Title: Statistical Modelling for ICU Capacity Planning and Simulation of Pandemic Conditions on ICU Capacities based on AmsterdamUMC Database

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Background: Intensive care unit (ICU) beds are a valuable and expensive resource (1). Data science can be used to optimise ICU capacity planning and resource allocation by analyzing historical ICU data and predicting needs (2,3,4). The unavailability of ICU beds was associated with increased mortality during the COVID-19 pandemic (5,6).

Methods: We simulated ICU bed occupancy using SimPy, a Python framework, with data from the University hospital centre Amsterdam database (AmsterdamUMCdb). It included 23106 de-identified ICU patient records from 2003 to 2016.

After analyzing length of stay (LOS) distribution and calculating ICU admission rate (AR) for urgent (eAR) and planned (pAR) admissions using AmsterdamUMCdb data, we simulated maximum ICU bed occupancy (MO) and generated a statistical ensemble of occupancy data by iterating the simulation.

AR followed a log-normal distribution (σ = 0.5, μ = Log(estimated average AR)) for both groups. pAR occurred on weekdays, eAR every day. LOS data from the dataset was used to determine LOS distribution. On each simulation day, eAR and pAR were randomly selected from the log-normal distribution and admissions were assigned based on LOS distribution. The simulation covered one year and provided daily MO.

We simulated a pandemic scenario with a high number of ICU-requiring ARDS patients using the ARDS patient cohort from AmsterdamUMCdb. Their LOS were used for two simulations, both run 1000x. The first simulation was run with constant eAR of 2x, 4x and 8x of the usual eAR. The second one used the AR based on a log-normal distribution with day 21 as the pandemic's peak, when the AR reached approximately 5x the usual total AR, and the pandemic lasted for 90 days.

Results: The simulation was run 10000 times, generating an ensemble of MOs. The average MO was 23 (SD = 4.25). Considering a trimming cut-off at 90% of MO in simulations, the maximum occupancy threshold (MOT) was 28. In individual simulations, crossing MOT occurred up to 2-3 times annually **(Figure 1)**. Aiming at {85%, 95%} occupancy rate (OR), the optimal ICU bed capacity (BC) was {33, 29}.

In the ARDS pandemic simulation with the constant AR, the average MO was 15, 29 and 57 (*SD*= 2.30, 4.37 and 8.31, respectively) for 2x, 4x and 8x normal eAR. Given a trimming cut-off of 90%, MOTs are 19, 35 and 68, making the optimal BC {22; 41; 80}, to achieve OR of 85% respectively. For the varying AR, the average MO was 45 (*SD* = 2.33). Given a trimming cut-off at 90% of MO, the MOT=48. Therefore the optimal BC at 85% OR is 56 (**Figure 2**).

Conclusions: Within its validity range, this model can be used to predict ICU bed needs and plan resources accordingly (staffing, equipment, etc.). The model also predicts ICU requirements during a pandemic when its clinical manifestation resembles a known entity and the AR is known or assumed.

Further research can enhance precision by exploring the correlation between LOS and other dataset features, enabling its use in predictive modelling.

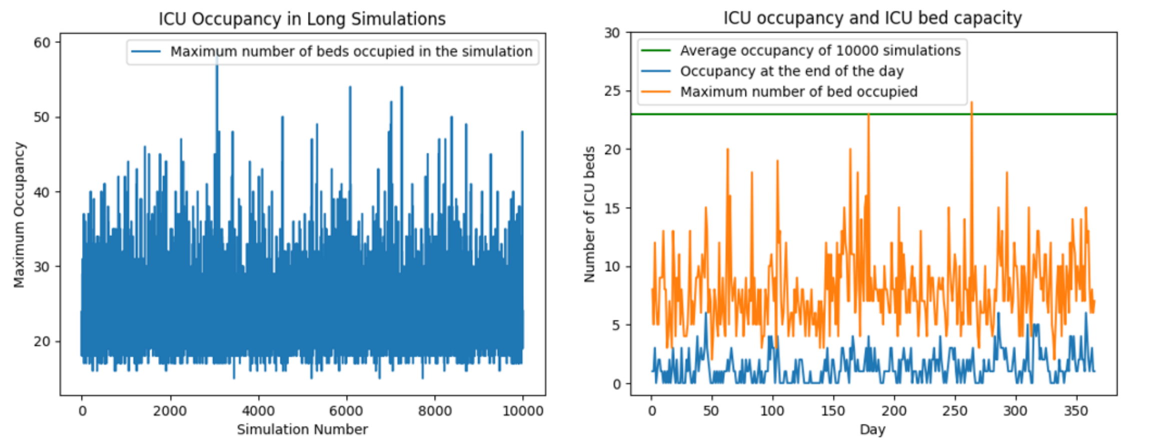

Figure 1: Maximum ICU bed occupancy simulation in 10000 repetitions and a single simulation showing ICU bed occupancy at the end of the day, daily maximum occupancy and where maximum occupancy crosses the threshold of average occupancy in 10000 simulations

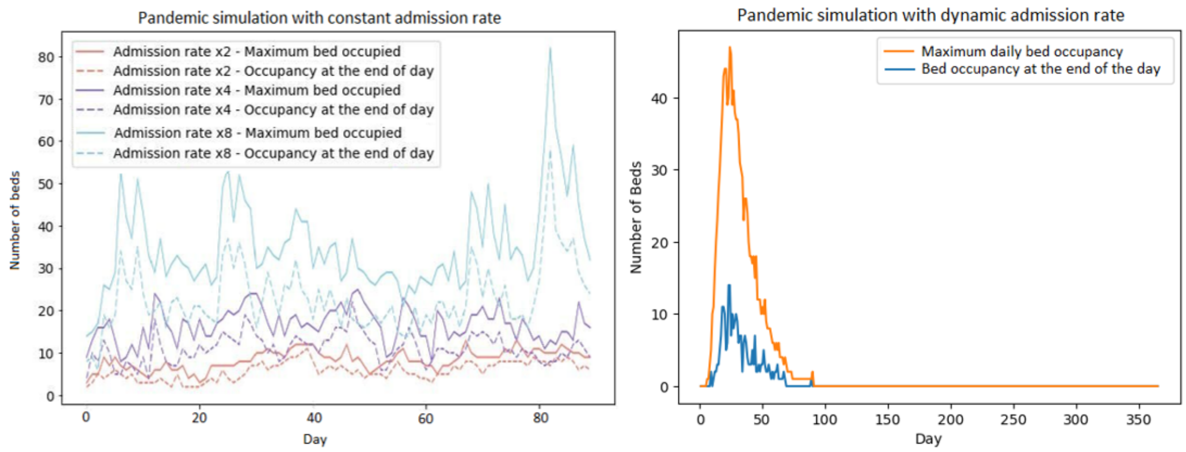

Figure 2: Simulations of ICU bed occupancy at the end of the day and maximal daily ICU bed occupancy in the simulation of a pandemic marked by spike in admission of ARDS patients to the ICU when the admission rates are constant vs. dynamical with peak at day 21

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