Forcasting Hospital Bed Capacity

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Using mic Literature Review

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# Introduction, Topics, and Objectives

## Research Question Definition and Explanation

While hospitals require a certain amount of hospital beds to be kept available for patient use, the Ontario Ministry of Health mandates the number of beds offline at any given time(). This is especially true after situations such as overfilled hospitals, following the third wave of COVID-19. There is a certain amount of hospital beds that are kept online and thus, available, in a unit at a time, each requiring their own allocation of resources to maintain the status of preparedness for a patient to occupy at a moment’s notice. Hospitals may also have a number of beds offline to ensure efficiency of resource usage so that the cost of maintaining unused available beds do not impede on the function of the unit. What this study seeks to find is the optimal number of beds to keep online in Ontario Intensive Care Units (ICU) during the COVID-19 pandemic. The aim is to achieve this by using known methods of machine learning on historical time series data from past studies to predict the days when high volumes of patients requiring critical care emerge.

If occupancy patterns of patients for these hospital beds can be tracked, studied, and understood, predictions can be made more accurately for the most efficient number of beds ready to go online at any time. This will be particularly useful when these predictions can be made in advance to anticipate rush times or downtimes to make best use of hospital resources. In this way, machine learning can be useful. Specific data of past historical occupancy rates for patients with COVID, and data during the different stages of the pandemic, can be used in time series data to try and accurately predict the amount available of beds needed overall. In addition, results of this machine learning can help set a stronger precedent for preparations in cases of future epidemics, natural disasters, and extreme cases of hospital overflow.

### Approach

To begin the approach for finding relevant literature, I begin by searching the Ryerson library database as well as the Ontario Ministry of Health public website. The type of literature that Is being searched for should, firstly, be from a field or industry perspective, looking to provide insight on the infrastructure of hospitals and how they approach capacity management, as well as Covid-19 news and reports which can be used to provide more insights on the applications of the research question. Secondly, academic literature focusing on the applications of predictive data analytics on time series with relevant methodology in the medical field.

For the initial search to understand the field in which the topic is being studied, I consulted Google For newspaper findings and Google Scholar for journal articles. Reports on the state of the disease spread, health care response, risk analysis for variants, and weekly statistical reports from Public Health Ontario, Ontario Health Data Catalogue, the Canadian Institute for Health Information(CIHI) shed light on the historical trends of the pandemic which provided insight on finding useful measures for effective health care action such as infection rates, hospital admission rates, all of which are relevant for discerning the required availability of facilities in hospitals including hospital bed capacity.

Through consulting the advice found on the Ryerson university data science and research guide, I was able to find \_\_ paper on Ebscohost in the specific database search and from the Ryerson library search function I was able to access the Science Direct database for peer reviewed journals. The ScienceDirect database is where G. Peter Zhang’s paper, *Time series forecasting using a hybrid ARIMA and neural network model* was found and will be used to guide the methodology for this project. Further supporting studies focused on the applications of time series models in hospitals and their methodologies were found from the ScienceDirect database and the JAMA Network Open published by the American Medical Association.

# The Literature

#### Industry Background

from the background provided by the 2016 report of care in Canadian hospitals, the overall state of intensive hospital care has been increasing in necessity due to the aging overall population and an increase in illness severity. While this report may be used to draw a general background understanding it was conducted in 2016 during regular non pandemic times. I expect the data during the COVID-19 period would have an upward shift in volume across the board as well as more dramatic increases of ICU occupancy during surges, behaviors such as plateaus, and decreases as vaccines roll out to the population.

Interestingly the Canadian Institute for Health information's report on December 9th, 2021, regarding COVID-19 impact on hospital services reports add that with each wave two and wave 3 hospital impatient admissions were actually lower in comparison to the pre-pandemic period. However, the report also states that Non COVID-related admissions for procedures were delayed and cancelled with the rising numbers of COVID infections. respiratory conditions were found to rise in accordance with infection rate as well as ICU admission and ventilator demand increased.

More recent statistics in the Weekly Epidemiological Summary for COVID-19 in Ontario: Focus on January 30, 2022 to February 5, 2022 indicates an overall decrease in outbreaks. Public Health Ontario does warn, however, that the ICU admission and death rates may be under reported due to detection may not have happened in time before death or infection after follow up completion. Public Health Ontario’s January 31, 2022 report *on Omicron in Ontario: Risk Analysis for Approaching Public Health Measures in Winter 202*2 predicts a peak in Omicron infection around 4 weeks, states that currently infection rates are low but warns that there is massive uncertainty regarding the trajectory of the variant in Ontario specifically highlighting higher risk level during the winter of 2022. It is important to examine the wider context of the pandemic in relation to the ICU hospital occupancy in that there is the implication that the trends found in the anticipated overall state and infection rate of the virus would affect ICU rates; during infection outbreaks the volume of patients is expected to rise and along with it, an increase in ICU //will be necessary.

#### Literature Applications of Time Series Methods in Hospitals

This research question specifically attempts to address patterns in ICU capacity during the pandemic. In some sense, it will help consolidate what hospitals already know and struggle with (in terms of ensuring the correct number of beds available) into relevant data that can be used to make quantitative predictions. It will give insight not only on the rate of patients going in and out of intensive care, but also overall patients’ needs as the coronavirus evolves.

Comparing this proposed methodology with what other practitioners have done in the in the consulted literature for the purpose of this endeavor, the research pertaining to the specific aim of forecasting ICU bed capacity during a pandemic is unavailable at this time. However, several researchers have conducted related studies, Jones et al. in *A Multivariate Time Series Approach to Modeling And Forecasting Demand In The Emergency Department* used the Vector Autoregression (VAR) model to forecast the demands and to analyze the relationship between 8 different resources within the emergency department at three different hospitals. While VAR was shown to be effective in Jones et al.’s study, it would not be as suitable of an approach for this specific research due to the nature of the research question and dataset required. Jones et al. required datasets which had multiple variables for different hospital resources which could be used to study their relationships among the variables as they change over time unlike the dataset for this project which only focuses on one variable changing upon itself throughout time. However, it does illuminate the option and provides insight on the path of using univariate VAR as a forecasting method which could be applied to this research question. Furthermore, the study *Predicting Patient Visits to an Urgent Care Clinic Using Calendar Variables* by Batal et al. uses stepwise linear regression to isolate "significant" variables, using which the authors developed their own prediction equation to forecast patient visits depending on weather conditions. In addition to the multivariate differences in Jones et al., the methods in Batal et al. also cannot be applied in the same way, and because a main focus of the topic is to use machine learning, the specifically developed prediction equation would not apply either. There is no doubt, however, that provided with a different dataset with more recorded details on outside variables such as weather, hospital resources, and/or patient information in addition to ICU occupancy it would be beneficial and worth analyzing through employing the methods used in Jones et al. and Batal et al.’s papers as they have shown how to include and consider the influences of multiple variables in their forecasting methodology.

Two studies examining predictive analytics in hospital care units report similar results in their model usage. *Predicting Patient Volumes in Hospital Medicine: A Comparative Study of Different Time Series Forecasting Methods* by Kim et al., *Time Series Forecasts of Emergency Department Patient Volume, Length of Stay and Acuity* by Tandberg and Qualls, both used ARIMA methods for forecasting.

The two main papers used to guide the project is G.P. Zhang’s *Time series forecasting using a hybrid ARIMA and neural network model* and Khashei and Bijari’s study *An Artificial Neural Network (P, D, Q) Model For Timeseries Forecasting*. In these studies the authors both examine the use of autoregressive integrated moving average (ARIMA) model and the artificial neural networks (ANN) for timeseries forecasting. the study illuminates the strengths in which the ARIMA model has been diploid as well as the strength and circumstances in which ANN have been used and found to be most effective and appropriate. They then combines the two methods in attempt to utilize the advantages in each model to compensate for the other model’s shortcomings. his research and insight on the models state that ARIMA is linear in its prediction of future values and are typically constrained to linear behaviors in past observations. due to the nonlinearity of some datasets, the performance of linear prediction models such as ARIMA may not most effectively capture those nonlinear behaviours in its forecasting. To address the issue of nonlinearity, Zhang suggests the use of ANN. they assert that artificial neural networks R one type of model suitable for “approximating various nonlinearities in the data.” (Zhang, p163).

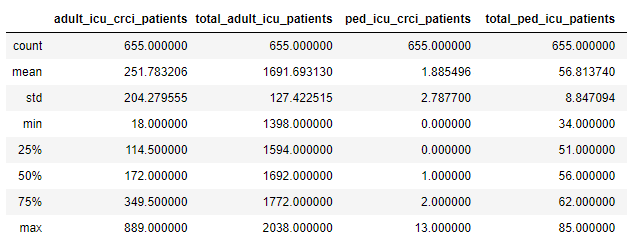
## The Working Dataset

The working dataset is the *Availability of Adult and Pediatric ICU Beds and Occupancy For Covid-Related Critical Illness (CRCI)* from the Ontario Data Catalogue. The variables include the date and eight variables measuring the number of persons, adult or pediatric in the following four categories:

* number of patients in ICU/pediatric ICU for COVID-related critical illness (CRCI)**\*\***
* number of patients in ICU/pediatric ICU for non-CRCI reasons
* number of patients ICU/pediatric ICU beds that are unoccupied
* total number of patients in ICU/pediatric ICU for any reason

A brief examination of the descriptive statistics of the dataset in the attached Jupyter Notebook finds the following: Table

Description automatically generated



While there are four variables to the dataset, the main two categories of focus for pediatric patients and adults are the number of number of patients in ICU/pediatric ICU for CRCI and the total number of patients in ICU/pediatric ICU for any reason. This is because these best represent the quantity of those who require high resources ventilators in CRCI, and those who still need to be in the ICU regardless of infection status.

that there were no zeros in the number of available ICU or pediatric beds at any time during the period, implying that overall across Ontario there the occupancy of ICUs were not exceeded. Despite this, it has been repeatedly reported that hospitals were at maximum occupancy. A possible explanation for this could be that hospitals in more populated locations in Ontario were experiencing shortages while less populated areas had an excess. Including the hospital names or locations in the dataset could have helped combat this constraint and would be more helpful in finding ways to allocate resources throughout the province.

Chart, line chart

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Above graph representing the CRCI adults in the ICU (Blue) and total adults in ICU (Orange)

Chart, line chart

Description automatically generated

Above graph representing the CRCI children in the ICU (Blue) and total children in ICU (Orange)

# Citations

**Data**

<https://data.ontario.ca/dataset/availability-of-adult-icu-beds-and-occupancy-for-covid-related-critical-illness-crci>

Github: https://github.com/Jneny/Hospitalcapacity

**Industry**

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<https://files.ontario.ca/moh-covid-19-weekly-epi-report-en-2022-02-05.pdf>

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