Optimization and Adaptation of a Resource Planning Tool for Hospitals Under Special Consideration of the COVID-19 Pandemic

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***Abstract*—Hospitals and health-care institutions need to plan the resources required for handling the increased load, i.e., beds and ventilators during the COVID-19 pandemic. BaBSim.Hospital, an open-source tool for capacity planning based on discrete event simulation, was developed over the last year to support doctors, administrations, health authorities, and crisis teams in Germany. To obtain reliable results, 29 simulation parameters such as durations and probabilities must be specified. While reasonable default values were obtained in detailed discussions with medical professionals, the parameters have to be regularly and automatically optimized based on current data.**

We investigate how a set of parameters that is tailored to the German health system can be transferred to other regions. Therefore, we use data from the UK. Our study demonstrates the flexibility of the discrete event simulation approach. However, transferring the optimal German parameter settings to the UK situation does not work—parameter ranges must be modified. The adaptation has been shown to reduce simulation error by nearly 70%. The simulation-via-optimization approach is not restricted to health-care institutions, it is applicable to many other real-world problems, e.g., the development of new elevator systems to cover the last mile or simulation of student flow in academic study periods.

***Index Terms*—optimization-via-simulation, surrogate-model-based optimization, COVID-19, hospital resource planning, prediction tool, capacity planning**

I. Introduction

BaBSim.Hospital is an open-source resource-planning tool for hospitals that considers problems caused by the Coronavirus disease 2019 (COVID-19) pandemic. It provides many advantages for crisis teams, e.g., comparison with their own local planning, simulation of local events, simulation of several scenarios (worst / best case). There are benefits for medical professionals, e.g, analysis of the pandemic at local, regional, state and federal level, the consideration of special risk groups, tools for validating the length of stays and transition probabilities. Finally, there are potential advantages for administration, management, e.g., assessment of the situation of individual hospitals taking local events into account, consideration of relevant resources such as beds, ventilators, rooms, protective clothing, and personnel planning, e.g., medical and nursing staff.

Discrete Event Simulation (DES) models are valuable tools for resource usage estimation and capacity planning [1]. They are used to model the hospital resource planning problem. BaBSim.Hospital simulates the path of many thousands or possibly even millions of patient trajectories through hospitals. This simulation requires considerable computational resources. Therefore, a very efficient simulator is necessary, because only a limited number of simulations can be performed in a reasonable time frame. We have chosen “Discrete-Event Simulation for R” (simmer), a DES package which enables high-level process-oriented modeling [2]. The code required for running the simulations is published as an open-source R-Package [3], [4].

The DES software simmer is based on the concept of a trajectory (common path in the simulation model for entities of the same type) and takes available hospital data into account. It offers a means to simulate the progression of the pandemic in terms of available and occupied hospital resources and capacity. The modeling approach is inspired by Lawton and McCooe [5] and is enhanced by an Surrogate Model-Based Optimization (SMBO) approach [6], i.e., our system combines two powerful approaches:

Discrete event simulation: the ’simmer’ R-package is used to generate a simulation with 29 parameters with default values, established in cooperation with medical professionals [2]. These parameters are essential for the accuracy of the simulation and require careful optimization. Although domain knowledge, i.e., from medical

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professionals, provides valuable information to perform realistic simulations, further fine-tuning is required.

Model-based optimization: the Sequential Parameter Optimization Toolbox (SPOT) R-package is used to perform SMBO to identify the best values for the 29 parameters in a fast and accurate manner, which results in an optimization-via-simulation approach [7].

However, the relatively large number of parameters limits the quality of the optimization process.

The BaBSim.Hospital tool has been online for several months[1]. This article reports the experiences that were collected during this period and provides answers to the following questions:

(Q-1) How to extend the interface that enables usage of data, independently of the German DIVI and RKI data sets?

(Q-2) How to integrate domain knowledge and how to adapt a complex simulation model to a new environment?

We illustrate how this model, that was based on data from Germany, can be transferred to other regions, especially to the UK.

The rest of this paper is structured as follows: Section II discusses the available data and its preparation, Section III introduces the BaBSim.Hospital simulator and Section IV describes the corresponding optimization problem. Section V describes how domain knowledge can be used to adapt the search boundaries. Specifically, we will discuss the different availability of ventilated Intensive Care Unit (ICU) bed in Germany and in the UK. After presenting simulation results from optimization runs in Section VI, the findings of this study are discussed in Section VII.

II. Automated Data Collection and Curation

The BaBSim.Hospital simulator models resources usage in hospitals, e.g., number of ICU beds (y), as a function of the number of infected individuals (x). In addition to the number of infections, information about age and gender can be used as simulation input. Extract, Transform, and Load (ETL) processes integrate data from various sources into complex collections [8]. After the successful extraction of data, the next step is to transform it. This step includes several approaches to gain accurate data which is correct, complete, consistent, and unambiguous. The final step consists of loading the processed data into a data collection of choice accessible for the data analyst for further use. Especially in terms of the COVID-19 pandemic, it is important to integrate and process the vast amount of constantly growing data.

1) Germany: The online version of the BaBSim.Hospital simulator implements an ETL process to analyze the data from the Robert Koch Institut (RKI), https://www.rki.de, as well as the Deutsche interdisziplinäre Vereinigung für Intensiv- und Notfallmedizin (DIVI), https://www.divi.de. The associated data sets contain anonymous information about every recorded case in Germany. The RKI data set contains 780,065 observations of 18 variables such as age, gender, data of infection, etc., which were updated daily and are automatically integrated into BaBSim.Hospital. Information concerning ICU in Germany can be retrieved from the DIVI. DIVI provides an API and a daily report. The official simulator, which can be accessed via https://www.th-koeln.de/babsimhospital, uses DIVI and RKI data. Its parameters are based on discussions with experts from Germany, especially ICU doctors and experts from health administration. The online version is described in Section III-B.

2) UK: This paper describes an extension of the interface that enables usage of data independently of DIVI and RKI data, i.e., an interface to Comma-separated Value (CSV) files and Excel files can be used so that any kind of field and simulation data can be processed, simulated, and optimized. To exemplify our approach, anonymized data from a region in the UK was used. The data was read from an Excel file, which has the following entries (columns):

- date
- bed: total number of patients in hospital with COVID-19 (includes ICU)
- intensiveBed: number of patients on non-invasive ventilators (CPAP). In normal circumstances they would be on ICU or equivalent but in the UK this has not always been possible.
- intensiveBedVentilation: number of patients intubated and ventilated with COVID-19 on ICU

The field data based on UK data used three bed categories:

1) bed: non ICU patients in hospital
2) intensiveBed: ICU bed without ventilation
3) intensiveBedVentilation: ICU bed with ventilation

Fig. 2 visualizes the UK data set that is used in this study. The whole data set consists of data from 240 days. Since our analysis considers the second COVID-19 wave only, we use data after September 2020.

III. The Simulator

A. Discrete Event Simulation

BaBSim.Hospital simulates the typical paths that COVID-19 infected patients follow during their hospital stays. The DES processes every single recorded infection until the patients' recovery or death. Patients follow a trajectory, i.e., they move with a probability p_{ij} from state S_i to state S_j after a transition-specific duration d_{ij}. The respective durations and probabilities are parameters of the model. A graph can be used to model this behavior. Fig. 3 illustrates the transition probabilities and describes the states.

For example, an infected patient (state S_1) goes to the hospital (state S_2) with probability p_{12} after d_{12} days. With probability p_{17}, she recovers (state S_7) after d_{17} days. The probabilities of outgoing nodes sum to 1, e.g., $p_{17} = 1 - p_{12}$. The modeling process includes four types of parameters:

transition probabilities, e.g., the probability that an infected individual has to go to the hospital,

[1]The online version of BaBSim.Hospital can be accessed via https://covid-resource-sim.th-koeln.de/app/babsim.hospitalvis

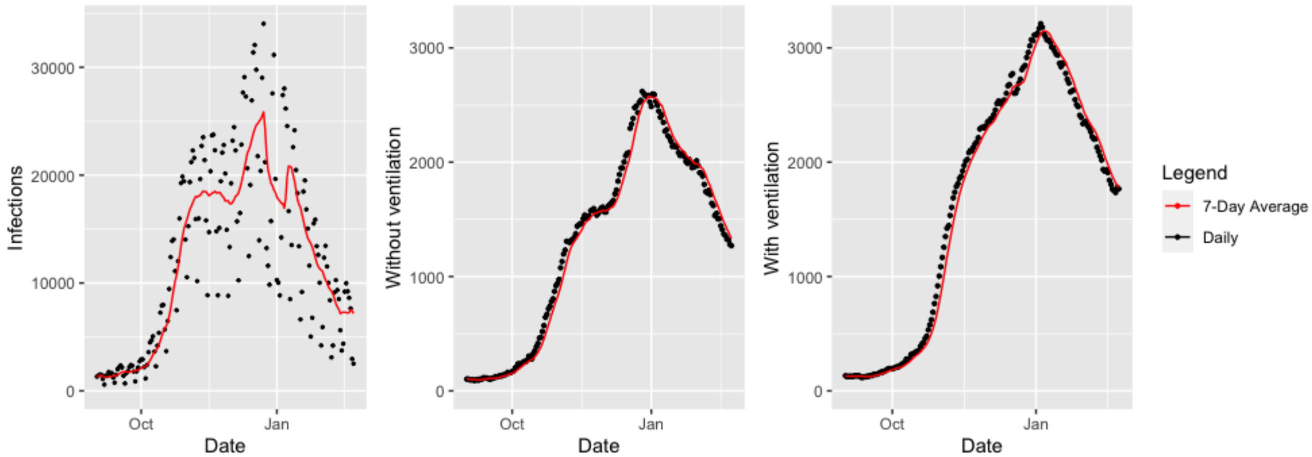

Fig. 1. Visualization of current German COVID-19 Data as used in BABSIM.HOSPITAL. From left to right: Daily new infections as published by the Robert-Koch Institute, amount of occupied intensive care beds in hospitals (without invasive ventilation), amount of intensive care beds with invasive ventilation.

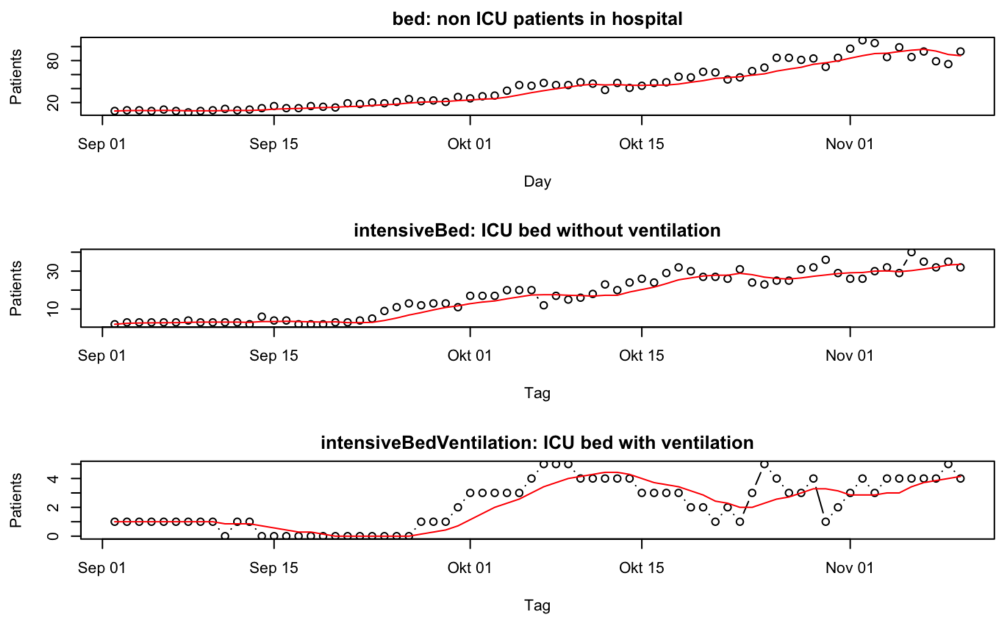

Fig. 2. UK data. Dots denote real-world data, red lines represent the seven-day average. ICU beds with ventilation are shown in the last row. The UK has far fewer ICU ventilator beds than Germany.

durations, e.g., the time span until an infected individual goes to the hospital (in days), and

distribution properties, e.g., truncated and translated gamma distribution,

risk factors depending on demographic groups, e.g., age, gender.

The online version of the BABSIM.HOSPITAL simulator uses risk information: every new patient is assigned a unique risk. Although the "risk" attribute is an important factor for the duration and severity of a COVID-19 infection, it was not considered in our study. However, it can easily be integrated in future studies. Table III-A presents an overview of the parameter ranges of the 29 parameters used in the BABSIM.HOSPITAL simulation model.

Proper tuning of these parameters is essential to obtain accurate predictions based on up-to-date and local data. The time-dependent changes require a frequent refitting of the model parameters to the current situation. Thus, a daily parameter tuning procedure is run for each German region in order to provide an accurate prediction. An initial estimate for each of the given parameters was specified in cooperation with medical professionals. For example, the rate of successful treatments in Germany drastically changed between the first and the second wave of COVID-19 infections. Also, political decisions on national and local level can affect the situation significantly. While reducing the access to nursing homes might reduce

TABLE I

DEFAULT (DE) AND ADAPTED (UK) RANGES OF THE 29 PARAMETERS. PARAMETERS THAT WERE MODIFIED FOR THE UK SETTING ARE SHOWN IN **BOLD FACE**. THE PREFIX *AmntDays** REFERS TO DURATIONS (IN DAYS), WHEREAS THE PREFIX *FactorPatients** REFERS TO PROPORTIONS/PROBABILITIES. THE COLUMN *default* SHOWS RECOMMENDATIONS FROM EXPERTS IN GERMANY, *minUK* AND *maxUK* DENOTE ADAPTED RANGES FROM THE UK, AND *minDE* AND *maxDE* REPRESENT THE PARAMETER RANGES FROM GERMANY.

Variable	Name	default	minUK	maxUK	minDE	MaxDE
x_1	AmntDaysInfectedToHospital	9.5	6	14	6	14
x_2	AmntDaysNormalToHealthy	10	7	13	7	13
x_3	AmntDaysNormalToIntensive	5	3	7	3	7
x_4	AmntDaysNormalToVentilation	3.6	3	9	3	9
x_5	AmntDaysNormalToDeath	5	3	7	3	7
$\mathbf{x_6}$	**AmntDaysIntensiveToAftercare**	$\mathbf{7}$	$\mathbf{10}$	$\mathbf{18}$	$\mathbf{5}$	$\mathbf{9}$
$\mathbf{x_7}$	**AmntDaysIntensiveToVentilation**	$\mathbf{4}$	$\mathbf{6}$	$\mathbf{10}$	$\mathbf{3}$	$\mathbf{5}$
$\mathbf{x_8}$	**AmntDaysIntensiveToDeath**	$\mathbf{5}$	$\mathbf{6}$	$\mathbf{14}$	$\mathbf{3}$	$\mathbf{7}$
x_9	AmntDaysVentilationToIntensiveAfter	30	25	35	25	35
x_{10}	AmntDaysVentilationToDeath	20	17	25	17	25
x_{11}	AmntDaysIntensiveAfterToAftercare	3	2	5	2	5
x_{12}	AmntDaysIntensiveAfterToDeath	4	1	7	1	7
x_{13}	GammaShapeParameter	1	0.25	2	0.25	2
x_{14}	FactorPatientsInfectedToHospital	0.1	0.05	0.15	0.05	0.15
x_{15}	FactorPatientsHospitalToIntensive	0.09	0.07	0.11	0.07	0.11
$\mathbf{x_{16}}$	**FactorPatientsHospitalToVentilation**	$\mathbf{0.01}$	$\mathbf{0.001}$	$\mathbf{0.004}$	$\mathbf{0.005}$	$\mathbf{0.02}$
x_{17}	FactorPatientsNormalToIntensive	0.1	0.07	0.13	0.07	0.13
$\mathbf{x_{18}}$	**FactorPatientsNormalToVentilation**	$\mathbf{0.001}$	$\mathbf{2e-05}$	$\mathbf{0.0004}$	$\mathbf{0.0001}$	$\mathbf{0.002}$
x_{19}	FactorPatientsNormalToDeath	0.1	0.08	0.12	0.08	0.12
$\mathbf{x_{20}}$	**FactorPatientsIntensiveToVentilation**	$\mathbf{0.3}$	$\mathbf{0.05}$	$\mathbf{0.07}$	$\mathbf{0.25}$	$\mathbf{0.35}$
x_{21}	FactorPatientsIntensiveToDeath	0.1	0.08	0.12	0.08	0.12
x_{22}	FactorPatientsVentilationToIntensiveAfter	0.7	0.5	0.9	0.5	0.9
x_{23}	FactorPatientsIntensiveAfterToDeath	1e-05	1e-06	0.01	1e-06	0.01
x_{24}	AmntDaysAftercareToHealthy	3	2	4	2	4
x_{25}	RiskFactorA	0.02	1e-06	1.1	1e-06	1.1
x_{26}	RiskFactorB	0.01	1e-06	0.062	1e-06	0.062
x_{27}	RiskMale	1.5	1	2	1	2
x_{28}	AmntDaysIntensiveAfterToHealthy	3	2	5	2	5
x_{29}	FactorPatientsIntensiveAfterToHealthy	0.67	0.5	0.75	0.5	0.75

infections in the high risk parts of the population, opening schools might cause many infections in the younger parts of the population. The optimization problem can be stated as follows: the BABSIM.HOSPITAL simulator requires two input parameters (vectors), $\vec{x}_t$, the model parameters, and $\vec{u}_t$, the number of infections. Based on these two inputs, BABSIM.HOSPITAL estimates the required resources—in our case, the beds, ICU beds, and ICU beds with ventilators. The simulation output, i.e, the required resources on each day t will be denoted as $\hat{\vec{y}}_t$, i.e.,

$$\hat{y}_t = \left(\hat{R}_{\text{bed}}(t), \hat{R}_{\text{icu}}(t), \hat{R}_{\text{vent}}(t)\right) \tag{1}$$

The DES delivers valid results and enables predictions, which are valuable for capacity planning in hospitals. The simmer software presents a good basis for implementation and was able to handle more than half a million data (infections) under very limited time constraints.

B. The Online-Version

An online version of BABSIM.HOSPITAL, which includes a graphical user interface, makes the simulator available and accessible to the public, see https://covid-resource-sim.th-koeln.de/app/babsim.hospitalvis. Fig. 4 shows a screenshot of this application.

BABSIM.HOSPITAL is open source. It is programmed in the R programming language and freely available, see [4]. The online-version is running fully automatically for several months. It allows processing the RKI data set, which consists of more than 750,000 observations of 18 variables, which are updated daily and are automatically integrated into BABSIM.HOSPITAL simulator. The Continuous Integration / Continuous Deployment (CI/CD) approach minimizes human interaction, so that simulations and optimizations are started automatically after the data is downloaded.

IV. OPTIMIZATION

Based on the simulation results, optimization runs can be performed to improve parameter settings proposed by the experts. The Root Mean Squared Error (RMSE) as shown in Eq. 2, is used to measure the error of the simulator. We formulate the *minimization* problem:

$$\min \sum_{k \in \{\text{bed,icu,vent}\}} w_k \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(R_k(t) - \hat{R}_k(t)\right)^2} \tag{2}$$

Here, T denotes the number of days simulated and k the three different bed categories. Since the different bed types are not equally important a weighted average of the RMSE for each bed category is used as the final error measure. A detailed description can be found in [9].

The extensive amount of data that the tool has to process combined with the high dimension of the problem, and the required accuracy make simplifying the modeling process

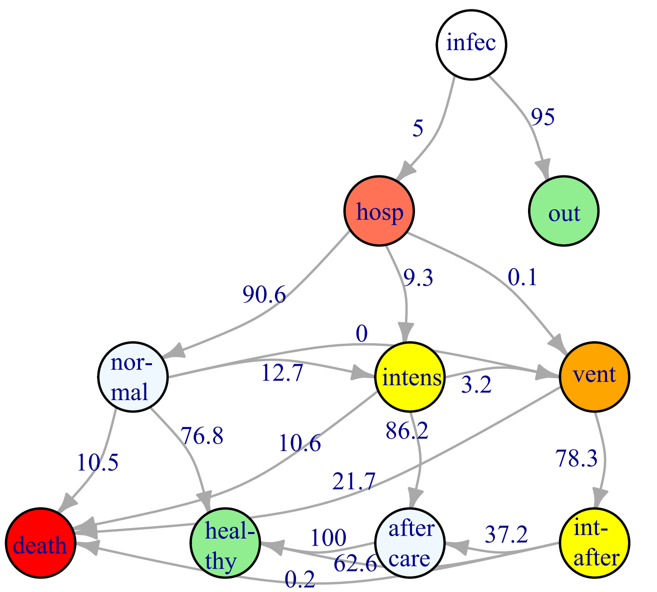

Fig. 3. Full model of patient flows in a hospital. Nodes represent states (S_i). Edges represent state changes with associated probabilities (p_{ij}). The nodes are labeled as follows: *Infec:* Number of people tested positive for Covid-19, published by RKI, *out:* Infected people not hospitalized, *hosp:* Hospitalized infected people, *normal:* Isolation ward, *intens:* Intensive care ward without invasive ventilation, *vent:* Intensive care ward with invasive ventilation, *intafter:* Intensive aftercare ward without invasive ventilation, *aftercare:* Aftercare isolation ward, *healthy:* Discharged as recovered, and *death:* Deceased. This graph shows the core of BABSIM.HOSPITAL. This sets BABSIM.HOSPITAL apart from other simulators. It enables a detailed analysis of the underlying events. Upon request, it can be adapted to the individual circumstances of interested parties.

to improve performance a big challenge. The limited time available for each optimization run requires the use of efficient algorithms.

The following state-of-the-art optimization approaches were considered:

- stand-alone, standard optimization algorithms, e.g., BOBYQA [10], CMA-ES [11], Simulated Annealing [12],
- response surface methodology and surrogate model-based optimizers [13],
- parallelized combinations of global with local optimizers [14],
- massively parallel single-iteration optimizers [15], [16], and
- SMBO approaches [17].

First, the applicability of these different approaches was tested. Pre-experimental results revealed that only SMBO approaches produced good results. Therefore, we decided to use SMBO, based on the implementation in SPOT [18], [19]. Specifically, we selected a configuration of SPOT that proceeds as follows.

- SPOT starts with generating and evaluating a set of initial solutions via a space filling design (here: Latin hypercube design [20]).
- Then, a surrogate model is trained with the generated data. Here, a Gaussian process regression model is trained [6]. The hyperparameters of the model are determined with maximum likelihood estimation, using a search strategy from Evolutionary Computation (EC), specifically, Differential Evolution [21].
- Next, SPOT determines the candidate solution with most promising performance according to the surrogate model. This constrained global search is performed with another EC-Technique: the Improved Stochastic Ranking Evolution Strategy (ISRES). The constraints are identical to those of the actual simulator (BABSIM.HOSPITAL), e.g., the parameters that represent probabilities of leaving the same state have to sum up to one.
- The determined candidate solution is evaluated with the actual, expensive simulation.
- After this SMBO step, a model-free search is employed to refine the found solution (i.e., the model-free search uses that solution as a starting point). Here, the same Algorithm as above (ISRES) is applied to the actual error measure of the simulator, rather than the surrogate model.

V. ADAPTATION OF THE SEARCH BOUNDARIES

The UK has markedly fewer ICU beds than Germany (6.6 per 100,000 versus 29.2 per 100,000 in 2011 [22]). Therefore, patients may be treated differently: the clinical threshold for a patient to be admitted to ICU may be higher than in Germany. We can adapt the boundaries of the search space (constraints) to reduce the probability of a patient being sent to ICU.

1) First Adaptation—Reducing Probabilities: To implement the different setting, we modified the parameter boundaries (see Table III-A) as follows: vent, i.e, the ICU with ventilation node that is colored in orange in Fig. 3) has three incoming edges: from node normal, node hosp, and node intens. By introducing a reduction factor, say $c_1 \in \mathbb{R}_+$, that simply multiplies the default probabilities of patients reaching the ICU ventilated node, we were able to redirect patients to other bed categories. Because the sum of the probabilities of the outgoing edges must be 1.0, the modification of one probability also changes the probabilities of the associated edges in the model (see Fig. 3). Choosing a value of $c_1 = 0.2$ results in improved simulation outputs, and plausibly reflects real-world differences in the provision of ICU beds in the UK compared to Germany. Please note that c_1 does not directly affect the probabilities, it modifies the search boundaries (constraints) of the optimizer.

The range of the parameter x_{16} that describes the proportion of patients that go directly to ICU with ventilation was reduced from $[0.01; 0.02]$ to $[5.0e-04; 0.004]$. In addition, the range of the parameter x_{18}, which represents the proportion of patients that go from normal beds to ICU with ventilation was reduced from $[0.1; 0.2]$ to $[0.02; 0.04]$. Furthermore, the range of parameter x_{20} that describes the proportion of patients that go from ICU to ICU with ventilation was reduced from $[0.1; 0.2]$ to $[0.02; 0.04]$.

As a consequence of the reduced search intervals of x_{16}, x_{18}, and x_{20}, simulation results of the ventilated ICU beds were significantly improved.: the numerical RMSE goes down

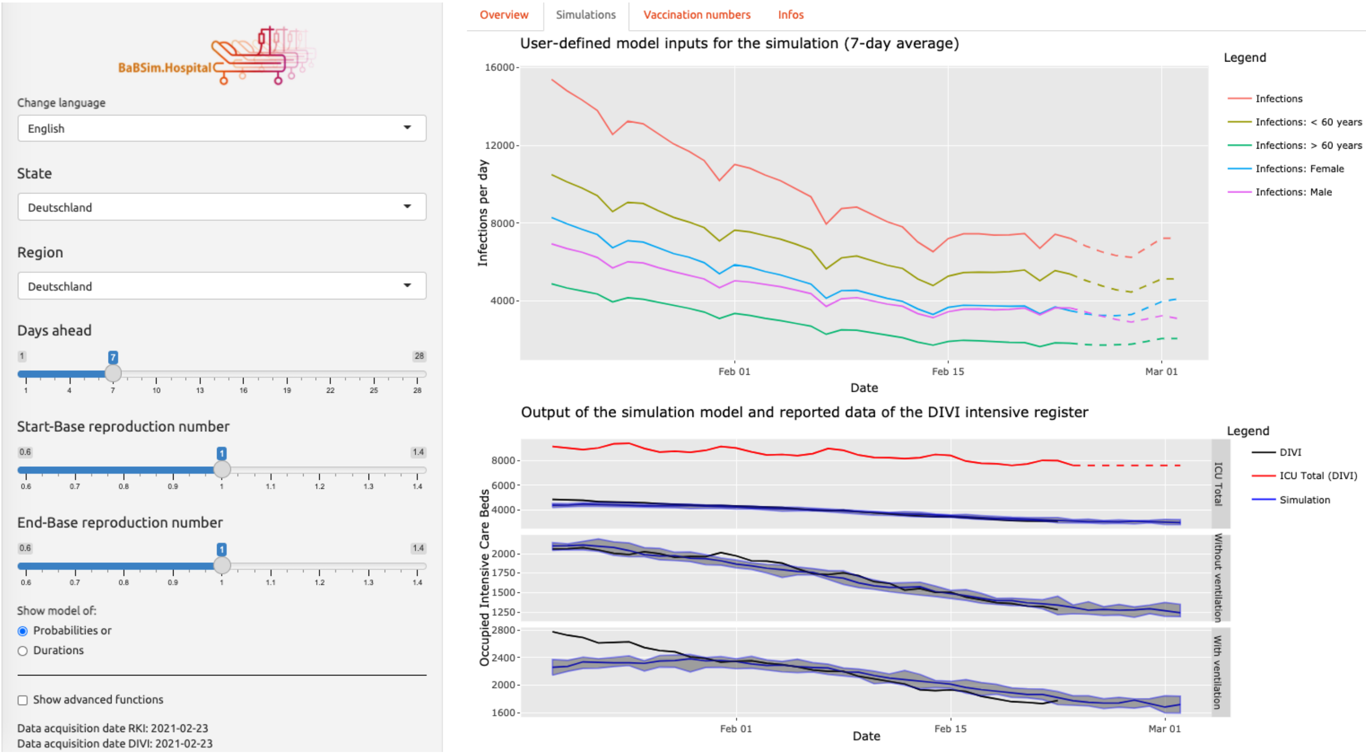

Fig. 4. Online version. Users are able to select different countries and regions to simulate for, as well as some very general configurations (time window for the simulation, assumptions about the virus' reproduction factors, as well as some choices of different visualizations).

from 184.10 to 46.94. This improvement is also validated by visual inspection as can be seen in the *right* panel of Fig. 5.

2) Second Adaptation—Increasing Durations: However, even if the ventilated ICU bed usage was improved (bed category III), the simulation of the second bed category is not satisfying. We underestimate the number of ICU beds. This may be a result of the higher UK threshold for ICU admission meaning that the average UK ICU patient is more unwell than the average ICU patient in Germany. To fix this problem, we modified the duration of patients in ICU beds: the search intervals of these parameters were increased. Therefore, a second factor, say $c_2 \in \mathbb{R}_+$ was introduced to multiply the corresponding durations. A value of $c_2 = 2.0$ was chosen for our experiments. The range of the parameter x_6 that represents the number of days patients stay at ICU with ventilation before they go to intensive aftercare was increased from $[5; 9]$ to $[10; 18]$ days. The range of the parameter x_7 that defines the number of days before ICU patients go to ICU with ventilation was increased from $[3; 5]$ to $[6; 10]$ days. Finally, the interval of the parameter x_8, which specifies the number of days patients stay at ICU before they die, was increased from $[3; 7]$ to $[6; 14]$ days.

VI. Results

The adaptation of the parameter bounds based on domain knowledge results in a significant reduction of the RMSE, which was defined in Eq. 2. Using the default BABSIM.HOSPITAL parameter boundaries, which were based on the situation in Germany, the simulation error is $\epsilon_0 = 184.10$. The first adaptation, which reduces the percentage of patients treated in ICU beds with ventilation, results in a simulation error $\epsilon_1 = 46.94$, whereas the second adaption, which increases the time patients spend in an ICU bed results in a further reduction of the simulation error to $\epsilon_2 = 29.0$. In summary, the adaptation has been shown to reduce simulation errors by nearly 70%. Figures 5 and 6 clearly visualize the improvements.

VII. Discussion and Outlook

The BABSIM.HOSPITAL simulator, an open-source tool for capacity planning based on discrete event simulation, was developed over the last year to support doctors, administrations, health authorities, and crisis teams in Germany. The high dimension and computational expense of the BABSIM.HOSPITAL simulator poses a challenging optimization task. Solving this task for many regions in Germany under very different local circumstances requires efficient solutions to cope with the further growing infection numbers and thus also growing simulation run times. A SMBO approach delivers stable and valid results for every state and region in Germany.

Estimating the effort of transferring the simulator to different regions is of great interest. Based on data from the UK, we demonstrated that an adaption of the search ranges (bound constraints) of the associated optimizer leads to satisfactory results.

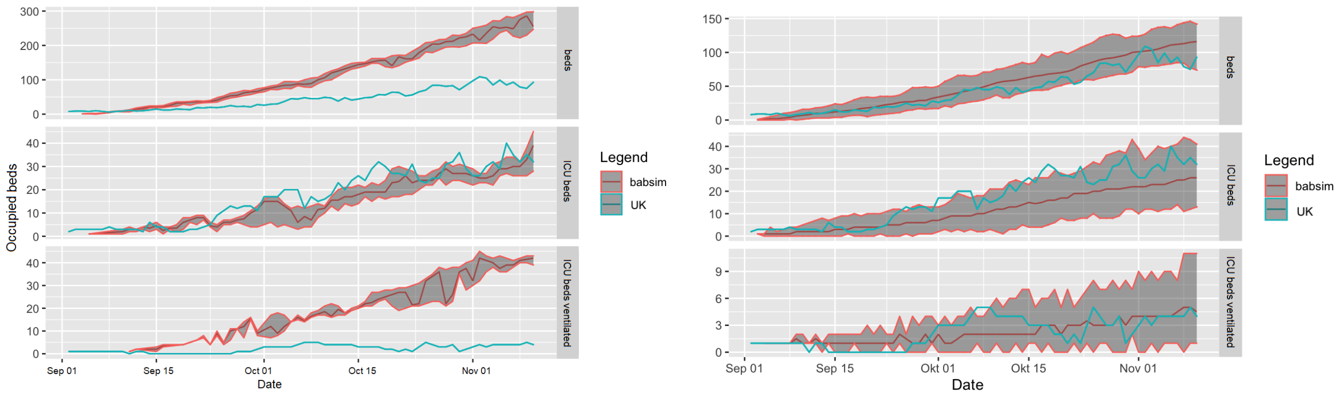

Fig. 5. *Left:* Real data compared to results from the BABSIM.HOSPITAL simulation with default parameters. Large residuals (errors), especially for normal bed and ICU beds with ventilation can be observed. BABSIM.HOSPITAL uses default parameter sets. These are based on domain knowledge (recommendations from doctors) from Germany. *Right:* Real data compared to results from the BABSIM.HOSPITAL simulation with optimized parameters. The c_1 value was set to 0.2. Considering the regular ICU beds (category II) there is still a difference between the real data from the UK and the simulated data. Therefore, a second adaption was necessary.

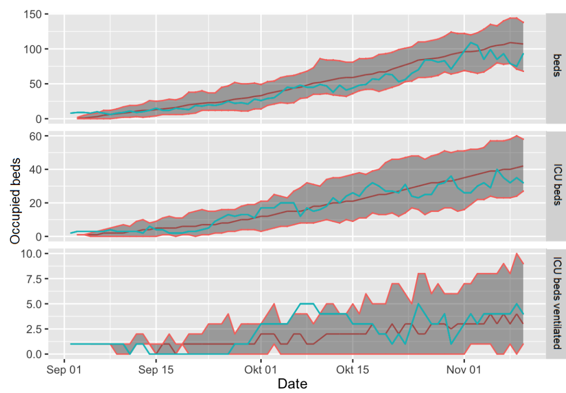

Fig. 6. Real data compared to results from the BABSIM.HOSPITAL simulation with optimized parameters. The comparison with the results from Fig. 5 shows a significant improvement. Residuals are much smaller, because the simulation model parameters were adapted to the situation in UK hospitals. Additionally, simulation results for category II beds improved.

The questions posed in Section I can be answered as follows:

(Q-1) The extended version of the BABSIM.HOSPITAL interface is able to process any input data that contains information about the date, the number of beds (this information is optional), the number of patients on non-invasive ventilation, and the number of patients intubated and ventilated. Using real-world data from the UK, we successfully demonstrated how these data can be processed by the simulator. The adaption from the German health-care system to the UK system can be achieved by changing the search ranges of the optimizer—-and not the absolute parameter values of the simulator. The modification of these ranges is much easier than the modification of specific values, because ranges are easier to specify than point values. Interestingly, the same factor as the relative number of ICU beds (c_1 was chosen as $1/5$, which reflects the difference in the number of ICU beds in the UK versus Germany [22]) was useful for the first adaptation (as even $c_1 = 1/5$ seems extreme until you know how different the two countries are!). Our study reveals that simulations with BABSIM.HOSPITAL are not restricted to the health system in Germany.

(Q-2) This study clearly demonstrates that domain knowledge is essential for obtaining reliable and valid simulation results. Especially in high dimensional search spaces, optimizers can deliver results that are mathematically optimal, but practically irrelevant. The discussion delivers important insights into the problem.

Furthermore, the BABSIM.HOSPITAL simulator can be used as an attractive simulation and optimization benchmark for EC algorithms, since it presents a challenging real world problem. Especially, it provides a benchmark problem that is very noisy, relatively high-dimensional, has several inequality constraints, and is expensive to evaluate. It is freely available as open source, and hence, easily accessible to the research community. The BABSIM.HOSPITAL simulator was respectively used as the basis of a competition at the Genetic and Evolutionary Computation Conference[2]. Moreover, this work demonstrates how DES can profit from EC methods, and vice versa. This is important, since simulation via DES is applicable in a wide variety of other real world problems (such as the control of elevators or logistics).

From the real-world applications point of view, knowing the optimizer's output in terms of number of days for each transition in the model, and their probability, is interesting to

[2]GECCO 2021 Industrial Challenge: Optimization of a simulation model for a capacity and resource planning task for hospitals under special consideration of the COVID-19 pandemic, see:
https://gecco-2021.sigevo.org/Competitions and
https://tinyurl.com/gecco2021challenge

clinicians. Plausibly it could help compare treatment strategies where hospitals have acted differently. For example, some hospitals used a lot of Continuous positive airway pressure (CPAP) but other centers used less and therefore had to move to ventilation earlier. One particular advantage of the simulator for the UK data is estimating how much spare capacity there is in hospitals for continuing elective surgery such as arranging cancer operations.

REPRODUCIBILITY

The programming code as well as the data, which was used in this study, will be published on CRAN as a vignette of the next version of the R package BABSIM.HOSPITAL, see https://CRAN.R-project.org/package=babsim.hospital.

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REFERENCES

[1] J. Banks, J. S. Carson, B. L. Nelson, and D. M. Nicol, *Discrete Event System Simulation*. Upper Saddle River NJ: Prentice Hall, 2001.

[2] I. Ucar, B. Smeets, and A. Azcorra, "simmer: Discrete-event simulation for R," *Journal of Statistical Software, Articles*, vol. 90, no. 2, pp. 1–30, 2019.

[3] T. Bartz-Beielstein, F. Rehbach, O. Mersmann, and E. Bartz, "Hospital Capacity Planning Using Discrete Event Simulation Under Special Consideration of the COVID-19 Pandemic," *arXiv e-prints*, p. arXiv:2012.07188, Dec. 2020.

[4] ——, "babsim.hospital," 12 2020. [Online]. Available: https://cran.r-project.org/package=babsim.hospital

[5] T. Lawton and M. McCooe, "Policy: A novel modelling technique to predict resource -requirements in critical care – a case study," *Future Healthcare Journal*, vol. 6, no. 1, pp. 17–20, 2019. [Online]. Available: https://www.rcpjournals.org/content/6/1/17

[6] A. Forrester, A. Sobester, and A. Keane, *Engineering Design via Surrogate Modelling*. New York, NY: Wiley, 2008.

[7] M. C. Fu, "Optimization via simulation: A review," *Annals of Operations Research*, vol. 53, no. 1, pp. 199–247, 1994.

[8] S. H. A. El-Sappagh, A. M. A. Hendawi, and A. H. El Bastawissy, "A proposed model for data warehouse etl processes," *Journal of King Saud University - Computer and Information Sciences*, vol. 23, no. 2, pp. 91 – 104, 2011. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S131915781100019X

[9] T. Bartz-Beielstein, E. Bartz, F. Rehbach, and O. Mersmann, "Optimization of High-dimensional Simulation Models Using Synthetic Data," *arXiv e-prints*, p. arXiv:2009.02781, Sep. 2020.

[10] M. J. Powell, "The BOBYQA algorithm for bound constrained optimization without derivatives," *Cambridge NA Report NA2009/06, University of Cambridge, Cambridge, Department of Applied Mathematics and Theoretical Physics*, 2009.

[11] N. Hansen, "The CMA evolution strategy: a comparing review," in *Towards a new evolutionary computation. Advances on estimation of distribution algorithms*, ser. Studies in Fuzziness and Soft Computing, J. A. Lozano, P. L. naga, I. naki Inza, and E. Bengoetxea, Eds. Springer, 2006, vol. 192, pp. 75–102.

[12] P. J. M. van Laarhoven and E. H. L. Aarts, *Simulated annealing*. Dordrecht: Springer Netherlands, 1987, pp. 7–15.

[13] R. H. Myers, D. C. Montgomery, and C. M. Anderson-Cook, *Response surface methodology: process and product optimization using designed experiments*. John Wiley & Sons, 2016.

[14] E. D. Goodman, "Efficient and robust optimization/search algorithms," Contributed Talk at Evolutionary Computation in Practice Track at Genetic and Evolutionary Computation Conference (GECCO), July 2018.

[15] M. Cauwet, C. Couprie, J. Dehos, P. Luc, J. Rapin, M. Rivière, F. Teytaud, O. Teytaud, and N. Usunier, "Fully parallel hyperparameter search: Reshaped space-filling," in *Proceedings of the 37th International Conference on Machine Learning, ICML 2020, 13-18 July 2020, Virtual Event*, ser. Proceedings of Machine Learning Research, vol. 119. PMLR, 2020, pp. 1338–1348.

[16] Q. Renau, C. Doerr, J. Dréo, and B. Doerr, "Exploratory landscape analysis is strongly sensitive to the sampling strategy," *CoRR*, vol. abs/2006.11135, 2020.

[17] Y. Jin, "Surrogate-assisted evolutionary computation: Recent advances and future challenges," *Swarm and Evolutionary Computation*, vol. 1, no. 2, pp. 61–70, 2011.

[18] T. Bartz-Beielstein, C. Lasarczyk, and M. Preuss, "Sequential parameter optimization," in *2005 IEEE Congress on Evolutionary Computation (CEC 2005)*, B. McKay *et al.*, Eds. Edinburgh, Scotland, UK: IEEE, Sep. 2005, pp. 773–780.

[19] T. Bartz-Beielstein, M. Zaefferer, and F. Rehbach, "In a nutshell – the sequential parameter optimization toolbox," *arXiv e-prints*, p. arXiv:1712.04076v2, Mar. 2021.

[20] S. Leary, A. Bhaskar, and A. Keane, "Optimal orthogonal-array-based latin hypercubes," *Journal of Applied Statistics*, vol. 30, no. 5, pp. 585–598, jun 2003.

[21] R. Storn and K. Price, "Differential evolution – a simple and efficient heuristic for global optimization over continuous spaces," *Journal of Global Optimization*, vol. 11, no. 4, pp. 341–359, 1997.

[22] A. Rhodes, P. Ferdinande, H. Flaatten, B. Guidet, P. G. Metnitz, and R. P. Moreno, "The variability of critical care bed numbers in europe," vol. 38, no. 10, pp. 1647–1653. [Online]. Available: http://link.springer.com/10.1007/s00134-012-2627-8