

Covid-19 – A simple statistical model for predicting ICU load in exponential phases of the disease

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Abstract

One major bottleneck in the ongoing Covid-19 pandemic is the limited number of critical care beds. Due to the dynamic development of infections and the time lag between when patients are infected and when a proportion of them enters an intensive care unit (ICU), the need for future intensive care can easily be underestimated. To derive future ICU load from reported infections, we suggest a simple statistical model that (1) accounts for time lags and (2) allows for making predictions depending on different future growth rates. We evaluate our model for public data from Berlin, Germany, by first estimating the model parameters (i.e., time lag and average stay in ICU) for March 2020 and then using an exponential model to predict the future ICU load for April and May 2020. Assuming an ICU rate of 5%, a time lag of 5 days and an average stay of 14 days in ICU provide the best fit of the data and is in accord with independent estimates. Our model is then used to predict future ICU load assuming a continued exponential phase with varying growth rates (0–15%). For example, based on our parameters the model predicts that the number of ICU patients at the end of May would be 246 if the exponential growth were to continue at a rate of 3%, 1,056 if the growth rate were 5% and 3,758 if the growth rate were 7%. The model can be adjusted as estimates of parameters develop and can thus also help to predict a potential exceedance of ICU capacity. Although our predictions are based on a small data set, disregard non-stationary dynamics, and have a number of assumptions, especially an exponential development of cases, our model is simple, robust, adaptable and can be up-dated when further data become available.

Keywords: Coronavirus, pandemic, growth rate, forecast model, intensive care, Berlin, Germany

1 Introduction

The number of reported Covid-19 cases worldwide is steadily increasing and has reached 857,500 on March 31, 2020.¹ On March 26, 2020, the U.S. became the country with the largest number of officially reported infections (83.800 people). This number more than doubled to 188,200 people on

March 31, 2020, which corresponds to a daily growth rate of 17.56% in this period. Even though these numbers strongly depend on the number of conducted tests, they demonstrate the huge spread and severity of this pandemic.

It lies in the nature of exponential growth that it starts slowly and bears the risk that the future development is underestimated, as shown in multiple

¹ The numbers of daily infections are reported by the Corona Resource Center of the John Hopkins University: <https://coronavirus.jhu.edu/map.html>

psychological studies (Wagenaar and Sagaria, 1975). In the Covid-19-pandemic, this leads to the risk of underestimating case fatality rates (Baud et al. 2020; Lipsitch 2020) but also the risk that the health system might be overburdened due to a too high number of patients in intensive care units (ICUs; Grasselli et al. 2020). Although it is well-known that a certain number of Covid-19 patients needs intensive care, especially elderly people and people with pre-existing conditions (Verity et al. 2020), the exponential dynamics of infections along with the time lag between the number of reported infections and the number of ICU patients can lead to the false impression that the amount of ICU patients will be unproblematic (Baud et al. 2020; Ferriss 2020). Due to the lag and ICU durations of one to several weeks, even when the exponential growth of infections is stopped, it takes a while until the pressure on ICUs is reduced (Bhatraju et al. 2020; Clukey and Berthelsen 2020; Manca 2020).

In this early phase of the Covid-19 pandemic, in which epidemiological data is non-stationary, heterogeneous and regionally specific, the prediction of future ICU load (as well as mortality) is a highly challenging task (Deasy et al. 2020; Ferguson et al. 2020). In addition to certain assumptions (e.g., ICU rate or length of ICU stay) that have to be estimated from data or pre-specified, the dynamics of exponential growth are unforeseeable in times where containment measures ranging from closure of schools to home office or curfew have been applied to alleviate exponential growth (Ferguson et al. 2020). In most forecast models, however, the exponential growth is assumed to continue with the same rate over the prediction horizon (mostly 14 days) and is fitted either to the daily incidence of Covid-19 patients or ICU patients (Daisy et al. 2020; Grasselli et al. 2020; Remuzzi and Remuzzi 2020).

In this study, we suggest a simple and transparent statistical model that is able to account for (1) the time lag between reported infection and ICU admission and (2) different future growth rates. This allows us in particular to predict the time point when the ICU load exceeds a given capacity. We addressed the following research questions: Can the future number of ICU patients be predicted from the number of reported infections? And how does the growth rate influence the time when ICU capacity is expected to be overburdened?

In our empirical example, we apply the model to public data available for Berlin, Germany. Given the total number of Covid-19 patients and the number of Covid-19 patients on ICUs in March 2020, we first evaluate the performance of models with different time lags between the positive testing and the ICU admission and determine the best fitting time lag; and second, we predict for a time horizon of two

months (April and May 2020) the number of Covid-19 patients who need intensive care when assuming different future exponential growth rates of the number of reported infections. By incorporating the dependency between the total number of Covid-19 patients and Covid-19 patients on ICUs as well as holding growth rates flexible, our model extends previous models relying on fitting linear or exponential growth to initial ICU case data (Grasselli et al. 2020; Remuzzi and Remuzzi 2020). The predictions of our model in combination with additional epidemiological assumptions regarding disease dynamics can be used in turn to predict future ICU load and to potentially predict when the ICU load will exceed a given capacity.

2 Method

In this section, we introduce the theoretical model for predicting the number of ICU patients based on the number of reported infections. Denote PT_t the total number of positively tested people until day t in a particular region. $\Delta PT_t = PT_t - PT_{t-1}$ is then the number of newly positively tested people only on day t . A certain share α_l of the newly positively tested people needs intensive care l days later with lag $l, l = 1, \dots, L$, and some maximum lag L denoting the maximal duration between a positive test and ICU admission. Moreover, patients remain in intensive care for a longer time, which means that ICU admissions of the previous days also have to be considered. In early stages of a disease the exact distribution of the lengths of ICU stays might not be available and for simplification, the duration can be modelled as constant for all patients. We denote K the average number of days patients remain in an ICU.

The number of ICU patients at time t can then be predicted in dependence of K and a vector α_l with $l = 1, \dots, L$, which contains the probabilities that positively tested persons have transitioned to ICU after l days, in the following way:

$$\hat{IC}_t(K, \alpha_l) = \sum_{k=1}^K \sum_{l=1}^L \alpha_l \Delta PT_{t-l-k+1} \quad (1)$$

In case only the overall share of reported infected people needing intensive care without differentiating between the lags, the so-called ICU rate α with $\alpha = \sum_{l=1}^L \alpha_l$, is available, this can be used in combination with a specific average lag l^* . Eq. (1) then becomes:

$$\hat{IC}_t(K, \alpha, l^*) = \sum_{k=1}^K \alpha \Delta PT_{t-l^*-k+1} \quad (2)$$

Since Eq. (2) corresponds to the data situation in our empirical application, the subsequent considerations

will be based on this equation. They can, however, analogously be applied to Eq. (1).

To evaluate the performance of the models and to derive the lag length l^* that best explains the data (given a certain ICU rate α), the squared correlation coefficient and the root mean squared prediction error (RMSE) for each mode can be calculated by comparing the predicted value $\hat{IC}_t(K, \alpha, l^*)$ to the observed value IC_t . The RMSE is defined as

$$RMSE(K, \alpha, l^*) = \sqrt{\sum_{t=1}^T (IC_t - \hat{IC}_t(K, \alpha, l^*))^2} \quad (3)$$

with T denoting the number of days with observations available. The model with the lowest RMSE and highest squared correlation coefficient is supposed to fit best to the observed data.

After the parameters K, a , and l^* are estimated (based on prior knowledge or data), they can be used to predict the future development by assuming exponential growth with rate r for the number of infections, i.e., $PT_{t+1} = (1 + r) PT_t$, which also holds for the daily changes, $\Delta PT_{t+1} = (1 + r) \Delta PT_t$. The predicted number of ICU patients can then be compared with different levels of ICU capacities. Moreover, dates when a given capacity is expected to be exceeded can be calculated.

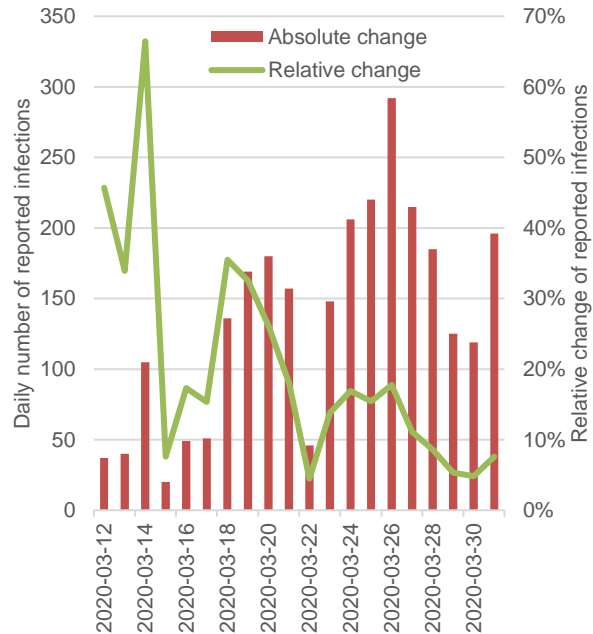
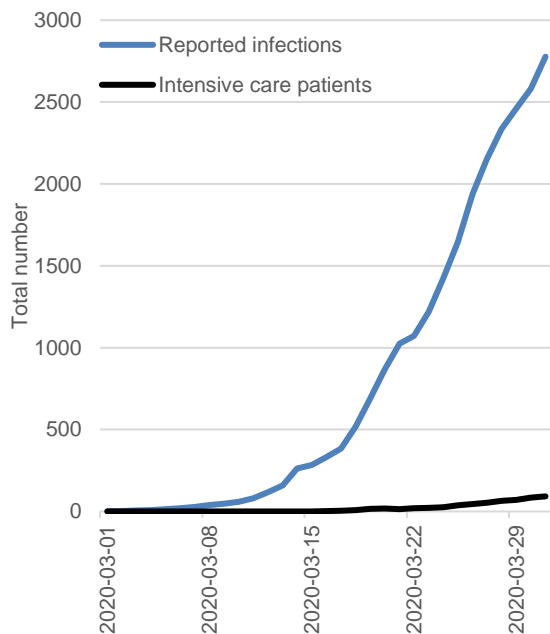


Figure 1: Number of reported infections and intensive care patients (left) and absolute and relative change of the number of infections (right, since 100 patients) in Berlin in March 2020 (based on data from the *Berliner Senatsverwaltung für Gesundheit, Pflege und Gleichstellung*³)

² <https://www.berlin.de/sen/gpqq/service/presse/2020/>

3 Empirical Application

We now apply the theoretical model from Section 2 to data available for Berlin, Germany, and determine the parameters K, α , and l^* . Please note that the model is sensitive to the assumed or estimated parameters and the underlying data. Since we are in a dynamic and non-stationary situation where the data and the development can change on a daily basis, we also demonstrate the sensitivity of the development regarding future growth rates.

3.1 Data

Data were obtained from the *Berliner Senatsverwaltung für Gesundheit, Pflege und Gleichstellung*.² For each day in March 2020, we retrieved the number of reported Covid-19 patients and the number of Covid-19 patients in ICUs for Berlin (Figure 1, left). The total number of Covid-19 infections increased from one on March 1, 2020, to 2,777 on March 31, 2020. The first patients in intensive care (three) were reported on March 16, 2020, and this number increased to 92 until the end of March. Figure 1 (right) depicts the daily change in the number of reported infections in absolute and relative terms since the first day more than 100 cases were reported (March 12, 2020, 118 cases). The overall daily growth rate for this period is 17% ($\sqrt[20]{2777/118} = 1.17$), but it decreased to 10.00% in the last week of March ($\sqrt[7]{2777/1425} = 1.10$) and seems to further decrease in early April. The

depicted daily numbers have to be handled with care since new cases on weekends are partly reported with delay.

The deployment of ICU beds is currently a highly dynamic process. According to the health senator of Berlin, Dilek Kalayci, the number of ICU beds in Berlin is currently 1,045 (Schröter 2020).³ This number is planned to increase to 2,267 until the end of April 2020 (Schröter 2020; SenGPG2020). Based on this, we defined the following capacity limits for our analysis:

- current maximal capacity (1,045 ICU beds)
- extended capacity by the end of April (2,267 ICU beds)

3.2 Assumptions

To perform the analysis, several assumptions are necessary. First, the ICU rate α has to be either estimated from the data or pre-specified. For Germany, this number was not available to us (SMC 2020). For other European countries, however, it has been reported to be between 0.4% (Austria) and 11% (France) with a median of 5% (SMC 2020). Wu and McGoocan (2020) also report an ICU rate of 5% based on data for 72,312 cases in China. Since 5% is also in line with the expectations of intensive care physicians in Berlin (Bach et al. 2020), we take $\alpha = 5\%$ as a reasonable value for Berlin. However, please note that the ICU rate depends on age and the total number of tests because more testing will lead to a higher number of mild cases and thus a lower ICU rate (Ferguson et al. 2020). Second, the average time lag l^* between a newly reported infection and ICU admission can vary largely. People with no or mild symptoms can be positively tested and might require intensive care ten days later. On the other hand, in certain cases the test will only be conducted when the patient arrives at the ICU. In our application, we will show how the reported data for Berlin in March 2020 can be used to estimate the best fitting average time lag l^* . And third, for the average time patients remain in intensive care (until recovery or death), we tested $K = 7$, $K = 10$, and $K = 14$ days based on reported ICU durations between 8 and 14 days (Bhatraju et al. 2020; Clukey and Berthelsen 2020; Manca 2020). Other forecast models assumed an average stay of 8 to 10 days (Deasy et al. 2020; Ferguson et al. 2020).

3.3 Results

First, the performance of the model is evaluated using the Berlin data for March 2020. Based on the

assumption that the ICU rate is $\alpha = 5\%$, the average time lag between a positive test for Covid-19 and ICU admission is estimated by comparing models with lags ranging from 1 to 10 days. Figure 2 depicts the observed number of ICU patients and the predicted number according to the different models for $K = 14$. It can be seen that the model with a time lag of 5 days seems to fit the observed data best. In Table 1, we depict the squared correlation coefficient and the RMSE for the ten models. In accordance with the visual impression from Figure 2, the best fit was found for the model with lag 5 (RMSE 3.26, $\rho^2 = 0.99$). A variation of K ($K = 7$ and $K = 10$ days) neither led to a higher squared correlation coefficient nor to a lower RMSE.⁴

Second, based on the model with estimated time lag of 5, we now predict the future development of the number of ICU patients. Since this number is derived from the number of reported infections, it depends on the future development of infections and thus on the growth rate. Here, we will make a simplified assumption that the growth can be approximated as exponential. We show the sensitivity of the results for growth rates between 0% and 15%. A growth rate of 0% means that from one day to another, no more new infections are reported, which is an unrealistic extreme case. The other extreme, 15%, corresponds to a duplication of reported infections every 5 days. As reported in Section 3.1, the daily growth rate in the last week of March was 10.00%, which corresponds to a doubling period of about one week. Please note that this rate has since further decreased, potentially due to various containment measures in Berlin. In contrast, our model focuses on exponential stages of disease spread.

Figure 3 depicts the predicted number of ICU patients for April and May 2020 assuming different future exponential growth rates and compares it with the two capacities introduced above: The current reported maximal capacity of 1,045 and an extended capacity by the end of April (2,267) (see above). Given our assumptions, it shows that only growth rates between 0% and 4% guarantee that the number of patients at the end of May remains below the current maximal capacity, a rate of up to 6% guarantees to stay below the extended capacity by the end of May (but exceeds the capacity in June). Please note that we restrict our analysis here to a fixed time horizon of 2 months (April and May) because, due to the dynamic situation and a potential saturation, predictions beyond are difficult to make.

³ For 2017, the Office for Statistics of Berlin-Brandenburg reported 1450 ICU beds (Statistisches Bundesamt 2018). However, since this number is already 4 years old, we thus prefer to use these current estimates.

⁴ For $K = 7$, the lowest RMSE is 9.23 ($l^* = 3$), the highest $\rho^2 = 0.98$ ($l^* = 6$). For $K = 10$, the lowest RMSE is 5.07 ($l^* = 4$), the highest $\rho^2 = 0.98$ ($l^* = 6$).

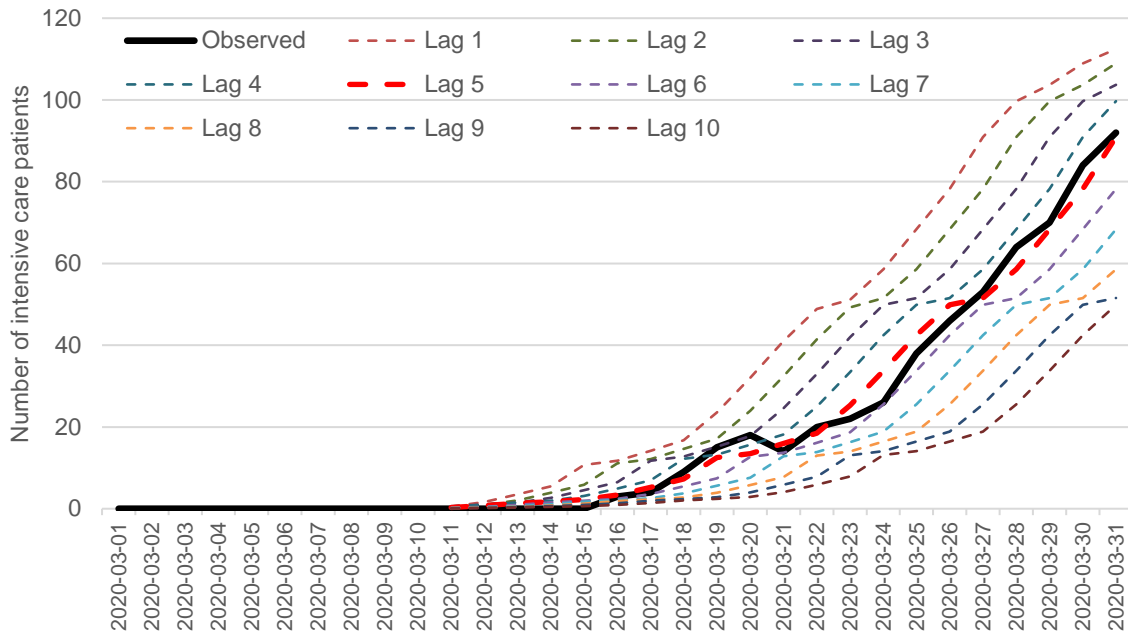


Figure 2: Observed and predicted number of patients in intensive care for March 2020 in Berlin; models vary in the time lag between a positive test and ICU admission (1–10 days); $K = 14$

	Lag									
	1	2	3	4	5	6	7	8	9	10
ρ^2	0.94	0.96	0.97	0.98	0.99	0.99	0.99	0.98	0.97	0.96
RMSE	22.88	17.31	11.89	6.50	3.26	6.52	10.95	15.06	18.60	21.84

Table 1: Squared correlation coefficient ρ^2 and RMSE for the models with $K = 14$ and different lags; the best model is characterized by a high squared correlation coefficient and a low RMSE

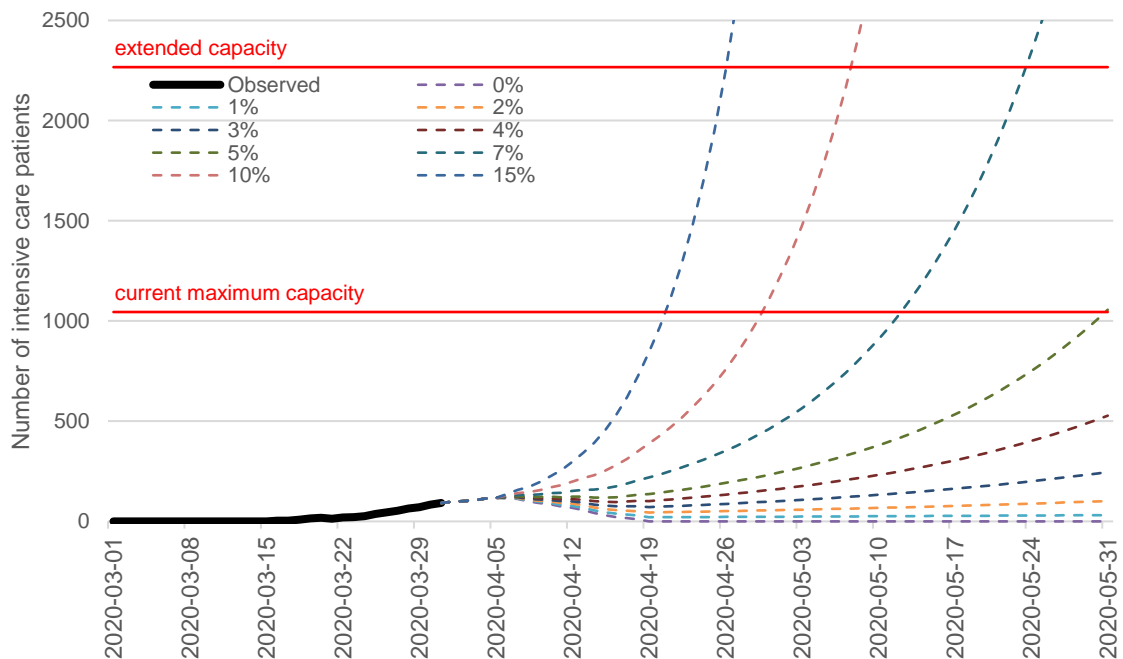


Figure 3: Model-based prediction of intensive care patients in Berlin in April and May 2020 based on different growth rates of infections (0%–15%) and assuming $\alpha = 5\%$. The capacity estimates are illustrative and preliminary and can be adjusted based on more detailed information. In the last week of March, the average growth was around 10% (the rate seems to have now dropped slightly).

In Table 2, we show the predicted number of ICU patients at the end of May for growth rates between 0% and 15% and the dates when the two capacities are expected to be reached. For example, for the growth rates 3%, 5% and 7% respectively, 246, 1,056 and 3,758 ICU patients are expected by the end of May. Furthermore, it can be seen that the current maximal capacity is expected to be reached on April 30, 2020, if the daily growth rate were to continue to be 10% as in the last week of March. However, the growth rate seems to be further decreasing since then. For a growth rate of 8%, this date shifts by one week to May 7, 2020, an additional extension of the capacity to May 17, 2020. If the growth rate reduces to 4%, this date would be changed to June 18 for the current maximal capacity and to July 8 for the extended capacity.

Figure 4 depicts the relation between different growth rates (0%–15%) and the dates of capacity exceedance for exemplary capacities of 500, 1,000, 1,500, 2,000, and 2,500. It demonstrates how the approach can be applied also for different phases of exponential growth or capacity extensions.

4 Discussion and Conclusion

The ongoing Covid-19 pandemic deeply concerns policymakers and health personnel to take the right actions to slow down the spreading of the coronavirus. In several regions (e.g., Wuhan/China, Lombardy/Italy, or Alsace/France), the need for ICUs surpassed the available capacity and not all Covid-19 patients who needed intensive care could be treated (Grasselli et al. 2020). To avoid a *triage*, several countries, including Germany, decided to apply containment measures – ranging from temporary closures of schools and kindergartens to travel restrictions, compulsory mask wearing, and curfew. Those measures, however, disrupt economic activity and lead to the risk of a recession. Thus, policymakers are confronted with the difficulty of making decisions that severely affect the healthcare system, the global economy as well as the everyday life of many individuals while facing a large amount of uncertainty within the pandemic (e.g., the time until new treatments or vaccinations have been developed). Since one major bottleneck for the healthcare system is the ICU capacity, risk models are needed that allow policymakers to estimate the future ICU load to take appropriate measures.

So far, most forecast models for ICU load fit exponential growth (e.g., using ordinary least-squares in the log-space) to either the cumulated number of positive Covid-19 patients or directly to the number of ICU patients (Daisy et al. 2020; Grasselli et al. 2020; Remuzzi and Remuzzi 2020). For different regions in the UK, Daisy et al. (2020) used

a Monte Carlo simulation to predict regional ICU capacity. Those models, however, assume that the initial exponential growth will hold over the forecast horizon (usually 14 days) and do not account for the alleviation of growth rates, e.g., due to containment measures. Moreover, these models do not exploit the underlying relationship between reported infections and ICU admissions, e.g., in terms of ICU rate. Here, we provide a simple, comprehensible, and transparent model that allows for predicting ICU load for different growth rates depending on assumptions on ICU rate and average stay in ICU. We evaluated this model for Berlin, where we had access to the number of ICU patients with Covid-19 (until March 2020). We first estimated the time lag between the positive Covid-19 testing and the ICU admission as well as the length of ICU duration and showed that the model with a time lag of 5 days and an average stay of 14 days is a good approximation to the observed data. For case studies in Hong Kong, Japan, Singapore, and South Korea, average time lags of 5.76 days for hospital admission and 8.20 days for ICU admission have been reported (Gaythorpe et al. 2020). We then used the model with the estimated time lag of 5 to predict the number of ICU patients for the future months April and May 2020. By assuming different exponential growth rates and different capacity levels, we evaluated different scenarios and show the sensitivity towards the growth rate in the exponential phase of Covid-19. The further the expected dates of a capacity exceedance can be shifted into the future, the higher the likelihood that new treatments or a vaccination are available or that a larger share of the population has become immune against Covid-19, which would further lower the growth rate.

To account for the dynamic situation of the deployment of ICU beds, we compare the predicted number of ICU patients to two illustrative capacity levels (maximum current capacity: 1,045 beds; extended capacity: 2,267; Schröter 2020). For simplicity, we assumed that all those beds are available for only Covid-19 patients and thus did not account for different utilization rates which might lead to an earlier capacity exceedance in practice. Generally, the utilization rates for ICUs have shown to be about 80% (Statistisches Bundesamt 2018) and media reports of experts assume that – in face of the spreading of Covid-19 – utilization rates can be reduced to 50% (e.g., by shifting not time-sensitive surgeries; Bach 2020). The new beds (1,222), however, are dedicated to only Covid-19 patients. Moreover, we did not differentiate here between high/low care ICUs (i.e., with and without invasive ventilator) and ICU ECMO since we only had numbers on the total ICU patients with Covid-19.

Growth rate	Doubling period (days)	Predicted number of ICU patients on May 31, 2020	Expected date capacity reached	
			Current maximal capacity (1,045 beds)	Extended capacity (2,267 beds)
0%	–	0	–	–
1%	69.66	32	2021-05-18	2021-08-04
2%	35.00	102	2020-09-26	2020-11-04
3%	23.45	246	2020-07-19	2020-08-15
4%	17.67	528	2020-06-18	2020-07-08
5%	14.21	1,056	2020-05-31	2020-06-16
6%	11.90	2,023	2020-05-20	2020-06-02
7%	10.24	3,758	2020-05-13	2020-05-24
8%	9.01	6,816	2020-05-07	2020-05-17
9%	8.04	12,134	2020-05-03	2020-05-12
10%	7.27	21,272	2020-04-30	2020-05-08
11%	6.64	36,813	2020-04-27	2020-05-05
12%	6.12	62,998	2020-04-25	2020-05-02
13%	5.67	106,756	2020-04-24	2020-04-30
14%	5.29	179,327	2020-04-22	2020-04-28
15%	4.96	298,849	2020-04-21	2020-04-27

Table 2: Prediction of the number of ICU patients on May 31st and expected dates when the capacity is reached for different scenarios (assuming constant growth rates)

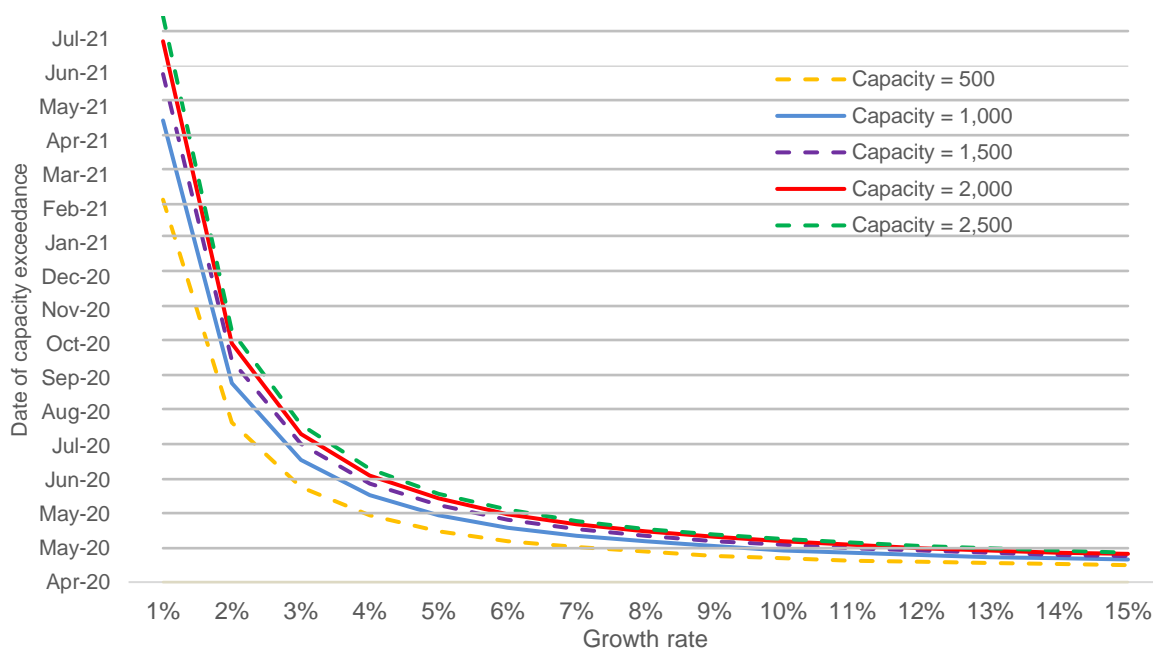


Figure 4: Expected dates of capacity exceedance for different growth rates and exemplary capacities assuming $\alpha = 5\%$. The capacities of 1,000 (blue) and 2,000 (red) are highlighted because they approximately correspond to current (1,045) and extended (2,267) estimates of ICU capacity for the Berlin data set (see above for details).

As most statistical and epidemiological studies, we had to make a number of assumptions. These assumptions were in particular necessary because the Covid-19 situation is still dynamic, and we do not have yet enough information about the statistical distribution in Germany. First, we assumed an ICU rate of Covid-19 patients of 5%. In similar models, relying only on exponential growth of intensive care patients, growth rates of 9–11% have been assumed (Remuzzi and Remuzzi 2020), so that we consider a rate of 5% as relatively moderate. We based this number on other European countries that have similar conditions as Germany (SMC 2020) and experiences from China (Wu and McGoogan 2020) and aligned it with the expectations of intensive care physicians in Berlin (Bach et al., 2020). This rate, however, depends on the testing capacity and is expected to decrease when the testing capacity increases because more mild cases will be revealed. Additionally, the ICU rate has been shown to be age dependent (e.g., Ferguson et al. 2020) so future studies might need to adapt this number for their specific circumstances and might include further demographical information (Deasy et al. 2020).

Second, in our model, we assume that the time lag as well as the growth rate are constant. The time lag, however, is known to be highly variable because Covid-19 patients may be tested at different time points due to different disease courses as well as regulatory and organizational issues (e.g., capacity of test units or eligibility to get a test). If information on the individual disease course were available, a distribution of different time lags could be derived and implemented into the model. However, we would not expect substantial differences in the results. Either the total ICU load at a certain timepoint is derived from a fixed time lag or it is accumulated over several days, which mainly leads to a smoothing of the curve. Also, the growth rates considerably vary from day to day; in the last seven days of March 2020, the daily relative change in reported infections ranged from 5% to 18% in Berlin and decreased further since then. To keep our models simple, we indeed tested for different growth rates, but for each model the growth rate over time was held constant. Please note that our results only hold true in the exponential phase of the disease and need to be adapted when the growth deviates from exponential, which currently appears to be the case in the Berlin data from early April.

Third, we have found that for an ICU rate of 5% an average ICU stay of two weeks resulted in a better fit to our data than the shorter stays of 7 and 10 days. Based on data from China, other forecast models assumed stays of 8 or 10 days (Ferguson et al. 2020;

Deasy et al. 2020). For Italy, however, longer residence stays (i.e., about 15 days for ICU patients who remain alive and about 10-12 days for patients who die after ICU treatment) have been reported (Manca 2020). For Seattle, a median length of at least 14 days for survivors have been reported (Bhatraju et al. 2020). In New York, Covid-19 patients typically need ICU care with ventilation for 11 to 21 days, some patients stay on ICU for 30 days (Clukey and Berthelsen 2020).

Although we tested the proposed model only for Berlin, our approach is generalizable to data of other cities, states, or whole countries as long as the overall numbers of reported Covid-19 patients and the ICU capacities are available. When data on ICU patients with Covid-19 are additionally available, it can further be evaluated if the estimated and assumed parameters hold also true in other regions. An informative repository in Germany is the DIVI registry⁵, in which most hospitals in Germany provides numbers of the current ICU load and capacity.

Although our predictions are based on a small data set data, and involve unclear dynamics and a number of assumptions, our analysis for Berlin demonstrates that a continued exponential growth rate as at the end of March would have led to an exceedance of the ICU capacity in the near future as already happened in several regions in other countries (China, Italy etc.). The predicted capacity exceedance is also in line with other forecast models for the UK or the USA (Deasy et al. 2020; Murray 2020). Due to the containment measures in Berlin (e.g., closure of schools, travel restrictions and curfew), the growth rate, however, seems to decrease since the end of March so that lower growth rates seem to be more realistic and the model need to be adapted in the future. Currently we are considering an extension of our model to include an attenuation of growth. Since our proposed model is quite generic, we hope that this study will help others to estimate the future need of intensive care in addition to sophisticated epidemiological approaches such as compartment or transmission models (Ferguson et al. 2006; Ferguson et al. 2020; Fox et al. 2020). However, as already pointed out by others any forecast models in these early times of the current pandemic needs to be taken with caution (e.g., Deasy et al. 2020) and assumptions need to be updated when further data become available.

⁵ <https://www.divi.de/register/kartenansicht>

Data and Code Availability Statement

The data is public and can be downloaded from the *Berliner Senatsverwaltung für Gesundheit, Pflege und Gleichstellung*. The code can be found here: <https://hu.berlin/ritter-covid-19> By adapting the different assumptions (growth rate, share of positively tested patients needing intensive care etc.), different scenarios can be run through.

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Declarations of interest

The authors report no conflict of interests.

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