Resource Planning for Hospitals Under Special Consideration of the COVID-19 Pandemic: Optimization and Sensitivity Analysis

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ABSTRACT

Pandemics pose a serious challenge to health-care institutions. To support the resource planning of health authorities from the Cologne region, BaBSim.Hospital, a tool for capacity planning based on discrete event simulation, was created. The predictive quality of the simulation is determined by 29 parameters with reasonable default values obtained in discussions with medical professionals. We aim to investigate and optimize these parameters to improve BaBSim.Hospital using a surrogate-based optimization approach and an in-depth sensitivity analysis.

CCS CONCEPTS

• Theory of computation → Continuous optimization; **• Computing methodologies → Model development and analysis**; **Discrete-event simulation**; **• Applied computing → Health informatics**.

KEYWORDS

simulation, optimization, surrogate models, sensitivity analysis, COVID-19, hospital resource planning, capacity planning

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1 INTRODUCTION

Our initiative is motivated by the challenges that health care institutions face in the current COVID-19 pandemic. Planning the demand and availability for specific resources, such as intensive care beds, ventilators, and staff resources, is crucial. Policies and decisions made by hospital management professionals as well as political officials need to be well informed to be effective.

We present a holistic approach that combines tools from evolutionary optimization, simulation, sensitivity analysis, and machine learning to predict and understand demanding resource allocation problems. BaBSim.Hospital can simulate the trajectories of millions of patients through hospitals via Discrete Event Simulation (DES). It uses data from the Robert Koch Institute (RKI), https://www.rki.de and Deutsche interdisziplinäre Vereinigung für Intensiv- und Notfallmedizin (DIVI), https://www.divi.de.

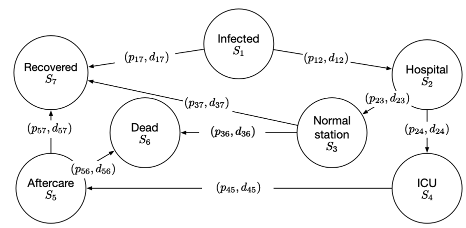

Figure 1: Patient flows in a hospital. Nodes represent states (S_i). Edges represent state changes with probabilities (p_{ij}) and durations (d_{ij}).

The simulation brings value to hospital resource planning and combines three approaches: **1) DES:** The modeling approach is inspired by Lawton and McCooe [6]. The 'simmer' R-package is used to generate a simulation with 29 parameters with default values, established in cooperation with medical professionals [10]. **2) Surrogate Model-Based Optimization (SMBO)** is used to efficiently optimize the 29 simulation parameters [4], using the R-package Sequential Parameter Optimization Toolbox (SPOT). This results in an optimization-via-simulation approach [5]. **3) Sensitivity analysis:** results from the SMBO, i.e., models and data, can be directly used to perform a sensitivity analysis [9], to deal with the relatively large number of parameters. Because our approach relies heavily on surrogate models, it will be referred to as Surrogate Model-Based Sensitivity Analysis (SMBSA). The data collected during optimization is analyzed using three models to identify the important as well as insignificant parameters. This outlines a way to reduce problem dimensions without compromising accuracy.

BaBSim.Hospital simulates the typical paths that COVID-19 infected patients follow during their hospital stays. The DES processes every recorded infection until the patients' recovery or death. Patients move with a probability p_{ij} from state S_i to state S_j after a transition-specific duration d_{ij}, as modelled in Fig. 1. The DES includes four types of parameters: **1) transition probabilities,** e.g., the probability that an infected individual has to go to the hospital, **2) durations,** e.g., the time span until an infected individual goes to the hospital (in days), **3) distribution properties,** e.g., truncated

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and translated gamma distribution, and **4) risk factors** depending on demographic groups, e.g., age, gender.

Proper tuning of these parameters is essential to obtain accurate predictions based on up-to-date and local data. An initial estimate for each of the given parameters was specified in cooperation with medical professionals. With the model parameters $\vec{x}$ and the underlying patient data, BaBSim.Hospital estimates the required resources (here: beds, Intensive Care Unit (ICU) beds, ICU beds with ventilators).

2 EXPERIMENTS AND RESULTS

Based on the simulation, optimization runs can be performed to improve parameter settings proposed by the experts. The Root Mean Squared Error (RMSE) is used to measure the error of the simulator and has to be minimized. Since the different bed types are not equally important, a weighted average of the RMSE for each bed category is used. Details can be found in [2].

The applicability of standard, model-free optimization algorithms was tested. Pre-experimental results revealed that these approaches failed under the hard time constraints. Only SMBO approaches produced good results [4]. They fit a data-driven model to a set of samples, replacing the expensive objective function. We chose SPOT for SMBO [1]. The surrogate models are re-used for SMBSA. We employ the following three surrogates: Linear regression models, Kriging [4], and Random Forest [3].

Step 1: Domain Analysis. A domain analysis of the 29 parameters provided for a qualitative comparison and a preliminary classification of importance, based on their expected real-life impact. Parameters x_{14} (`FactorPatientsInfectedToHospital`), x_{13} (`GammaShapeParameter`) and x_{26} (`RiskFactorB`) were determined to be highly important.

Step 2: Importance Index. A set of Latin Hypercube Designs (LHDs) [8] were generated to test evenly spread sample points over the entire feasible search space. A *normalized importance index* was computed. Based on that index, the five most important parameters ($x_{13}, x_{14}, x_{26}, x_{25}, and\ x_{17}$) are the same for the three surrogates. However, the bottom five parameters with the exception of x_5 differ considerably, indicating that the least important parameters are not straightforward to identify.

Step 3: Parameter Impact on the Simulation Error. This test was performed similarly to [7]. The sets of parameters from the SPOT initial design were used. For one parameter set, n simulation repeats were performed and the mean simulation error was calculated. Then, each parameter x_i was slightly changed and a new mean simulation error was determined for the same number of simulations. Finally, we calculated the differences in errors for each parameter. This quantifies the impact of each parameter on the simulation error. As shown in Figure 2, parameters x_{13} and x_{14} have a stronger effect on the simulation than any other parameter.

Step 4: Optimization Tests. The SPOT-Direct optimizer was run for 30 repeats in an attempt to tune the simulations parameters. One parameter after another was excluded from the optimization process and set to the mean of their bounds. This showed that less important parameters might be safely removed from the optimization, reducing optimizer runtime. However, the strong noise from the simulator makes it hard to observe changes in optimizer efficiency when adding or removing single simulation parameters.

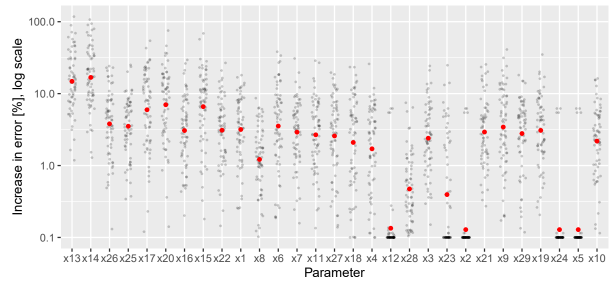

Figure 2: Change in error is calculated by changing one parameter value by $\pm 20\%$. Mean (*red* dot).

3 DISCUSSION AND CONCLUSION

The hard practical limitations that the BaBSim.Hospital simulator faces lead to challenging modeling and optimization task.
Automating Data Curation: Using a Continuous Integration / Continuous Deployment (CI/CD) approach, the system is running fully automatically for several months.
Selecting a Simulation Model: The DES delivers valid results and enables valuable predictions for capacity planning in hospitals. The "Discrete-Event Simulation for R" (simmer) package presents a good basis for implementation and is able to handle the large data loads under strict time constraints.
Finding an Optimization Algorithm: We chose a model-based optimizer to deal with this high-dimensional, noisy, dynamic real-world problem. The estimated parameter importance from the sensitivity analysis indicated that running the model-based optimizer with fewer parameters is possible without a significant quality loss.
Domain Knowledge: Our analysis provides valuable insights into the simulator. While there were a few parameters that dominate the simulation quality, many affect only slight changes.
Transferability: Although our specific results are highly dependent on the patient data under consideration, the SMBSA approach to sensitivity analysis can be applied to any model with a large number of parameters. The code required for running BaBSim.Hospital is published as an open-source R-Package (https://CRAN.R-project.org/package=babsim.hospital).

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