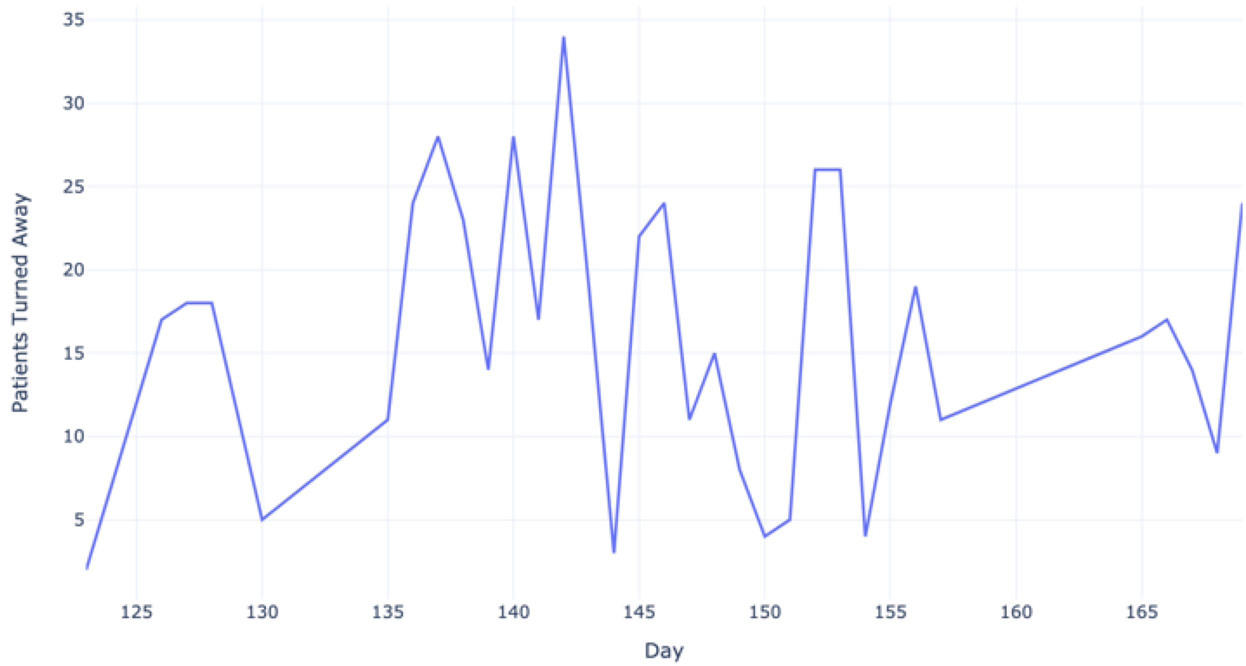

Figure 3: Number of agents turned away from one hospital by day.

We created a rolling average for each county equal to the mean capacity of all hospitals affected by a county across a 3-day period. To assess how long hospitals would have to prepare for a surge of additional agents, we considered all scenarios in which this rolling average did not exceed 80% during the 50 day ramp-up period (449 of 540 (83%) total viable runs). Of these scenarios, only 208 ever reached a rolling average of above 90%. Table 2 shows the average number of days after the epidemic began before the 90% threshold was reached.

Table 2: Count of counties surpassing a threshold of 90% capacity.

Epidemic Length	Epidemic Severity	County Reaching 90%	Avg. Days
60	2	0	n/a
60	5	30	30
60	10	62	27
180	2	4	90
180	5	43	80
180	10	69	71

For the final scenario, 69 out of 90 possible counties reached a threshold above 90%. On average, it took 71 days for this threshold to be reached after the epidemic began, giving all hospitals affected by the county's epidemic just over two months to prepare additional beds.

For Table 3, we considered all counties, regardless of whether the 80% capacity threshold was reached within the first 50 days. The columns represent threshold values. A county was counted if, at some point during the model run, the rolling average was above the threshold. For the final scenario, 72 out of 90 possible counties had a 3-day window in which every hospital that a county sends agents to was at 99% capacity. However, even for the shortest (60 days) and least severe (2x multiplier) epidemic, there were still five counties that surpassed 99% capacity for all hospitals.

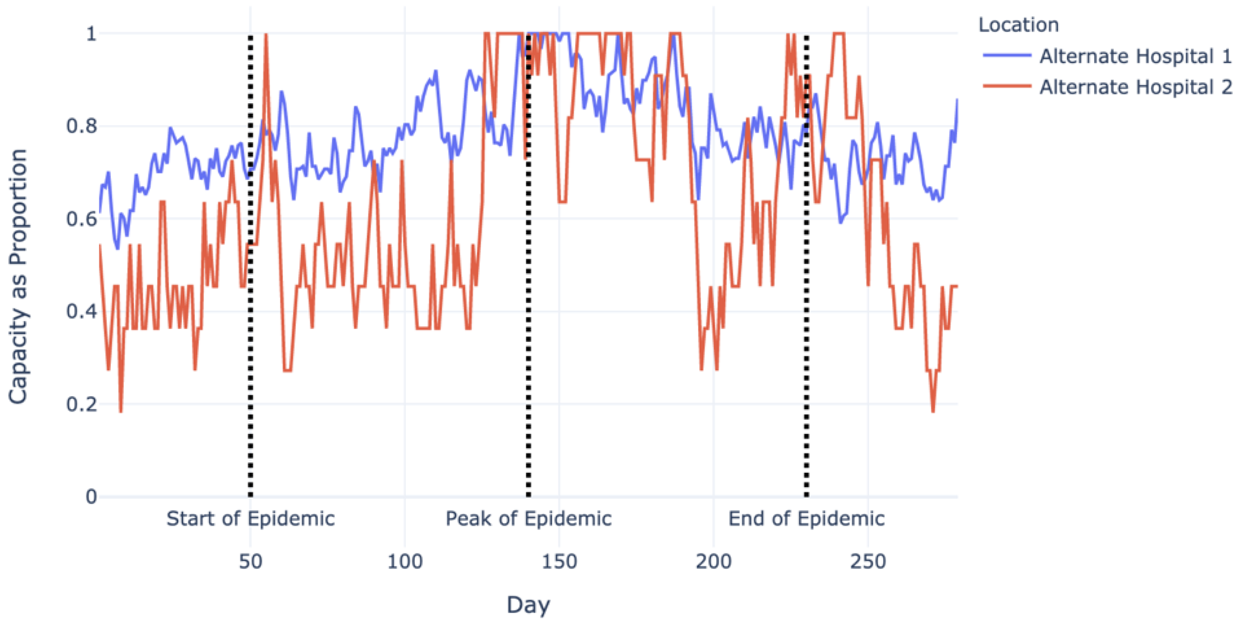

Figure 4: Hospital capacity by day for hospitals patients went to when turned away from hospital 1.

Table 3: Count of counties surpassing different thresholds for each scenario.

Epidemic		Capacity Threshold									
Length	Severity	90%	91%	92%	93%	94%	95%	96%	97%	98%	99%
60	2	8	8	8	8	8	8	8	8	5	54
60	5	44	43	40	37	34	32	30	28	25	24
60	10	76	73	72	68	66	61	61	60	58	55
180	2	17	15	14	14	14	13	13	12	9	6
180	5	57	55	55	54	52	50	47	45	44	38
180	10	83	82	82	80	79	76	75	75	73	72

5 CONCLUSION

We adapted a previously built agent-based model, developed to evaluate interventions that prevent the spread of healthcare-associated infections, to assess the strain on hospital capacity during an epidemic. Our microsimulation provides a platform for assessing the impact that epidemics could have on available hospital beds. It can also help counties and hospitals assess how quickly beds will fill up, where epidemic and non-epidemic patients can be expected to arrive, and how many additional beds will be needed to meet demand. The results of this analysis rely heavily on the epidemic or pandemic being simulated. For this paper, we made a few general simplifying assumptions that are likely to have large impacts on our results. With those assumptions in mind, epidemics that result in agents having a severe disease forced hospitals to reach maximum capacity within a matter of months, almost regardless of the county the epidemic took place. Even with length of stay remaining constant and the epidemic remaining concentrated in a single county, all hospitals receiving agents from the county of the epidemic will reach maximum capacity for several scenario and county combinations. We have begun working with public health experts and healthcare stakeholders to create a COVID-19 specific version of this model. Our next steps are to enable assessment of personal protective equipment and staffing needs, as well as allow agent interaction within hospitals to generate new cases. We also hope to Incorporate real time hospitalization counts by hospital to help create a more realistic analysis of when hospitals will reach capacity.

5.1 Next Steps

The model does not currently support agent interaction or disease spread through agent proximity. For a future agent-based model that does spread disease using something such a βSI transition probability, we will allow agents or hospitals the ability to spread out patients to other available beds (Braithwaite et al. 2013). Currently, all hospital locations treat agents in a similar manner. We have not included the concepts of contact precautions, disease identification, nurse or doctor availability, or access to personal protective equipment. These concepts will be incorporated into our model to increase the variety of analysis available and types of diseases that can be modeled. We would also like to consider the order of events in future models. Currently, all location updates are performed before the hospitalization of agents due to the epidemic. The model has no sense of daily time and does not randomly complete steps. All steps in the model are completed in order of the agents unique ID. We will incorporate more randomness into the model and consider alternative ways to order model steps.

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