Pablo R. Olmos* and Gisella R. Borzone

Stepwise Markov model: a good method for forecasting mechanical ventilator crisis in COVID-19 pandemic

<https://doi.org/10.1515/em-2020-0021>

Received July 4, 2020; accepted July 26, 2021; published online August 24, 2021

Abstract

Objectives: One important variable influencing day-to-day decisions in COVID-19 pandemic has been an impending shortage of mechanical ventilators due to the large number of people that become infected with the virus due to its high contagiousness. We developed a stepwise Markov model (a) to make a short-term prediction of the number of patients on ventilator, and (b) to determine a possible date for a ventilator crisis.

Methods: Starting with the exponential curve of new cases in the previous 14 days, we calculated a Markov model every 5 days thereafter, resulting in a daily estimate of patients on ventilator for the following 25 days, which we compared with the daily number of devices in use to predict a date for ventilator crisis.

Results: During the modeled period, the observed and predicted Markov curves of patients on ventilator were very similar, a finding confirmed by both linear regression ($r=0.984$; $p<0.0001$) and the near coincidence with the identity line. Our model estimated ventilator shortage in Chile for June 1st, if the number of devices had remained stable. However, the crisis did not occur due to acquisition of new ventilators by the Ministry of Health.

Conclusions: In Chile as in many other countries experiencing several asynchronous local peaks of COVID-19, the stepwise Markov model could become a useful tool for predicting the date of mechanical ventilator crisis. We propose that our model could help health authorities to: (a) establish a better ventilator distribution strategy and (b) be ready to reinstate restrictions only when necessary so as not to paralyze the economy as much.

Keywords: COVID-19; Markov; mathematical; mechanical ventilator; model.

Introduction

Given the high contagiousness of SARS-CoV-2, the most urgent concern of health authorities worldwide during the COVID-19 pandemic has been to reduce the exponential accumulation of new cases (“flattening the curve”) (WHO, February 1st, 2020, 5–6) to prevent an acute shortage of health personnel, supplies and equipment. The COVID-19 pandemic that has severely affected many countries worldwide has taught us that

Bouts of COVID-19 new cases (produced by SARS-CoV-2) occur whenever sanitary measures are relaxed, and in this context, our stepwise Markov model has a good capacity for short-term prediction of mechanical ventilator crisis.

***Corresponding author: Pablo R. Olmos**, MD, Service of Obstetrics & Gynaecology, UCChristus Health Network, Santiago, Chile; and Service of Nutrition, Diabetes and Metabolism, UCChristus Health Network, Santiago, Chile, Phone: +56 222317072, E-mail: polmos@med.puc.cl

Gisella R. Borzone, Service of Respiratory Diseases, UCChristus Health Network, Santiago, Chile, E-mail: gborzone@med.puc.cl

a substantial part of hospitalized patients require mechanical ventilator support to breathe due to severe interstitial pneumonia. While this condition is potentially reversible, ventilator support can be needed for weeks in many patients (Vergano et al. 2020, 1–2), imposing a large demand for intensive care, and thus causing an imbalance between the clinical needs of the population and the availability of intensive care resources, leading to difficult ethical decisions (Vergano et al. 2020, 1–2, Rosenbaum 2020, 1873–4). In this context, most countries have applied social distancing interventions for reducing morbidity, thus delaying the demand for health care resources and aiming to gain time to regain treatment capacity. Among these, quarantine is recognized as the single most important measure to reduce morbidity, and hence the demand for scarce mechanical ventilators (Rainisch, Undurraga and Chowell 2020, 376). Although a lockdown lowers the number of new cases as well as the *R value*, the effective reproduction number (Kupferschmidt 2020, 1–3), it has a negative economic impact (ECLAC. United Nations 2020, 1–3). Thus, until vaccines against SARS-CoV-2 or a specific treatment become widely available, health authorities worldwide find themselves in a fragile equilibrium, forced to choose between ordering quarantines to reduce the number of new cases, and relaxing quarantines thus contributing to accumulation of new cases that increases the demand for mechanical ventilators.

The usual approach for coping with this challenge has been the use of mathematical models based on differential equations (Chen 2014, 19). These models, while giving excellent short and long-term estimates of the number of cases and deaths (Bracher 2021, 1), predict ventilator needs with a time horizon of several months (Mohandas et al., 2020, 9122; Wells et al., 2020, 1123). However, more important than the time horizon is that a large majority of those models initially took for granted a *single peak* of contagions, while the fact is that most countries shortly experienced multiple asynchronous local peaks rather than a single one (Wells et al., 2020, 1125), making these predictions needed earlier, in 3–4 weeks. However, as explained by Vergano et al. (2020, 1–2), at this time in the pandemic, when we still have limited data and multiple assumptions, health authorities must often use tactical strategies, since what that was considered to be true the day before, often must be completely revised the day after because a new piece of information emerges. In this setting, health authorities are in urgent need for a mathematical model capable of predicting the demand for mechanical ventilators with a time horizon that allows them to react promptly.

It has been shown that in most countries, approximately two weeks pass between a slow rise in daily new cases of COVID-19 and the start of a new exponential growth (Worldometer 2020). In Chile, the first case was reported on March 3rd 2020 (MINSAL-Chile 2020a March 3rd), and after flattening of a first wave, by April 20th new cases rose again into what became a second wave of unforeseen proportions that took place in May 2020. In the first week of May, we became interested in the short-term (3–4 weeks) worst-scenario prediction of the need for mechanical ventilators, which could be used at national and regional level, to provide useful information to allocate available ventilators where most needed, as suggested by Wells et al. (2020, 1126).

We carried out a Markov model based on the exponential curve of new cases in the 14 days preceding the model, obtaining a daily estimate of mechanical ventilator use for the following 25 days, and compared results with the daily number of devices being in use to predict an estimated date of mechanical ventilator shortage crisis.

Material and methods

Whereas modeling of infectious diseases has been oriented mostly to study the spread of the disease within a population (MRC Centre for Global Infectious Disease Analysis 2020), there has been less interest on modeling shortage of medical resources. To our knowledge, during the COVID-19 pandemic, two publications have concentrated on estimating the demand for mechanical ventilators. The first one assumed a single-peak of infection at week number 18 after the index case in the USA and resulted in a 33-week projection of mechanical ventilator demand (Wells et al. 2020, 1125). The second publication, in the U.K., also assuming a single peak of infection, mathematically modelled the pandemic for several countries worldwide, resulting in estimated 28-day curves of ventilator demand. Based on a system of differential equations (S.E.I.R.=Susceptible-Exposed-Infectious-Recovered), the investigators used reported mortality to ‘back-calculate’ an inferred number of SARS-CoV-2 infections. Results of this work showed a wide variability. Chile was not included among the countries analyzed in this fashion

(MRC Centre for Global Infectious Disease Analysis 2020). Taking into consideration the characteristics of these two studies, we decided to use a stochastic model instead of a differential equation-based model.

Stochastic models, instead of relying on classic mathematic analysis of continuous variables, examine the probabilistic behavior of categorical variables. Among those methods, we chose the Markov model, that divides a single process into a set of different “states”, where the transition from one state to another is regulated by probabilities, and the future state is independent of the past state (Grimmett and Stirzaker 2001, 213). The most important characteristic of the Markov model is its dependence on the “state” of patients during a specific moment in a series of discrete periods, called “cycles”. Thus, we divided the situation of individuals with regard to the COVID-19 epidemic in seven states (Figure 1), named as follows: A=healthy subjects. B=asymptomatic COVID-19 individuals. C=symptomatic non-hospitalized COVID-19 patients. D=symptomatic hospitalized COVID-19 patients, not connected to mechanical ventilator. E=symptomatic hospitalized COVID-19 patients on mechanical ventilator. F=deceased patients. G=recovered patients. Each one of these states refers to the stage reached by the individuals during their whole evolution (in a sense, the severity of the condition).

We attributed “transition probabilities” (θ), to the changes between these states (Sato and Zouain 2010, 377). As seen in Figure 1, States C, D & E are all “symptomatic patients” and cannot be connected to each other by transition probabilities. This is due to the following: State “C” (not hospitalized) cannot be connected to “D” (hospitalized but not on mechanical ventilator) or to “E” (hospitalized and on mechanical ventilator), because the phrase “not hospitalized” means in fact “never hospitalized due to COVID-19”. In addition, State “C” (not hospitalized) cannot be connected to State “F” (deceased due to COVID-19), since COVID-19 patients who are not hospitalized are assumed to be those with mild disease who do not die because of the condition.

In our Markov model, an important “initial condition”, the actual number of daily new cases of COVID-19, is not constant but grows exponentially. Below, we provide the technique used to deal with this non-constant boundary condition.

Figure 1: Influence diagram of the Markov model. The ovals, named A, B, C, D, E, F and G, are the seven states of the model. Arrows represent the daily transition probabilities (θ) of passing from one state to another. Small, curled arrows with repeated subscript letters represent the daily probability of remaining in the same state. Note that θ_{FF} and θ_{GG} , which are the transition probabilities of remaining in states F and G, are both equal to one, as patients who reach these absorbing states never leave them, because they are either dead or recovered from COVID-19.

Exponential curve fitting of new cases between April 20th and May 4th

We used data of daily new cases of COVID-19 between April 20th and May 4th 2020 to feed our Markov model. These data were adjusted to an exponential function of the type $Y=Y_0 \times e^{(k \times t)}$, where Y =new cases per day, $e=2.718$, k =constant (days^{-1}), and t =time in days. We then extrapolated this curve to the next 25-day period (from May 5th to May 29th), defined by us as the “modeled period”.

Unlike modelling the spread of the virus using differential equation models that yields cumulate cases, cumulate deaths, incident cases and incident deaths, we modeled the use of a scarce medical resource – i.e. mechanical ventilators–by means of a stochastic model that nourishes itself from the actual incident new cases in the previous mobile two weeks. In other words, we can summarize the sequence of events of the COVID-19 pandemic as follows: (i) measures dictated by health authorities to contain the pandemic, which (ii) produce changes in the spread of the virus, and (iii) affect the incidence of new cases and, result in (iv) changes in mechanical ventilator use. Our model, by not dealing with stages “i” or “ii”, uses instead real data published daily by the Chilean Ministry of Health in “iii”, to estimate “iv”.

We subdivided the modelled period into five sub-periods of 5 days each. We then determined the middle time point of each one of these sub-periods, which were used to calculate the “mean daily cases” at days 17 1/2, 22 1/2, 27 1/2, 32 1/2, and 37 1/2 after April 20th. Prior to calculating the Markov model for each sub-period, we used each one of those mean daily cases to calculate the “specific” parameters of the sub-period before applying the transition probabilities (θ) by means of matrix multiplication (see Figure 2 and Table SM-1 in supplementary material).

Figure 2: Flow diagram of the Markov model.

Observed vs estimated by Markov model

We tabulated, analyzed by statistical regression, and incorporated into graphs the Markov-estimated number of patients on mechanical ventilator (Figure 6). This figure also shows three straight lines corresponding to linear regressions of published data on mechanical ventilators, extrapolated from data between April 20th and May 4th: (a) total number of mechanical ventilators, (b) ventilators in use for any reason, and c) unused (“free”) ventilators. The time point at which the Markov-estimated curve crossed the “ventilators in use” regression line, was determined as the worst-scenario date for a shortage crisis of ventilators. That worst-scenario date was then compared to the actual date at which crisis occurred (or not) according to the Chilean Ministry of Health’s data.

Results

The statistical regression of new COVID-19 cases diagnosed between April 20th and May 4th resulted in the best-fit exponential function as follows:

$$Y(t) = 315.16 \times e^{0.085t} \quad (1)$$

where: t =time in days, $k=0.085 \text{ days}^{-1}$, $r=0.878$, and $p<0.0001$ (Table SM1 in supplementary material).

The function given by Eq. (1) was extrapolated from May 5th to May 29th, and was subdivided into five 5-day sub-periods. Within this 25-day period, *mean daily cases* at days 17 1/2, 22 1/2, 27 1/2, 32 1/2, and 37 1/2 (counted after April 20th) were calculated from Eq. (1), the results being, respectively, 1,396.8, 2,136.6, 3,268.1, 4,998.9, and 7,646.2 new daily cases. These five *mean daily cases* were loaded into five Markov models (one for each 5-day sub-periods) which yielded five estimates of the number of patients on mechanical ventilator. Figure 3a shows these and the best-fit exponential regression of Markov-estimated patients on mechanical ventilator between May 5th and May 29th as follows:

$$Y(t) = 123.9 \times e^{0.054t} \quad (2)$$

where: t =time in days, $k=0.054 \text{ days}^{-1}$, $r=0.977$; $p<0.0001$.

Figure 3: Chilean COVID-19 patients on mechanical ventilator. Prediction by Markov model and comparison with data observed in the period May 5th–29th.

(A) Open triangles (V) are the best-fit exponential regression of Markov-estimated patients on mechanical ventilator in the period between May 5th and May 29th ($r=0.977$; $p<0.0001$; $Y(\text{days})=123.9 \times e^{0.054 \times \text{days}}$). (B) Closed circles (•) are observed patients on mechanical ventilator between May 5th and May 29th, with the best-fit regression (continuous line) being an exponential line ($r=0.990$; $p<0.0001$; $Y(\text{days})=164.1 \times e^{0.048 \times \text{days}}$). The segmented line represents the best-fit exponential regression of Markov-estimated patients on mechanical ventilator between May 5th and May 29th. Note that observed and exponential curves are nearly coincident. (C) Linear regression between patients on mechanical ventilator from two sources: X-axis, from observed data ($r=0.984$; $p<0.0001$), and Y-axis from Markov model. Note that the line of regression and the line of identity are nearly coincident.

Figure 3b shows both the Markov curve and the curve of observed number of patients on mechanical ventilator between May 5th and May 29th, with the best-fit regression (continuous line) being an exponential line ($Y(\text{days}) = 164.1 \times e^{0.048 \times \text{days}}$; $r = 0.990$; $p < 0.0001$). The observed and Markov curves are nearly coincident, a finding that is confirmed in Figure 3c, where the linear regression between patients on mechanical ventilator from observed data, and from the Markov model ($r = 0.984$; $p < 0.0001$) shows near coincidence with the identity line.

For comparison purposes, we also calculated the expected number of patients on mechanical ventilator by the usual approach, which is the simple extrapolation of the regression curve of observed patients on mechanical ventilator. Figure 4a shows the observed number of patients on mechanical ventilator between April 20th and May 4th, with the best-fit regression being a quadratic line ($r = 0.832$; $p = 0.001$; $Y(\text{days}) = 382.9 - (17.0 \times \text{days}) + (1.164 \times \text{days}^2)$). The exponential regression of the same data did not reach statistical significance ($r = 0.277$; $p = 0.317$). Figure 4b shows both the quadratic regression curve and the observed number of patients on mechanical ventilator between May 5th and May 29th, with the best-fit regression being an exponential line ($Y(\text{days}) = 164.1 \times e^{0.048 \times \text{days}}$; $r = 0.990$; $p < 0.0001$). The observed and quadratic regression curves are highly divergent, a finding that is confirmed by Figure 4c, where the linear regression between patients on mechanical ventilator from observed data, and from quadratic regression ($r = 0.990$; $p < 0.0001$) shows a progressive difference with the identity line.

Figure 5 shows the prediction of mechanical ventilator crisis during SARS-CoV-2 epidemic in Chile. On day 44 after April 20th (June 1st 2020), the Markov curve of COVID-19 patients on ventilator crossed, at 1,333 patients, the line of mechanical ventilators in use for any reason in Chile. From that time onwards, patients with COVID-19 and non-COVID medical conditions would be competing for any available mechanical ventilator. This being our definition of potential “mechanical ventilator crisis”, our next step was to compare the situation depicted in Figure 5, with the observed status of mechanical ventilators in Chile that actually took place in the whole period between April 20th and May 29th. Figure 6 shows that, notwithstanding the decreasing number of unused mechanical ventilators, the Markov-estimated curve never crossed the “occupied” curve. Therefore, no ventilator crisis occurred. As shown by stepping of the “total mechanical ventilators” line of Figure 6, the Chilean Ministry of Health averted the crisis by a series of purchases of new ventilators, carried out during May 2020.

Figure 4: Chilean COVID-19 patients on mechanical ventilator. Prediction by extrapolation of statistical regression and comparison with data observed in May 5th–29th.

(A) Open circles (•) are observed patients on mechanical ventilator between April 20th and May 4th, with the best-fit regression being a quadratic line ($r = 0.832$; $p = 0.001$; $Y(\text{days}) = 382.9 - (17.0 \times \text{days}) + (1.164 \times \text{days}^2)$). (B) The upper dotted line is the extrapolated quadratic regression of patients on mechanical ventilator between April 20th and May 4th. Closed circles (•) are observed patients on mechanical ventilator between May 5th and May 29th, with the best-fit regression (continuous line) being an exponential line ($r = 0.990$; $p < 0.0001$; $Y(\text{days}) = 164.1 \times e^{0.048 \times \text{days}}$). (C) Linear regression between patients on mechanical ventilator according to two sources: X-axis, from observed data ($r = 0.990$; $p < 0.0001$), and Y-axis from extrapolation of the quadratic regression shown. Note that the linear regression line and the identity line are highly divergent.

Figure 5: Prediction of mechanical ventilator crisis during COVID-19 epidemic in Chile. The three straight lines are linear regressions of published data on mechanical ventilators, extrapolated from data between April 20th and May 4th: The little-dot line represents total mechanical ventilators ($r=0.924$; $p<0.0001$). The small-segment line represents mechanical ventilators in use for any reason ($r=0.770$; $p=0.01$). The long-segment line represents unused (“free”) mechanical ventilators ($r=0.942$; $p<0.0001$). The continuous curve represents the best-fit exponential regression of Markov-estimated patients on mechanical ventilator between May 5th and May 29th ($r=0.990$, $p<0.0001$). Note that this curve crosses “in use” curve by June 1st (day 44 of the modelled period), a date when the 1333 COVID-19 patients on ventilator would coincide with the total occupancy of mechanical ventilators for any reason in Chile. This situation did not occur due to an increment in the total number of ventilators (see Figure 6).

Figure 6: Real situation of mechanical ventilators in Chile between April 20th and May 29th, 2020, compared to Markov-estimated patients on mechanical ventilator between May 5th and May 29th. Black dots (•) and the dotted straight line ($r=0.955$; $p<0.0001$) represent total mechanical ventilators (occupied or not). Open dots (o) and the short-segment straight line ($r=0.936$; $p<0.0001$) represent mechanical ventilators in use for any reason. Closed diamonds (◆) and long-segment straight line ($r=0.740$; $p<0.0001$) represent unused (“free”) mechanical ventilators. The thick continuous curve represents the best-fit exponential regression of Markov-estimated patients on mechanical ventilator between May 5th and May 29th ($r=0.990$, $p<0.0001$). Note that, notwithstanding the decreasing number of unused ventilators, the Markov-estimated curve never crossed the “occupancy” curve, due to a series of purchases of new ventilators made by the Chilean Ministry of Health (see the stepped succession of black dots).

Cross-validation of the model

We carried out a cross-validation of the model by means of applying it to a non-Chilean data set. We searched the Internet for numerical data on this epidemic affecting countries other than Chile. We found that Canada

has enough information available in Internet. In the “Canada Model” of the datasheet, we re-calculated some parameters according to the published information (Table SM1 in supplementary material).

In Figure 7, September 16th – October 10th curves of observed and Markov-estimated Canadian patients on mechanical ventilator showed near-coincidence. In Figure 8, on the other hand, the extrapolated September 1st and 15th curve of observed patients on mechanical ventilator, was very different from the observed patients on mechanical ventilator between September 16th and October 10th.

Figure 7: Canadian COVID-19 patients on mechanical ventilator. Prediction by Markov model and comparison with data observed in the period September 16th – October 10th.

(A) Open triangles (V) are the best-fit exponential regression of Markov-estimated patients on mechanical ventilator in the period between September 16th–October 10th. ($r=0.997$; $p=0.0001$; $Y(\text{days})=33.3 \times e^{0.039 \times \text{days}}$). (B) Closed circles (•) are observed patients on mechanical ventilator between September 16th–October 10th, with the best-fit regression (continuous line) being an exponential line ($r=0.991$; $p=0.0001$; $Y(\text{days})=32.1 \times e^{0.038 \times \text{days}}$). The segmented line represents the best-fit exponential regression of Markov-estimated patients on mechanical ventilator. Note that observed and Markov curves are nearly coincident. (C) Linear regression between patients on mechanical ventilator from two sources: X-axis, from observed data ($r=0.985$; $p=0.0001$), and Y-axis from Markov model. Note that the line of regression and the line of identity are nearly coincident.

Figure 8: Canadian COVID-19 patients on mechanical ventilator. Prediction by extrapolation of statistical regression and comparison with data observed in the period September 1st–15th 2020.

(A) Open circles (o) are observed patients on mechanical ventilator between September 1st and 15th, with the best-fit regression being an exponential line ($r=0.970$; $p<0.001$; $Y(\text{days})=20.5 \times e^{0.075 \times \text{days}}$). (B) The upper dotted line is the extrapolated exponential regression of patients on mechanical ventilator between September 1st and September 15th 2020. Closed circles (•) are observed patients on mechanical ventilator between September 16th and October 10th 2020, with the best-fit regression (continuous line) being an exponential line ($r=0.991$; $p<0.0001$; $Y(\text{days})=32.1 \times e^{0.038 \times \text{days}}$). (C) Linear regression between patients on mechanical ventilator (September 16th–October 10th) according to two sources: X-axis, from observed data, and Y-axis from extrapolation of the exponential regression shown in “a” ($r=0.990$; $p<0.0001$). Note that the linear regression line and the identity line are highly divergent (compare to Figure 7c).

Discussion

Based on 14-day retrospective data, and using a staggered Markov model, we predicted the number of COVID-19 patients on mechanical ventilation for the following 25 days in Chile, and the figures obtained in this fashion fitted observed data in a more exact fashion than those provided by the extrapolation of statistical regression of data alone.

Our Markov model estimated a mechanical ventilator crisis in Chile for June 1st, 2020, a date when the predicted 1,333 COVID-19 patients connected to a mechanical ventilator would coincide with the total number of mechanical ventilators being in use at that time in Chile.

By comparing this prediction with the actual number of patients on mechanical ventilation, we found that the Markov-estimated curve never crossed the “*ventilators in use*” curve, thanks to a series of purchases of new ventilators made by the Chilean Ministry of Health, which amounted to 760 new devices between May 5th and May 29th (MINSAL-Chile 2020b).

Early during the pandemic, Xie et al. (2020) coined the term *Critical Care Crisis*, based on their experience with COVID-19 in China. The crisis considered shortage of ICU beds, trained personnel, personal protective equipment, and supplemental oxygen. These authors realized that whereas most of these elements could be transferred from one region to another, the lack of mechanical ventilators remained a problem more difficult to solve. Their data showed that among patients who died, 75% did so because of the lack of these devices.

The original motivation for our work was inspired by the World Health Organization’s worldwide call to reduce the exponential accumulation of new COVID-19 cases (WHO 2020) and thus prevent an acute shortage of health supplies, personnel and equipment. Convinced that it was possible to contribute to prevent shortage of mechanical ventilators by mathematical modeling of future demand for these devices we used 14-day retrospective data to construct a staggered Markov model to predict the number of COVID-19 patients on mechanical ventilation for the following 25 days in Chile. The main characteristic of our work is the development of a model that provides predictions of ventilator occupancy within a short-middle time horizon (25 days), compared with other available models that can only predict with much longer time horizons (33–53 weeks) (Mohandas et al. 2020; Wells et al. 2020). Thus, our Markov model added short-middle-term information to data provided by other mathematical models developed during the COVID-19 pandemic.

In Chile and in other countries, the population has been experiencing several asynchronous local peaks of COVID-19, where the stepwise Markov model described here could become a useful tool for predicting the date of mechanical ventilator crisis. We propose that our model could allow for a better ventilator distribution strategy, taking into consideration that it could be applied not only at a national, but also at state, county or provincial levels. Thus, multiple local Markov models in each country, recalculated as frequently as needed, would allow central governments to decide where the need for mechanical ventilators is more urgent, thus having enough time to transfer the available resources from one region to another.

However, preventing a shortage of mechanical ventilators is not all, as in Chile and around the world restrictive measures have been successful in reducing the rate of new cases, but when these measures are relaxed, new cases increase again. Therefore, health authorities have to reduce the restrictive measures in a stepwise fashion, watching closely the figures of daily new cases and ventilator use, while being ready to reinstate the restrictions only in the areas where they are necessary so as not to paralyze the economy as much. For them to succeed in this fragile equilibrium, the Markov model could add some useful information.

Weaknesses and strengths

It could be argued that the Markov model would only work if the spread of the virus during the precedent two weeks was undisturbed by changes in public health measures. However, it is also true that this “weakness” could also be regarded as a strength because the model can be responsive to short term changes in those measures, since the Markov model nourishes itself from a “mobile fortnight”, i.e., the incidence of new cases in the precedent 14 days. This incidence, analyzed by exponential regression provides by extrapolation, the

expected incidences for the following 25 days. We feel that our Markov model has two strengths that can compensate its potential weakness: first, it can be re-calculated every day, using both the “mobile fortnight” and the same 25-day “modeled period”. Second, the Markov model can be re-calculated daily, but with a shorter “modeled period”, say of 15 days or three sub-periods of five days each. In this sense, Markov modelling may provide theoretical verification of the effectiveness of changing measures.

Another strength of the model resides in the fact that we cross validated it with a different dataset, obtained from published data of Canadian COVID-19 epidemic.

In the COVID-19 pandemic, the evidence produced by mathematical models has been critical in shaping rapid policy responses in infection control (Rhodes and Lancaster 2020). We propose a mathematical model dealing with a different but complementary aspect of the pandemia, whose results although not related directly with infection spread, can constitute a tool of anticipatory governance.

Other areas affecting management of patients with COVID-19 can be studied using Markov modelling techniques in order to contribute to policy decision making. For instance, shortage of other medical resources such as oxygen, pharmaceutical products and personal protective equipment can also be modelled in this way.

It is important to keep investigating and improving our Markov model to fit other variables that have potential impact on the results.

Acknowledgments: The authors are grateful to Mrs Carolina Torres for her excellent secretarial assistance

Research funding: None declared.

Author contribution: All authors have accepted responsibility for the entire content of this manuscript and approved its submission.

Competing interests: Authors state no conflict of interest.

Informed consent: Not applicable

Ethical approval: Not applicable

Appendix

(See Table SM-1 in Supplementary Material: spreadsheet for the calculation of the Markov series of the five sub-periods in both Chile and Canada).

References

- Bracher, J. 2021. *German & Polish COVID-19 ForecastHub*. Also available at <https://kitmetricslab.github.io/forecasthub/forecast> (consulted March 1, 2021).
- Chen, D. 2014. “Modeling the Spread of Infectious Diseases: A Review.” In *Analyzing and Modeling Spatial and Temporal Dynamics of Infectious Diseases*, edited by D. Chen, B. Moulin, and J. Wu, 19–42. New York: Wiley Series in Probability and Statistics, John Wiley & Sons Inc.
- ECLAC. United Nations. 2020. “Latin America and the Caribbean and the COVID-19 Pandemic Economic and Social Effects.” In *Special Report COVID-19. N° 1*. Also available at https://repositorio.cepal.org/bitstream/handle/11362/45351/1/S2000263_en.pdf (accessed May 30, 2020).
- Grimmett, G. M., and D. R. Stirzaker. 2001. “Chapter 6. “Markov Chains”.” In *Probability and Random Processes*, edited by G. M. Grimmett, and D. R. Stirzaker, 213–304. Oxford: Oxford University Press.
- Kupferschmidt, K. 2020. “Ending Coronavirus Lockdowns Will Be a Dangerous Process of Trial and Error.” *Science*, 1–3 (posted in: Health, Coronavirus. April 14th, 2020). Also available at [Sciencemag.org/news/2020/04/ending-coronavirus-lockdowns-will-be-dangerous-process-trial-and-error](https://www.sciencemag.org/news/2020/04/ending-coronavirus-lockdowns-will-be-dangerous-process-trial-and-error) (accessed April 30, 2020).
- MINSAL-Chile. 2020a. *First Case of Coronavirus Confirmed in Chile*. Chile: Ministry of Health. Also available at <https://www.minsal.cl/ministerio-de-salud-confirma-primer-caso-de-coronavirus-en-chile/> (posted March 3rd, 2020 accessed May 30, 2020).
- MINSAL-Chile. 2020b. “Coronavirus Action Plan.” In *Coronavirus Daily Report*. Chile: Ministry of Health. Also available at https://cdn.digital.gob.cl/public_files/Campa%C3%B1as/Corona-Virus/Reportes/10.04.2020_Reporte_Covid19.pdf (accessed May 29, 2020).

- Mohandas, S. M., A. Shoukat, M. C. Fitzpatrick, C. R. Wells, P. Sah, A. Pandey, J. D. Sachs, Z. Wang, L. A. Meyers, B. H. Singer, and A. P. Galvani. 2020. "Projecting Hospital Utilization during the COVID-19 Outbreaks in the United States." *Proceedings of the National Academy of Sciences* 117 (16): 9122–6.
- MRC Centre for Global Infectious Disease Analysis. 2020. *Forecasting the Healthcare Burden of COVID-19 in LMICs*. Imperial College London. Also available at <https://mrc-ide.github.io/global-lmic-reports/> (accessed May 30, 2020).
- Rainisch, G., E. A. Undurraga, and G. Chowell. 2020. "A Dynamic Modeling Tool for Estimating Healthcare Demand from the COVID19 Epidemic and Evaluating Population-wide Interventions." *International Journal of Infectious Diseases* 96: 376–83.
- Rhodes, T., and K. Lancaster. 2020. "Mathematical Models as Public Troubles in COVID-19 Infection Control: Following the Numbers." *Health Sociology Review*, 1–18. <https://doi.org/10.1080/14461242.2020.1764376>.
- Rosenbaum, L. 2020. "Facing Covid-19 in Italy — Ethics, Logistics, and Therapeutics on the Epidemic's Front Line." *New England Journal of Medicine* 382: 1873–5.
- Sato, R. C., and M. D. Zouain. 2010. "Markov Models in Health Care." *Einstein (São Paulo)* 8 (3): 376–9.
- Vergano, M., B. Guido, A. Giannini, G. R. Gristina, S. Livigni, G. Mistraletti, L. Riccioni, and F. Petrini. 2020. "Clinical Ethics Recommendations for the Allocation of Intensive Care Treatments, in Exceptional, Resource-Limited Circumstances: The Italian Perspective during the COVID-19 Epidemic." *Critical Care* 24 (165): 1–3.
- Wells, C. R., M. C. Fitzpatrick, P. Sah, A. Shoukat, A. Pandey, M. Abdulrahman El-Sayed, B. H. Singer, S. M. Moghadas, and A. P. Galvani. 2020. "Letter: "Projecting the Demand for Ventilators at the Peak of the COVID-19 Outbreak in the USA"." *The Lancet Infectious Diseases* 20 (10): 1123–5.
- World Health Organization. 2020. Novel Coronavirus (2019-nCoV) Situation Report-12. February 1st. Also available at https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200201-sitrep-12-ncov.pdf?sfvrsn=273c5d35_2 (accessed May 30, 2020).
- Worldometer. 2020. "Daily Cases Excluding Mainland China." In *Covid-19 Coronavirus Cases*. Also available at <https://www.worldometers.info/coronavirus/coronavirus-cases/#daily-cases> (posted April 28 accessed May 30, 2020).
- Xie, J., Z. Tong, X. Guan, B. Du, H. Qiu, and A. S. Slutsky. 2020. "Critical Care Crisis and Some Recommendations during the COVID-19 Epidemic in China." *Intensive Care Medicine* Mar 2: 1–4.

Supplementary Material: The online version of this article offers supplementary material (<https://doi.org/10.1515/em-2020-0021>).