A Scalable Forecasting Framework to Predict COVID-19 Hospital Bed Occupancy

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Abstract: The coronavirus disease 2019 (COVID-19) pandemic has led to capacity problems in many hospitals around the world. During the peak of new infections in Germany in April 2020 and October to December 2020, most hospitals had to cancel elective procedures for patients because of capacity shortages. We present a scalable forecasting framework with a Monte Carlo simulation to forecast the short-term bed occupancy of patients with confirmed and suspected COVID-19 in intensive care units and regular wards. We apply the simulation to different granularity and geographical levels. Our forecasts were a central part of the official weekly reports of the Bavarian State Ministry of Health and Care, which were sent to key decision makers in the individual ambulance districts from May 2020 to March 2021. Our evaluation shows that the forecasting framework delivers accurate forecasts despite data availability and quality issues.

Introduction

The initial local outbreak of the coronavirus disease 2019 (COVID-19) developed into a pandemic with more than 150 million cases and more than 3.1 million deaths worldwide as of April 30, 2021. In light of the COVID-19 outbreak, one challenge for hospitals and disaster control has been to estimate the short-term occupancy of their wards and intensive care units (ICUs) to adjust bed and personnel capacity, as well as their hospital admission policies, accordingly. These forecasts need to be performed on different hierarchical levels—starting from individual hospitals up to a supraregional level—to serve a multitude of different key decision makers. An overestimation of required COVID-19 bed resources because of inaccurate forecasts should be avoided to minimize the negative impact from, for example, canceled treatments of elective patients. An underestimation may result in bed shortages, potentially leading to severe consequences for untreated patients.

This paper presents a scalable forecasting framework to predict the short-term bed occupancy of patients with confirmed and suspected COVID-19 in ICUs and wards (i.e., four output measurements in total). The framework addresses different stakeholders that contribute, collect, analyze, and/or receive data. At the heart of this framework, we use a simulation model to incorporate the stochastic nature of the underlying problem. The forecasting framework can be easily adapted to different use cases, whether there is a need to forecast the bed occupancy within one specific hospital on a LOCAL level or in a more aggregated form on a REGION or STATE level. For more than nine months, we provided forecasts to the Bavarian State Ministry of Health and Care, which is responsible for the second-largest federal state in Germany, with more than 13 million inhabitants. On a STATE and LOCAL granularity level, we achieved a coverage rate of more than 95% with our forecasts. The coverage rate is defined and further described in the section Performance Evaluation of the Forecasting Framework.

Disease spread and pandemic development have been studied extensively over the last decades (Walters et al. 2018). For instance, Aleman et al. (2011) present a susceptible-infected-removed model (SIR) combined with an agent-based simulation model to analyze disease spread. During the COVID-19 pandemic, different approaches were used to help society by providing tools or forecasts. Meares and Jones (2020) use a basic queuing model to calculate the required ICU capacity nationwide in Australia.

Khailaie et al. (2021) use infection-epidemic models to predict the reproduction number of COVID-19–infected persons. Shoukat et al. (2020) develop an agent-based model with different self-isolation strategies by simulating different COVID-19 outbreaks in Canada. Rather than modeling the future development of the pandemic, our focus lies in developing a short-term forecast of the associated bed occupancy levels.

Short-term forecasts of patient flows and bed occupancy in healthcare have been an ongoing topic in the literature, and various methodologies have been used. Harrison et al. (2005), for example, present a simulation model that is capable of identifying regular bed occupancy fluctuations and substantive deviations from the ordinary patient flow. Akcali et al. (2006) use a network flow approach to improve capacity planning of hospital beds. Ting et al. (2017) use multiple models, such as seasonal regression and Markov chains, to forecast daily patient discharges and assess their capability to predict which beds may be available for admissions on the following day. Likewise, Abraham et al. (2009) compare the performance of moving average, single exponential smoothing, and autoregressive integrated moving average models that are used to forecast emergency inpatient arrivals. They stress that none of the models is useful for forecast horizons of longer than one week. Our work combines regression analysis, used to preprocess our input data, with a simulation approach to generate bed occupancy forecasts for a suitably short forecast horizon.

Forecasting short-term bed occupancy or related resource utilization for COVID-19 patients has received limited attention thus far. Stang et al. (2020) use a deterministic forecasting model that calculates the required ICU capacity throughout Germany for different scenarios. Römmele et al. (2020) use a stochastic approach and present a Monte Carlo simulation approach to forecasting the short-term bed occupancy of COVID-19 patients for a university hospital. Our forecasting model is an extension of their model. Epstein and Dexter (2020) present an approach that forecasts the required capacity of ventilators for a specific hospital for up to one week. Because the COVID-19 pandemic is still ongoing, some research work has not been peer reviewed but, available mostly as preprints, is worth mentioning. Bekker et al. (2021) present a model that combines linear programming and queuing theory to predict the admissions and occupancy of COVID-19 patients in the Netherlands for an individual hospital. Zhang et al. (2020) present an interactive online tool to forecast the number of ICU and acute care beds and other required resources such as necessary ventilators based on deterministic input parameters. The tool was developed in the early stages of the pandemic and uses deterministic mean input parameters to predict the following few days. Klüsener et al. (2020) provide an age-structured simulation model using a susceptible-exposed-infectious-recovered model to forecast demand for intensive care. Similar to our approach, they apply their model on different granularity levels. However, their forecasts are limited to the bed occupancy of ICU patients. Moreover, they use publicly available data provided by the German Interdisciplinary Association for Intensive Care and Emergency Medicine (DIVI), whereas we use additional data on ward patients and suspected COVID-19 cases.

The previously mentioned papers either forecast ICU capacity or other required resources for a single hospital or provide forecasts on an aggregated national level, thus lacking information for individual regions and hospitals. Furthermore, most of the literature thus far has ignored information on the statistical distributions of input parameters but rather uses deterministic assumptions. The main focus in the literature has been on ICU patients, whereas we provide forecasts for ICU and regular wards, both for patients with suspected and for patients with confirmed COVID-19. Last, although methodologically relying on established concepts, we fill a gap in the literature by providing researchers with insights from the successful implementation of a forecasting tool that addresses the needs of multiple stakeholders, ranging from individual hospitals to the entire state of Bavaria.

In the next section, we present the problem description. The section Stakeholder Analysis describes the different stakeholders and the development of the forecasting framework for automated data collecting, transformation, simulation, and reporting. The section Analysis, Forecasting, and Reporting Module highlights the required input parameters as well as the analysis, forecasting, and reporting modules (AFRMs) in more detail. The Implementation of the Forecasting Framework section shows the application to the different granularity levels. The section Performance Evaluation of the Forecasting Framework presents the results of our forecasting framework in close collaboration with the Bavarian State Ministry of Health and Care. Finally, we provide a conclusion and discuss the limitations of our study in the last section.

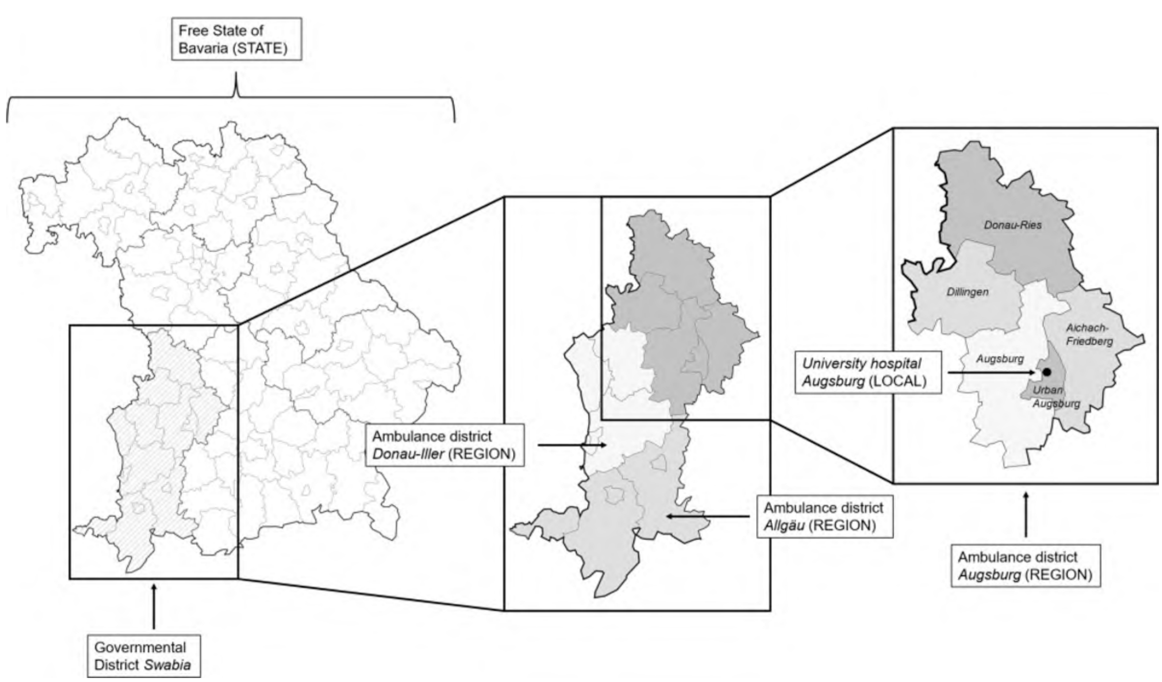
Problem Statement

The problem we consider is forecasting the bed occupancy for patients with COVID-19 in the ICU and ward. For the ICUs and wards, we differentiate between confirmed and suspected COVID-19 cases. Whereas the former undoubtedly require isolation during their stay, the latter need isolation as long as they cannot be ruled out to be COVID-19 positive. Neglecting these cases in bed occupancy forecasts distorts the required bed capacity, as the suspected cases put an additional burden on the (local) health-care system.

We consider three different spatial granularities with their specific particularities. As shown in Figure 1, the granularity level consists of the already mentioned three layers: STATE, REGION, and LOCAL. First, we consider a single forecast for the entire Free State of Bavaria (STATE). On that level, the forecasting framework is used as a guideline for strategic political decision making for multiple regions. This includes imposing, lifting, or maintaining lockdown measures and establishing or adjusting visitation guidelines. The continuous updates of the Bavarian Infection Protection Act, which focuses on refining conditions when lockdown measures take effect, resemble the importance of our project. Specifically, the focus of moving from pure incidence numbers to hospital capacity performance measures has been well supported by our research. Second, we provide forecasts for each of the 26 ambulance districts (REGION) in the Free State of Bavaria. On a REGION level, the forecasting framework supports resource management to allocate resources such as specialized nurses, physicians, or medical devices between hospitals. Moreover, patient transfer and admission policies can be adjusted in response to the occupancy forecasts. For example, smaller hospitals would dedicate wards to COVID-19 treatments only in times when the specialized COVID-19 wards in larger hospitals were forecasted to be (close to) fully occupied. Neidel et al. (2021) present a coordination effort performed during the second COVID-19 wave in November 2020. The hospitals' capacities can be pooled on an ambulance district level because these hospitals closely collaborate on patient transportation, medical personnel, and COVID-19–related medical devices such as ventilators. Therefore, in our forecasts for each of the two categories REGION and STATE, we pool the resources (e.g., ICU beds) dedicated to treating COVID-19 patients into a single artificial hospital. Third, we focus on a single hospital, the University Hospital Augsburg, which provided us with detailed patient data, on the local granularity level (LOCAL). For instance, we incorporate precise information about the distribution of patients over the different hospitals within the catchment area to model the arrival rates of patients with COVID-19. Our forecasts support the pandemic coordinator of the hospital in the decisions related to reserving capacity for COVID-19 patients while trying to maintain the elective surgery program as much as possible. During the first wave, for example, all elective surgeries were canceled (unless medically indispensable) until forecasts showed sufficient available bed capacity to slowly phase in elective surgeries.

In Figure 1, we present a map of the Free State of Bavaria. The state consists of seven governmental districts. Each governmental district contains three to four ambulance districts. Each ambulance district comprises two to six counties. In total, there are 26 ambulance districts and 96 counties. The governmental district of Swabia, for example, contains three ambulance districts (Allgäu,

Figure 1. Map of the Free State of Bavaria Presenting the STATE, REGION, and LOCAL Levels



Augsburg, and Donau-Iller) and 14 counties. The ambulance district Augsburg (REGION) in the northern area of the governmental district of Swabia encompasses the five counties: Aichach-Friedberg, Urban Augsburg, Augsburg Regional, Dillingen, and Donau-Ries. The University Hospital Augsburg is located in the county of Urban Augsburg.

Our framework is capable of producing accurate forecasts on each of the different granularity levels. Each projection has a forecasting horizon of one week. The goal of the forecasts is not to predict the pandemic evolution but rather to forecast the expected bed occupancy associated with different potential developments of the pandemic. Therefore, we use three scenarios to model a constant (MED), a decreasing (LOW), and an increasing (HIGH) evolution of the number of confirmed and suspected COVID-19 cases. Zhao et al. (2021) use a similar approach in their approach to forecasting COVID-19 infections. Each of the forecasts is made for ICU and ward patients separately. In total, we have 12 forecasts for each STATE and LOCAL granularity level and each of the 26 ambulance districts on the REGION level, resulting in a total of 336 forecasts. The forecasts were generated twice a week, on Mondays and Thursdays, to ensure a constant and reliable update of the pandemic situation.

We use a Monte Carlo simulation at the center of our forecasting tool. This allows us to incorporate the stochastic nature of a multitude of input parameters (e.g., length of stay (LOS), infection rate, and hospitalization rate) and to generate distributions for each of the output measurements (e.g., ICU bed occupancy for confirmed COVID-19 cases).

Our input data come from multiple sources. For example, we collect the number of confirmed COVID-19 cases from governmental agencies (e.g., the Bavarian State Ministry of Health and Care; Bayerisches Landesamt für Gesundheit und Lebensmittelsicherheit 2020). Hospital-specific data are provided by IVENA eHealth: a registry in which all hospitals in Bavaria report their daily bed occupancy (IVENA eHealth 2020). Furthermore, we use the information on the stochastic distribution of the length of stay and the infection and hospitalization rates, as well as the approximated number of patient admissions from the occupancy records.

Stakeholder Analysis

Our forecasting framework involves different stakeholders: *healthcare providers*, *governmental agencies*, and *scientists*, as depicted in Figure 2. The dashed lines represent the shortened process between an individual hospital and the scientists, circumventing the need for a centralized data warehouse.

Healthcare providers predominantly represent the hospitals. They collect detailed patient data and supply the information to governmental agencies. In return, the healthcare providers receive the bed occupancy

Figure 2. (Color online) Forecasting Framework Structure of the COVID-19 Decision Support Tool Representing the Three Different Stakeholders: Healthcare Providers, Government, and Scientists

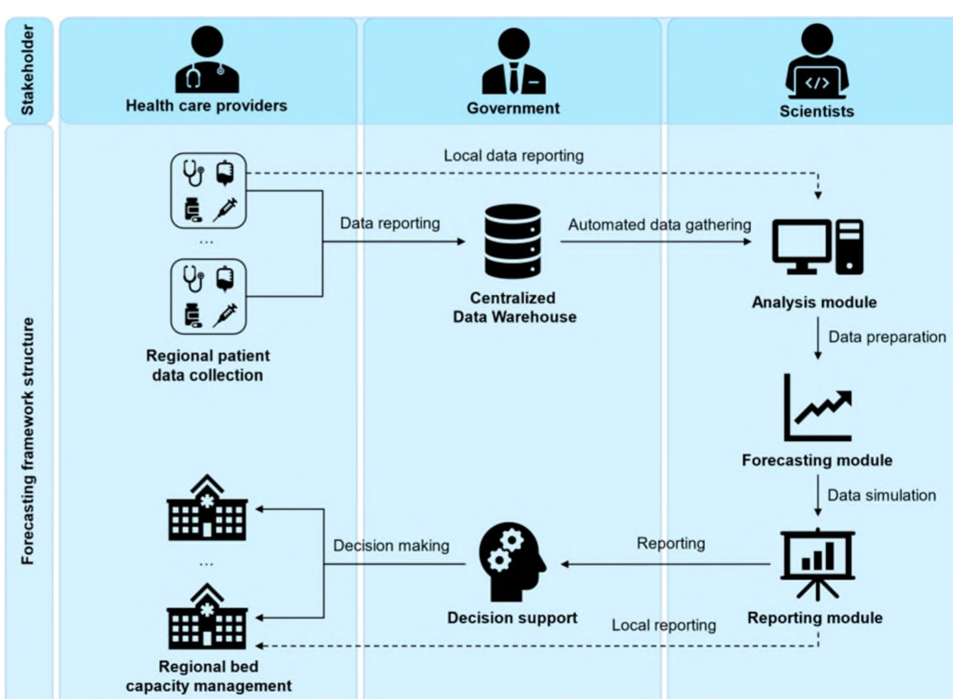
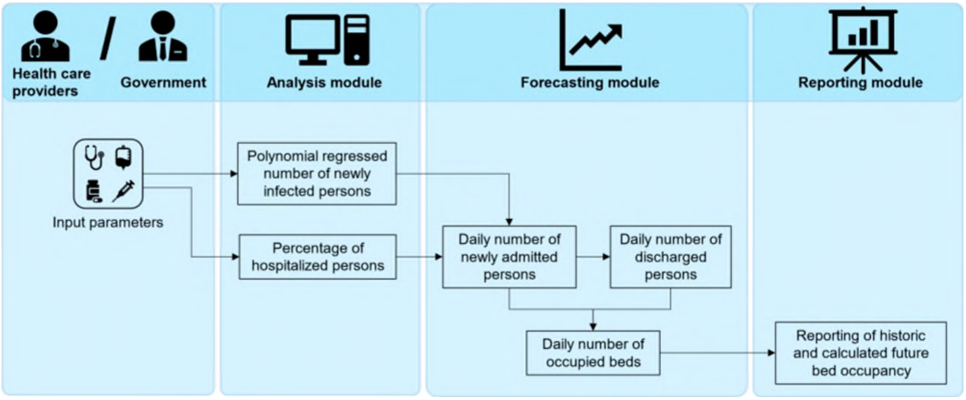


Figure 3. (Color online) Simplified Process Flow of the AFRM



forecasts from the governmental agencies to assist them in their short-term capacity-related decision making.

Governmental agencies operate as a transmitter between healthcare providers and scientists, setting up the database structure required to enable the sharing of sensitive data between practitioners and scientists. The forecasts provide a scientific foundation for the policies enacted by the government. These policies range from recommendations on how to proceed with regular operations for hospitals to setting different minimum targets of reserved COVID-19 beds or defining restrictions for the society trying to lower the number of newly infected cases.

The third party, the scientists, has access to the centralized data warehouse to automatically collect necessary information as input parameters. After analyzing the validity of the data, simulation forecasting models can be executed and followed by a reporting module to present the used input and obtained output data.

Analysis, Forecasting, and Reporting Module

We present our AFRM that we developed to forecast the short-term bed occupancy of patients with suspected and confirmed COVID-19 in the ICUs and wards for all mentioned granularity levels in this section. The simplified process flow of the AFRM can be seen in Figure 3, and the complete process flow is shown in Figure A.1.

We use robotic process automation (RPA) to automate the process of collecting the data and downloading it from the centralized data warehouse. The simulation process is implemented in Vose ModelRisk (Vose and Koupeev 2020). The data transformation and the reporting are coded in Visual Basic for Applications (VBA). Although there exist more powerful programming languages, acceptance and integration in running operations are key factors when implementing scientific research in corporate or civil service environments. The use of VBA for successful project implementation is prominent in different operational areas (Onggo et al. 2010, Heider et al. 2018, Schoenfelder and Pfefferlen 2018, Bailey and Waddell 2020, Haket et al. 2020).

Data Input and Analysis Module

Multiple input parameters must be gathered, analyzed, and (partially) processed before running the simulation. As previously mentioned, some of the parameters are readily available from the governmental centralized database, whereas others are not collected and need to be derived from the existing data. The available input parameters and the respective shareholders responsible for their collection are listed in Table 1, whereas the parameters that must be derived from existing data to run the simulation are listed in Table 2.

The number of newly infected persons is necessary for the simulation to derive the number of daily admissions (which are not publicly shared by the hospitals). Whereas the reported infection numbers are accurate during the weekdays, the accuracy on weekends suffers from issues such as reduced testing and reporting by the involved stakeholders. Because this causes the variability in the number of newly infected persons to artificially increase, we use a polynomial regression model to

Table 1. List of Collected Input Parameters

Input parameter	Source
Daily historical bed occupancy of COVID-19 patients	Healthcare provider
LOS of patients with confirmed and suspected COVID-19 in the ICU and ward	Healthcare provider
Daily number of newly infected persons	Government

Table 2. List of Calculated Input Parameters

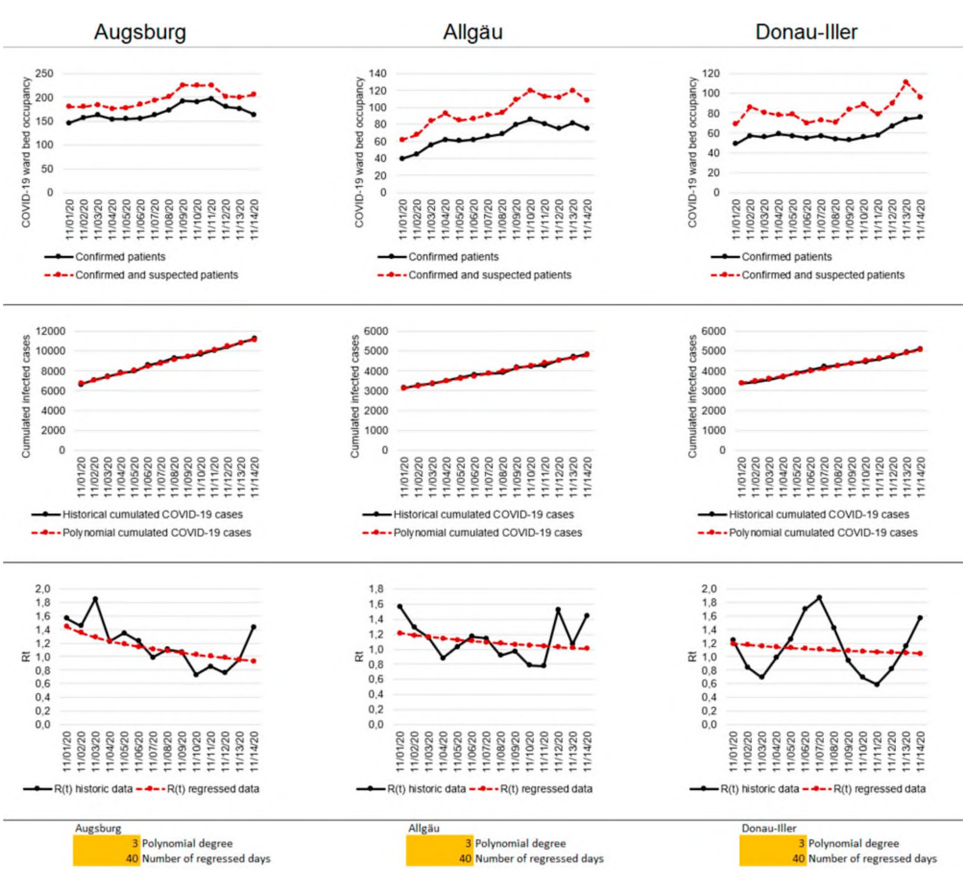
Input parameter	Data derived from
Polynomial regression of the number of newly infected persons	Daily historical number of infected persons
Reproduction number R_t	Polynomial regression of the number of newly infected persons
Assumed daily admissions	Daily bed occupancy and mean of LOS
Percentage of hospitalized persons	Assumed daily admissions and number of newly infected persons

smoothen the number of newly infected persons. Polynomial regression is a popular method that has been extensively studied and applied in the literature (Fan and Gijbels 2018). The polynomial degree was chosen between three and five, as displayed in Figure 4. As the polynomial degree determines the curvature of the regression, we decided on the value that would best reflect the trend over the most recent days by visual inspection. We then tested for a range between 30 and 50 regressed days to find the best ordinary least squares results. For further details on the polynomial regression, please see the Appendix.

Furthermore, we calculate the effective reproduction number (R_t) on day t, also used by the Robert Koch Institute (RKI), based on the polynomial regression of the number of newly infected persons. The RKI is a governmental scientific institution in Germany that focuses on safeguarding public health in Germany (Robert Koch Institute 2021). An der Heiden and Hamouda (2020) describe the concept of R_t in more detail. Our calculation of R_t is based on the last eight days of the newly infected cases. It shows the relative change between newly infected persons within the last four days compared with the newly infected persons four days in advance.

Our simulation model requires the percentage of newly infected persons that need to be hospitalized, which is the number of daily admissions divided by the number of newly infected persons, each summed over a time horizon specified by the scientist to strike a balance between responsiveness and stability. As the number of daily admissions is not available, we

Figure 4. (Color online) Excerpt of the Simulation Management Dashboard in the Data Analysis Module



approximate it by dividing the daily bed occupancy by the mean LOS.

Our tool provides an overview of all data on an internal simulation management dashboard (see Figure 4), in which a small excerpt is shown for three ambulance districts. In the top row is the daily historical bed occupancy of confirmed and suspected COVID-19 ward patients. In the second row, a comparison of the historical and the polynomial-regressed cumulated number of newly infected persons is presented. Finally, the calculated R_t values based on the reported and the polynomial-regressed number of newly infected persons are compared. Below the diagrams, the scientist can edit the regression parameters to fit the polynomial regression to the data. Especially in ambulance districts with low number of infection cases (e.g., Donau-Iller at the bottom right in Figure 4), the artificial variability of the R_t values introduced by the reporting and data collection process is significant. Furthermore, the dashboard enables the scientist to detect heavy outliers in the raw data from faulty data entries by the data-reporting stakeholders.

Forecasting Module

Our forecasting module comprises an overview of the collected and calculated input data and the simulation logic. Figure 5 presents an excerpt of the forecasting module. The Monte Carlo simulation is executed 5,000 times for each scenario, geographical and granularity level, and bed type (ward and ICU). Triangular distributions are assumed for each stochastic input parameter for the following reasons: (a) they are easy to understand by the involved stakeholders with various knowledge backgrounds; (b) they allow the modeler to control for the shape of the distribution function (unlike, e.g., an exponential distribution); (c) triangular distributions are regularly used when little or no reliable information is available, which was the case for data related to patients with COVID-19 at the beginning of the pandemic; and (d) we had fairly good estimates of the required LOS parameters (minimum, mode, maximum) after conducting a survey among 23 Bavarian hospitals at the beginning of our collaboration with the Bavarian State Ministry of Health and Care.

The output of a single simulation run includes the forecast number of beds occupied by confirmed patients and the number of beds occupied by the sum of confirmed and suspected cases. A detailed mathematical and graphical description of our simulation logic is provided in the Appendix. After 5,000 runs, we obtain confidence intervals for our outputs for each day in the forecasting horizon.

Reporting Module

In the reporting module of the AFRM process, we display the historical bed occupancy shared by the healthcare providers and information on the stochastic future bed occupancy levels. Specifically, we report the mean values, the quantiles, and the confidence intervals of the forecast bed occupancy levels. With the help of VBA macros, the output data are automatically consolidated, and diagram-based reports in the form of PowerPoint slides are generated. Furthermore, key performance indicators (KPIs), such as the seven-day incidences per 100,000 inhabitants and the ICU and ward utilization with COVID-19 patients, are reported in a table format. These KPIs can be adapted depending on the relevance for the different stakeholders. The reports, separated for each granularity level, are sent to the governmental agencies and the healthcare providers to serve as decision support. The assumptions and input parameters of the different distribution functions are also delivered with

Figure 5. (Color online) Excerpt of the Forecasting Module

	Rand. Value	Min	Max	Mode	Value	Distribution
Percentage hospitalized confirmed		0,86%	0,93%	0,90%	Daily	Triangular distribution
Percentage hospitalized suspected		0,68%	0,85%	0,76%	Daily	Triangular distribution
Length of Stay confirmed		1	29	5	Daily	Triangular distribution
Length of Stay suspected		1	6	2	Daily	Triangular distribution
Reproduction factor Rt	0,26	0,83	1,33	1,08	1,01	Triangular distribution

											Simulation phase						
t =	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6
Date	05-Nov-20	06-Nov-20	07-Nov-20	08-Nov-20	09-Nov-20	10-Nov-20	11-Nov-20	12-Nov-20	13-Nov-20	14-Nov-20	15-Nov-20	16-Nov-20	17-Nov-20	18-Nov-20	19-Nov-20	20-Nov-20	21-Nov-20
Number of newly infected persons	3290	3385	3476	3561	3643	3720	3792	3859	3922	3980	3989	3998	4006	4015	4024	4033	4042
Random value percentage hospitalized confirmed	0,99	0,05	0,02	0,21	0,71	0,24	0,63	0,17	0,60	0,92	0,72	0,41	0,55	0,06	0,23	0,44	0,25
Daily value percentage hospitalized confirmed	0,9%	0,9%	0,9%	0,9%	0,9%	0,9%	0,9%	0,9%	0,9%	0,9%	0,9%	0,9%	0,9%	0,9%	0,9%	0,9%	0,9%
Random value percentage hospitalized suspected	0,82	0,32	0,08	0,21	0,16	0,28	0,62	0,57	0,39	0,35	0,02	0,30	0,60	0,83	0,87	0,43	0,56
Daily value percentage hospitalized suspected	0,8%	0,7%	0,7%	0,7%	0,7%	0,7%	0,8%	0,8%	0,8%	0,7%	0,7%	0,7%	0,8%	0,8%	0,8%	0,8%	0,8%
Number of admissions confirmed	31	30	30	32	33	33	34	34	35	37	36	36	36	35	36	36	36
Number of admissions suspected	26	25	25	26	26	28	29	30	30	30	28	30	31	32	32	31	31
Historic occupancy confirmed	*317*	*331*	*340*	*360*	*379*	*391*	*418*	*430*	*448*	*453*							
Historic occupancy suspected	*43*	*47*	*37*	*34*	*41*	*35*	*37*	*39*	*38*	*36*							
Random value LOS confirmed	0,18	0,63	0,40	0,24	0,01	0,45	0,74	0,57	0,22	0,93	0,48	0,21	0,39	0,75	0,93	0,59	0,36
Daily LOS confirmed	6	13	9	6	2	10	16	12	6	22	10	6	9	16	22	12	8
Number of discharges confirmed											0	30	0	0	65	33	0
Random value LOS suspected	0,54	0,44	0,25	0,58	0,88	0,70	0,07	0,11	0,42	0,22	0,71	0,34	0,14	0,46	0,88	0,45	0,11
Daily LOS suspected	3	3	2	3	4	4	2	2	3	2	4	2	2	3	4	3	2
Number of discharges suspected											0	59	0	30	59	0	32
Occupancy confirmed	317	331	340	360	379	391	418	430	448	453	489	495	531	566	537	540	576
Occupancy suspected	43	47	37	34	41	35	37	39	38	36	64	34	65	67	41	71	70
Occupancy confirmed and suspected	360	378	377	394	420	426	455	469	486	489	553	529	596	633	578	611	646

each forecasting report. This proved particularly fruitful during the early stages of the project, as physicians could give feedback on the validity of our assumptions.

Implementation of the Forecasting Framework in Practices

The development of the simulation model started in March 2020. From March 2020 to April 2020, our focus lay on forecasts for the COVID-19–related bed occupancy of ICU and ward patients at a maximum-care hospital. Hereby, the simulation model is used on a LOCAL level. During that time, the forecasting framework structure as shown in Figure 2 was developed. Because of the achieved forecast accuracy and provided utility in decision support, the ambulance district of Swabia quickly asked for an adapted version of the forecasting framework to be used on a REGION level. During that time, governmental agencies already helped us to collect the necessary hospital data to perform these forecasts. Soon after, in May 2020, the Bavarian State Ministry of Health and Care requested a rollout to forecast all of the 26 ambulance districts in the Free State of Bavaria. Furthermore, a forecast with an aggregated bed occupancy for the whole Free State of Bavaria was requested. These 26 ambulance districts consist of more than 180 hospitals that treat COVID-19 patients in their ICUs and wards and more than 70 hospitals in wards exclusively. The number of inhabitants of these areas is in total more than 13 million, which is about 15% of the population of Germany.

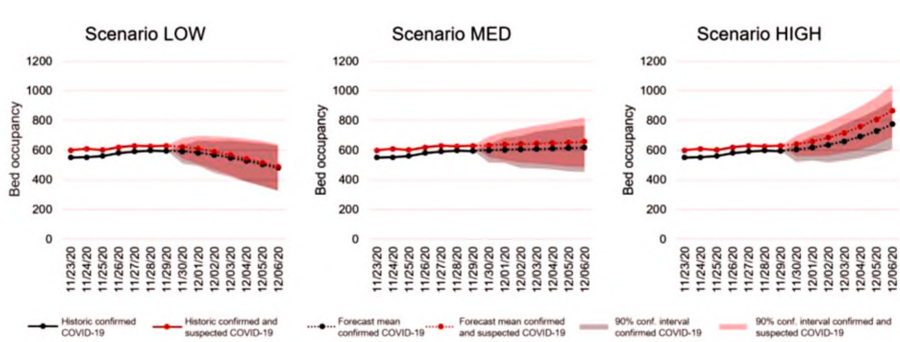
Initially, the processing time to create the forecasts and reports of all the different ambulance districts amounted to approximately six hours. After implementing the VBA macros and the RPA, human interaction was reduced to a minimum and only necessary to refine the input parameters via the simulation management dashboard. The documents sent to the Bavarian State Ministry of Health and Care consisted of more than 180 pages. They included diagrams that presented the historical and forecasted bed occupancy of the different patient types. Moreover, the historical and assumed future reproduction numbers for each granularity and geographical level were reported. Additionally, more than 80 tables showing parameters such as the ratio of beds specifically occupied by COVID-19 patients were added to the reports. A page of an example report is shown in Figure 6.

Performance Evaluation of the Forecasting Framework

In this performance evaluation section, we retrospectively assess the accuracy of our forecasts from May 2020 until January 2021. Over this period, more than 75 reports and more than 25,000 forecasts were generated and sent to the Bavarian State Ministry of Health and Care, which distributed the forecasts to the relevant stakeholders. The forecast accuracy was continuously evaluated to determine potential shortcomings in our approach and to adapt input parameters as new information on the pandemic became available.

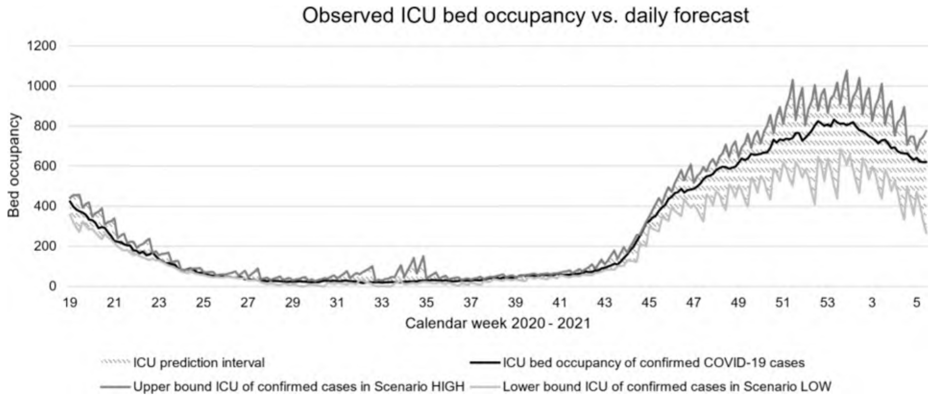
Our three main evaluation measures include the coverage rate—a success being defined as the actual number of occupied beds of the forecast day being within the 5% quantile of Scenario LOW and the 95% quantile of Scenario HIGH. In the following, this interval is called the *prediction interval*. Similar evaluation approaches have been used in various research areas such as medicine (IntHout et al. 2016), tourism (Kim

Figure 6. (Color online) Example Forecasting Report for the ICU Delivered to the Free State of Bavaria on a STATE Level in November 2020



		Beds ICU (n)	Beds ICU (%)	Bed quotient ICU	% COVID-19 occupied ICU beds
Historic (11/29/20)		1098	37%	0.8	19.8%
	Scenario LOW	-	-	1.0	16.3%
Forecast (12/06/20)	Scenario MED	-	-	0.8	21.0%
	Scenario HIGH	-	-	0.7	26.3%

Figure 7. Prediction Interval and Actual Bed Occupancy for the ICU of All Forecast Days from May 2020 Until January 2021 for the Forecast of the Free State of Bavaria



et al. 2011, Li et al. 2019), and revenue management (Fiori and Foroni 2020). The second evaluation is based on the mean values of the bed occupancy forecast for a specific future day of each delivered forecast compared with the observed bed occupancy. The third evaluation compares our method with a last observation carried forward (LOCF) approach.

Results Forecasting Level: STATE

On the STATE level, the average coverage rate (the observed bed occupancy of the patients with confirmed COVID-19 being inside the prediction interval) is at 95.2% for the ICUs and 96.3% for the wards. On 3.0% (1.8%) of the days within the project duration, the observed values were below (above) the prediction interval for the ICUs. For the wards, the observations were below (above) the prediction interval on 3.0% (0.7%) of all days. The coverage rate being inside the prediction interval for the patients with confirmed and suspected COVID-19 combined is at 98.4% for the ICUs and 100% for the wards.

The results for the bed occupancy of COVID-19 patients over the complete forecasting horizon from May 2020 until January 2021 are visually presented in Figure 7 for the ICUs and in Figure 8 for the wards. The government reported our forecasts on Mondays and Thursdays. In this analysis, the forecasted bed occupancy on Mondays through Wednesdays stems from the forecasts delivered on Mondays, whereas the values on forecasting days in the second half of the week—Thursday until Sunday—derive from the forecasts delivered on Thursdays. The further bed occupancy values are forecast into the future, the more the distance between the confidence intervals of the LOW and HIGH scenarios grows. This explains the zigzag shape of our prediction intervals in Figures 7 and 8. The shape in the confidence intervals over the following days proved to be a piece of key information for the stakeholders. Therefore, the impact of the

Figure 8. Presentation of the Prediction Interval and the Actual Bed Occupancy for the Wards of All Forecast Days from May 2020 Until January 2021 for the Forecast of the Free State of Bavaria

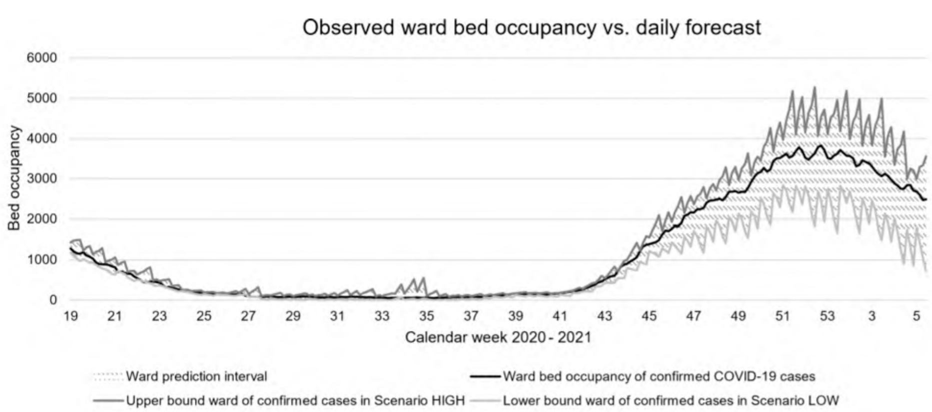
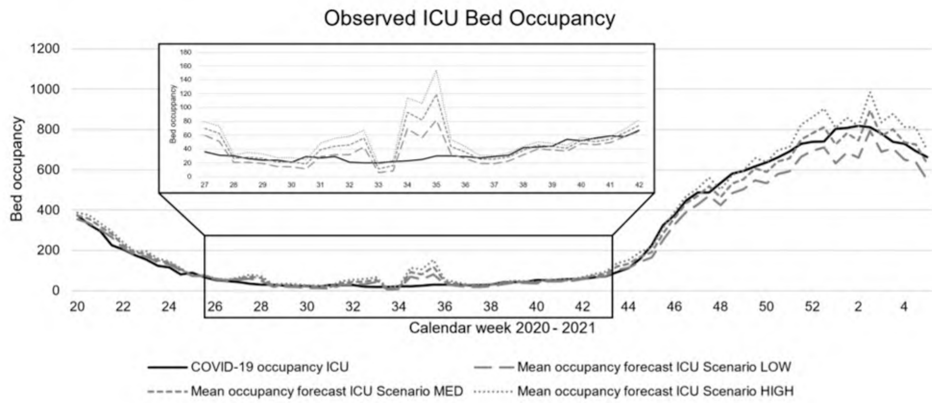


Figure 9. Comparison of the Coverage Rate for the ICU for the Fourth Forecast Day from May 2020 Until January 2021 for the Forecast of the Free State of Bavaria



uncertainty regarding the pandemic development—which, of course, increases for each additional day the bed occupancy is forecast into the future—was important information in our reports. The second wave started around week 43 in Germany, at which point the prediction intervals started to widen because of the increased stochasticity in the pandemic development.

In Figure 9, the mean values of the forecast ICU bed occupancy on the fourth day after executing each forecast over the whole forecasting horizon from May 2020 until January 2021 are presented. As shown in Figure 9, the mean of the bed occupancy forecast of Scenario HIGH, which is projecting an increasing number of newly infected individuals, is closest to the real bed occupancy at the beginning of the second COVID-19 wave during the calendar weeks 44–48. During that time, the infection numbers, as well as the number of hospitalized persons, increased. Because of low and nonstationary numbers of newly infected persons in July and August 2020 (weeks 30–35), we saw inaccuracies in the calculation of the R_t values. This prompted us to make changes in the data analysis module that led to the implementation of the simulation management dashboard, as shown in Figure 4. After the implementation of the management board, the forecasting accuracy improved considerably. The accuracy remained satisfactory until and throughout the second wave of the pandemic.

Another method to assess the forecast accuracy of our model is to compare the mean absolute deviation (MAD) of our forecasts with those resulting from a simple LOCF method. We provide the MADs of both approaches for ICU and ward patients in Figures 10 and 11, respectively. In both figures, we show the MAD resulting from both approaches separately for each number of days forecast into the future—for the sake of comparability, we assume that each reported forecast had a forecast horizon of seven days (although the forecast reports were actually updated every Monday and

Figure 10. Comparison of the LOCF and Our Forecast for the ICU for Every Forecast Day and the Daily Forecasts of the Free State of Bavaria

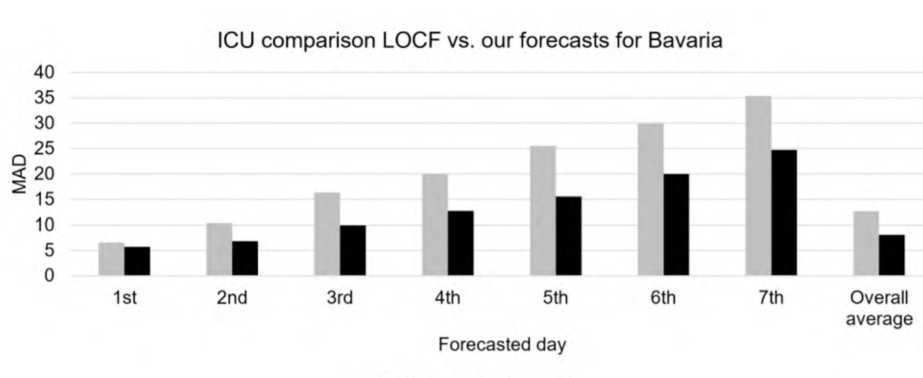
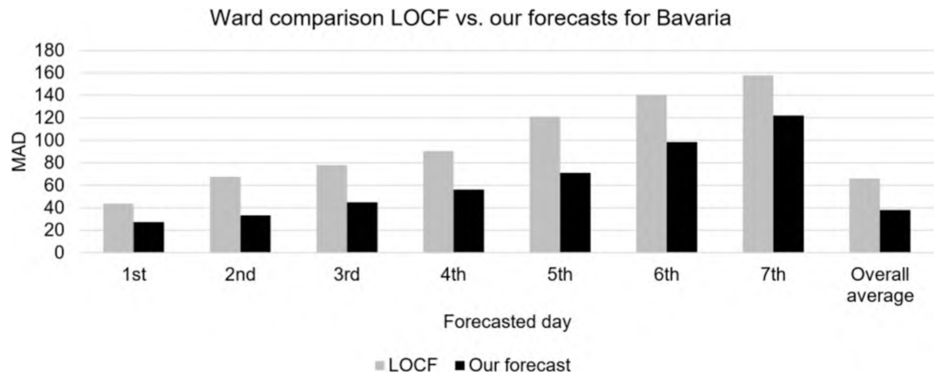


Figure 11. Comparison of the LOCF and Our Forecast for the Ward for Every Forecast Day and the Daily Forecasts of the Free State of Bavaria



Thursday). Naturally, the further we forecast into the future, the higher the MAD becomes. On average, our forecasts outperform the LOCF approach by 30%–40%.

Results Forecasting Level: REGION

The results of the coverage rate, being inside the prediction interval on the REGION level, are shown in Table 3. For every 26 ambulance districts, the coverage rate is split up for each reported forecasting month from May 2020 until January 2021 and each hospitalization type (ICU and ward). In Table 3, the ambulance districts are sorted by their population in decreasing order. As an example, the largest ambulance district Munich has an overall coverage rate of 91% and 93% for ICU and ward patients, respectively, throughout the nine months. It is worth mentioning that the results were noticeably poor in June 2020.

Because of the low observed numbers of newly infected and hospitalized persons, the confidence intervals were relatively small—in smaller ambulance districts, sometimes even less than one bed wide. Therefore, we updated the forecasting module to allow for a minimum interval size dependent on the size of the ambulance district. Without this buffer, even the smallest differences in the bed occupancy from one day to another would result in observed values outside the prediction interval. This change affected the smallest ambulance districts but had no impact on larger ambulance districts or the STATE level.

Results Forecasting Level: LOCAL

During the second pandemic wave in Germany, starting in November 2020, the forecasting framework was used to forecast the bed occupancy of the different types of patients with COVID-19 for one specific maximum-care hospital in the Free State of Bavaria. On a LOCAL level, the application of the framework is slightly adapted. Besides the historical bed occupancy, the admission and discharge days of each COVID-19 patient are known. Therefore, no need for calculation of further input parameters is necessary to run the model. Whereas on the STATE and REGION level, 100% of the number of newly infected persons within a given county were assumed to be potentially hospitalized within the same county, the catchment area (spanning multiple counties) of a single hospital is taken into account. Using the same KPI measure as in the STATE and REGION forecasts, the coverage rate inside the prediction interval over the forecasting horizon was 97.8% (ICU) and 98.9% (ward).

Discussion and Outlook

In this paper, a forecasting framework for providing short-term future bed occupancy for different geographical and granularity levels as decision support during the COVID-19 pandemic is presented. The number of beds occupied by patients with confirmed and suspected COVID-19 in the ICU and wards is forecasted. The presented work can be used on a STATE level using aggregated data to forecast the bed occupancy of a complete state. The aggregated data can also be used on a smaller REGION level, in which the bed occupancy of one ambulance district with multiple hospitals is forecasted. On a LOCAL level, the framework supports an individual hospital with short-term forecasts of bed occupancy. The implementation of the framework is demonstrated on multiple granularity and geographical levels in the Free State of Bavaria—the second-largest federal state in Germany, with more than 13 million inhabitants. These forecasts were sent to the Bavarian State Ministry of Health and Care and to the 26 ambulance districts twice a week to provide them with decision support. The forecasting model has been constantly adapted and developed. As shown in the evaluation of the

Table 3. Coverage Rate for the ICUs and Wards of All Ambulance Districts for Each Month Being Inside the Prediction Interval for the Bed Occupancy

Ambulance district	Month May 2020	June 2020	July 2020	August 2020	September 2020	October 2020	November 2020	December 2020	January 2021	Mean
Munich	86%/100%	77%/70%	97%/97%	87%/84%	100%/93%	94%/90%	80%/100%	100%/100%	100%/100%	91%/93%
Nuremberg	89%/79%	57%/63%	94%/77%	68%/84%	87%/73%	94%/94%	90%/93%	100%/100%	100%/100%	86%/85%
Augsburg	43%/57%	80%/70%	65%/94%	90%/90%	93%/63%	77%/71%	77%/97%	100%/90%	97%/97%	80%/81%
Fürstenfeldbruck	46%/54%	40%/67%	90%/87%	81%/71%	100%/83%	97%/68%	80%/77%	84%/77%	90%/100%	79%/76%
Regensburg	89%/71%	77%/70%	84%/94%	77%/77%	100%/93%	87%/87%	80%/97%	97%/100%	100%/97%	88%/87%
Traunstein	86%/79%	30%/33%	90%/94%	100%/97%	100%/87%	74%/77%	63%/80%	97%/100%	97%/100%	82%/83%
Würzburg	75%/64%	40%/53%	87%/94%	100%/100%	100%/100%	100%/58%	50%/80%	97%/94%	94%/97%	82%/82%
Ingolstadt	46%/75%	20%/50%	74%/52%	100%/94%	100%/100%	94%/74%	83%/87%	87%/100%	84%/100%	76%/81%
Allgäu	43%/57%	80%/70%	65%/94%	90%/90%	93%/63%	77%/71%	77%/97%	100%/90%	97%/97%	80%/81%
Donau-Iller	43%/57%	80%/70%	65%/94%	90%/90%	93%/63%	77%/71%	77%/97%	100%/90%	97%/97%	80%/81%
Erding	43%/36%	43%/80%	90%/71%	97%/81%	100%/73%	97%/87%	87%/90%	97%/100%	90%/94%	83%/79%
Landshut LA	32%/32%	37%/33%	74%/77%	74%/77%	100%/80%	100%/58%	90%/77%	94%/100%	97%/97%	78%/70%
Passau	75%/29%	13%/33%	87%/87%	100%/97%	97%/57%	87%/84%	77%/100%	90%/87%	90%/97%	80%/74%
Schweinfurt	54%/71%	17%/33%	90%/87%	100%/90%	100%/90%	87%/65%	77%/93%	81%/100%	84%/97%	77%/81%
Rosenheim	71%/86%	53%/70%	81%/81%	100%/100%	100%/90%	100%/71%	73%/80%	74%/81%	87%/97%	82%/84%
Bavarian Lower Mayn	75%/54%	60%/60%	81%/87%	100%/97%	100%/93%	100%/90%	57%/83%	81%/71%	97%/94%	83%/81%
Oberland	25%/25%	70%/7%	77%/65%	100%/87%	100%/63%	94%/68%	73%/87%	84%/100%	87%/68%	79%/63%
Straubing	57%/61%	47%/80%	94%/90%	100%/84%	90%/67%	77%/81%	83%/73%	94%/87%	100%/100%	82%/80%
Bamberg-Forchheim	61%/68%	83%/100%	100%/100%	100%/94%	80%/100%	100%/87%	70%/97%	87%/87%	90%/100%	86%/92%
Ansbach	64%/61%	53%/60%	84%/81%	100%/94%	100%/97%	100%/87%	87%/87%	71%/94%	81%/87%	82%/83%
Amberg	57%/57%	83%/93%	68%/100%	100%/100%	100%/100%	97%/61%	83%/87%	77%/100%	68%/100%	81%/89%
Middle Franconia South	57%/71%	83%/90%	94%/100%	100%/97%	100%/100%	100%/61%	90%/73%	68%/94%	71%/97%	85%/87%
Coburg	54%/57%	77%/90%	68%/71%	100%/94%	100%/100%	97%/97%	70%/60%	81%/94%	81%/100%	81%/85%
Bayreuth Kulmbach	93%/57%	77%/90%	94%/100%	100%/100%	100%/93%	100%/65%	97%/50%	74%/90%	77%/100%	90%/83%
High Franconia	61%/75%	100%/100%	90%/90%	100%/94%	100%/93%	100%/74%	87%/80%	61%/100%	68%/100%	85%/90%
Northern Upper Palatinate	36%/32%	30%/40%	94%/90%	100%/90%	100%/97%	94%/74%	83%/40%	81%/87%	97%/100%	79%/72%
Mean over all areas	60%/60%	58%/64%	84%/87%	94%/90%	97%/85%	92%/76%	78%/83%	87%/93%	89%/97%	

Note. Data values are presented as the coverage rate in the ICU/coverage rate in regular wards.

forecasts over the nine-month forecasting period, coverage rates of more than 95% were achieved for the Free State of Bavaria and a single maximum-care hospital. The governmental agencies used our forecasts as decision support to set up different minimum targets for reserved COVID-19 beds and to impose and/or lift restrictions for the public to manage the infection numbers on a STATE level. Every ambulance district in the Free State of Bavaria received the weekly forecasts on a REGION level to determine the necessity of resource pooling when capacity shortages were likely. On a LOCAL level, reliable information regarding the bed occupancy of COVID-19–related ICU and ward cases within the next days facilitates the hospital planning and scheduling.

One of the key drivers for the success of the project was the effective generation of stakeholder buy-in. Without proper stakeholder buy-in, it is generally not possible to create sustainable value from a project such as ours (Scheinker and Brandeau 2020). We certainly benefitted from the existence of previous collaborations between the different stakeholders in our project. This allowed us to use established channels of communication and receive prompt and detailed information from the healthcare providers to increase the quality of our forecasts. In turn, we analyzed the usefulness of the shared input parameters and provided feedback on the value of collecting and sharing additional pandemic-related parameters, which might not have been considered by the healthcare providers in the first run. The data collection process turned out to be one of the most challenging aspects of this project. Especially at the beginning of the pandemic, hospitals and governmental decision makers did not immediately realize the need to collect or provide detailed patient-related data. Whereas on a LOCAL level, there exists sufficient access to most of the patient-related data, that was not the case for the REGION or STATE level. In our project, we missed detailed regional LOS data as well as the number of daily admissions and discharges. Age-related data have not been made available to this day. As various research studies show, there are differences in the case fatality rate for different age groups (Kang and Jung 2020). The data provided by the Bavarian government were nevertheless sufficient to perform relatively adequate forecasts, but regional and national governments should seek to establish databases containing (anonymous) patient-related data, admissions and discharges, and bed and personnel capacity. Moreover, these databases should best be connected to the hospital patient management software systems to operate automatically and be kept up-to-date in real time, as we experienced data quality issues and delays in updates resulting from manual data entry.

The swift setup of the framework and the immediately achieved high forecasting accuracy levels helped the Bavarian government to prepare for upcoming pandemic waves starting in the second half of 2020. As a result, the Free State of Bavaria was the first state to share statewide forecasts with its healthcare providers by many months.

As a next step, it is already planned to use the forecasting framework in other federal states in Germany and other individual hospitals. Moreover, collaborations with researchers from other institutions have been ongoing to refine the forecasting methodology. Finally, these tools should be used after the COVID-19 pandemic for non–pandemic-related bed occupancy forecasts to offer decision support to the stakeholders.

Acknowledgments
The authors acknowledge the support of their graduate assistants who helped in the implementation and in the operation process of the forecasting framework. In particular, the authors thank Jennifer Anders, Marie Freitag, Ramona Frey, Milena Grieger, Patricia Heinz, Tobias Huf, Anna Pfahler, Markus Schüller, Elion Shala, Karina Sindermann, and Amelie Weresch.

Appendix. Mathematical Formulation
In this section, the mathematical formulation used by the AFRM is explained in more detail. A process flow of how input parameters are transferred into the simulation model is shown in Figure A.1.

A.1. Mathematical Notation in the Data Input and Data Analysis Module
When receiving multiple cumulated infection numbers for τ days, the basic polynomial structure with dimension τ is shown in Equation (A.1). Hereby, n is the degree of the polynomial for the vector of an independent variable x_τ defined as a continuous natural number within a time series, c represents the set of coefficients for each polynomial degree, and ϵ represents an unobserved random error value.

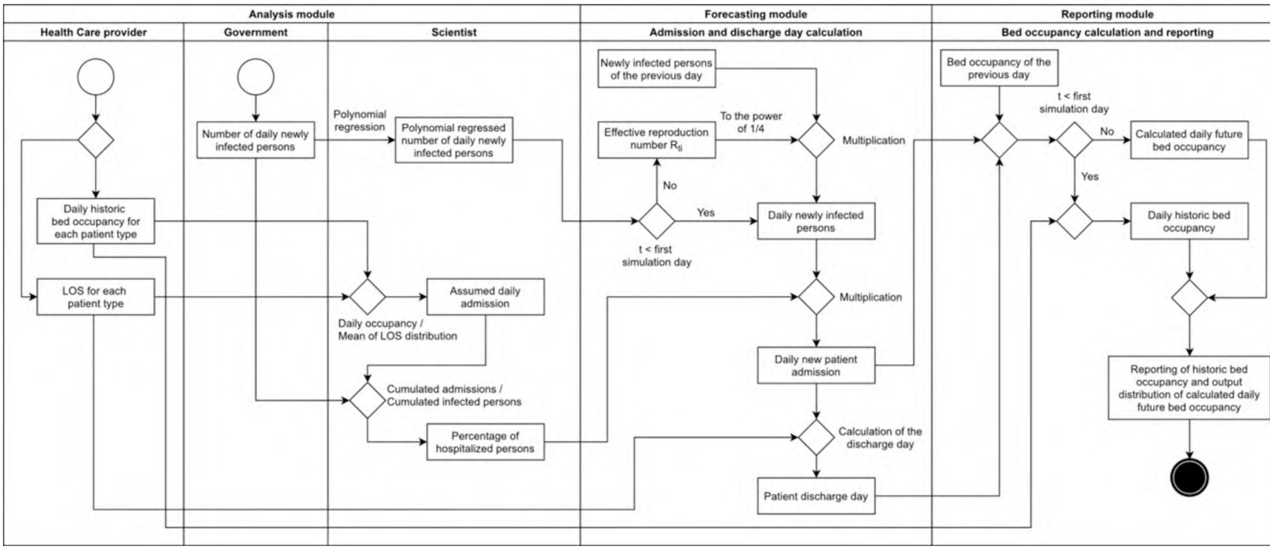
$$y_\tau = c_0 + c_1 x_\tau + c_2 x_\tau^2 + \ldots + c_n x_\tau^n + \epsilon_\tau \tag{A.1}$$

Equation (A.2) presents the polynomial equation expressed in matrix form.

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_\tau \end{bmatrix} = \begin{bmatrix} 1 & x_1 & x_1^2 & \cdots & x_1^n \\ 1 & x_2 & x_2^2 & \cdots & x_2^n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_\tau & x_\tau^2 & \cdots & x_\tau^n \end{bmatrix} \begin{bmatrix} c_0 \\ c_1 \\ \vdots \\ c_n \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_\tau \end{bmatrix} \tag{A.2}$$

The calculation of the reproduction number R_{ti} value is based on An der Heiden and Hamouda (2020) and shown in Equation (A.3). Based on the early experience of the pandemic, the RKI uses a doubling time with a mean of four days. Therefore, the R value is the quotient of the sum of newly infected persons of the latest four days and the sum of newly infected persons of the previous four days (An der Heiden and Hamouda 2020).

Figure A.1. Process Flow of the AFRM



The value $\eta_{\tau i}$ represents the number of newly infected persons for each geographical level $i \in I$, where I is a set of all geographical levels, and on a specific day $\tau \in T$, where T is a set of historic days. Furthermore, $t = \max\{T\}$.

$$R_{ti} = \frac{\sum_{\tau=t-3}^{\tau=t-0} \eta_{\tau i}}{\sum_{\tau=t-7}^{\tau=t-4} \eta_{\tau i}} \quad \forall \, \mathrm{i} \in I \tag{A.3}$$

Regarding the new calculation of the $\tilde{R}_{ti}$ values based on the polynomial regression of the infection numbers, Equation (A.3) changes to the form in Equation (A.4) with the condition of Equation (A.5). The dependent variable $y_{\tau i}$ represents the regressed cumulated number of infected persons after τ days, for geographical level i, and the updated parameter $\tilde{\eta}_{\tau i}$ represents the regressed number of newly infected persons on a specific day τ, for geographical level i.

$$\tilde{R}_{ti} = \frac{\sum_{\tau=t-3}^{\tau=t-0} \tilde{\eta}_{\tau i}}{\sum_{\tau=t-7}^{\tau=t-4} \tilde{\eta}_{\tau i}} \quad \forall \, \mathrm{i} \in I \tag{A.4}$$

$$\tilde{\eta}_{\tau i} = y_{\tau i} - y_{(\tau-1)i} \;\; \tau \in T \backslash \{0\}, i \in I \tag{A.5}$$

To receive a historical ratio of hospitalized persons out of the number of newly infected persons, we compare the daily admissions and the number of newly infected persons. Because the healthcare providers only offer bed occupancy, the assumed daily admissions have to be determined. This parameter $\lambda_{\tau si}$, in which τ represents a specific day and $s \in S$ represents a patient type—whereas S is a set of the patient types ICU or ward, confirmed or suspected case, and i a specific geographical level—is shown in Equation (A.6). It is calculated using the daily presented bed occupancy $\zeta_{\tau si}$ for each day τ, for each patient type s, and for each geographical level i divided by the mean of a sample size of the LOS $\overline{\omega}_s$ for each patient type s.

$$\lambda_{\tau si} = \frac{\zeta_{\tau si}}{\overline{\omega}_s} \;\; \forall \, \tau \in T, \, s \in S, \, i \in I \tag{A.6}$$

The formulation in Equation (A.7) provides the ratio of persons that have to be hospitalized ρ_{si} for each patient type s, in each geographical level i, comparing the number of newly infected persons with the number of assumed daily admissions within a time horizon of d days, and t represents the latest historical day.

$$\rho_{si} = \frac{\sum_{\tau=t-d}^{t} \lambda_{\tau si}}{\sum_{\tau=t-d}^{t} \eta_{\tau i}} \quad \forall \, \mathrm{s} \in S, \, i \in I \tag{A.7}$$

A.2. Mathematical Notation in the Forecasting Module

In the considered time horizon within the forecasting module, $\tilde{\eta}_{\tau i}$ is calculated differently depending on the time slot. If $\tau \leq t$, the values that were already calculated within the first module and presented in Equation (A.5) are passed to the forecasting module. Otherwise, the numbers of newly infected persons are calculated as shown in Equation (A.8). The calculated $\tilde{R}_{ti}$ value provides the factor of newly infected persons within the assumed doubling time of four days (An der Heiden and Hamouda 2020).

The nth root of $\tilde{R}_{ti}$, where n represents the doubling time, is multiplied with the latest number of newly infected persons to reach the number of newly infected persons in the next four days. This is common when dealing with quarterly interest rates, for example. This leads to an approximation of the correct $\tilde{R}_{ti}$ value after eight days.

$$\tilde{\eta}_{(t+j)i} = \tilde{\eta}_{(t+j-1)i} \cdot \tilde{R}_{ti}^{\frac{1}{4}} \;\; \forall \, 1 \leq j \leq 7, \, i \in I \tag{A.8}$$

In the forecasting module, the daily number of admitted patients $\tilde{\lambda}_{\tau i}$ can be calculated using Equation (A.9) with $\tau \in \tilde{T}$ and $T \subset \tilde{T}$ including historic and forecast days.

$$\tilde{\lambda}_{\tau si} = \tilde{\eta}_{\tau i} \cdot \rho_{si} \quad \forall \tau \in \tilde{T},\ s \in S,\ i \in I \tag{A.9}$$

Furthermore, the number of discharged patients on day $\delta_{\tau si}$ for each day τ, each patient type s, and each geographical level i can be calculated as shown in Equation (A.10), adding a certain LOS ω_s to the day τ of the number of admitted patients on a day τ, for each patient type s and for each geographical level i.

$$\delta_{(\tau+\omega_s)si} = \tilde{\lambda}_{\tau si} \quad \forall \tau \in \tilde{T},\ s \in S,\ i \in I \tag{A.10}$$

The calculated daily bed occupancy $\tilde{\zeta}_{\tau si}$ is presented in Equation (A.11).

$$\tilde{\zeta}_{\tau si} = \tilde{\zeta}_{(\tau-1)si} + \tilde{\lambda}_{\tau si} - \delta_{\tau si} \quad \forall \tau \in \tilde{T},\ s \in S,\ i \in I \tag{A.11}$$

On the first forecasting day $\tau = (t+1)$, the predicted bed occupancy is calculated slightly differently. Hereby, the latest historical bed occupancy ζ_{tsi} is considered rather than the calculated bed occupancy of the previous day $\tilde{\zeta}_{(\tau-1)si}$. More specifically, the calculation is shown in Equation (A.12).

$$\tilde{\zeta}_{\tau si} = \zeta_{tsi} + \tilde{\lambda}_{\tau si} - \delta_{\tau si}, \quad \forall s \in S,\ i \in I \tag{A.12}$$

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Verification Letter

Klaus Holetschek, Member of the Bavarian State Parliament, State Minister for Health and Care, Haidenauplatz 1, 81667 München, writes:

"I sincerely thank you and your fellow workers for the production of the load forecasts for the Bavarian hospitals within the framework of the Corona pandemic. You have tackled the problem vigorously at the decisive moment and provided foundations for assessments of the position and decisions for months ahead with these forecasts. In this way, you have made an important contribution to coping with the first two waves of the pandemic in Bavaria. Above all, I thank you for the fact that you and your team not only did the conceptional work but also invested numerous working hours in the actual production of the reports."

Jakob Heins is a research assistant and PhD student at the Chair of Healthcare Operations/Health Information Management at the University of Augsburg and the Department of Anesthesiology and Surgical Intensive Care Medicine. He received his BS in business information systems, MS in business administration (both at the University of Augsburg), and an MBA from the University of Dayton. His research is focused on optimization and decision support in the hospital.

Jan Schoenfelder is a postdoctoral researcher at the Chair of Healthcare Operations/Health Information Management at the University of Augsburg. He received his PhD in decision sciences and operations management from the Kelley School of Business at Indiana University. His research addresses operations and employee management in hospitals.

Steffen Heider is a research assistant and PhD student at the Chair of Healthcare Operations/Health Information Management at the University of Augsburg. He received his BS in business systems, MS in business administration (both at the University of Augsburg), and an MBA from the University of Dayton. His current research is focused on intensive care unit utilization in the hospital.

Axel R. Heller is chair of the Department of Anesthesiology and Surgical Intensive Care Medicine at the Medical Faculty of Augsburg University. As leading physician, he was part of the disaster response of north Swabia during the COVID pandemic. Until 2018, he held a professorship for emergency medicine at the Technical University of Dresden and was head of the University Simulation Center. His multiprofessional research group designs and implements improvements to the quality of care.

Jens O. Brunner has been permanently appointed as full professor of Healthcare Operations/Health Information Management at the Faculty of Business and Economics at the University of Augsburg. He received a PhD from the TUM School of Management in 2009 and a diploma degree in business administration from the University of Mannheim in 2006. His research interests center on design and analysis of service systems using quantitative methods. A special focus is on processes in healthcare.