Hospital Capacity Planning Using Discrete Event Simulation Under Special Consideration of the COVID-19 Pandemic

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Abstract

We present a resource-planning tool for hospitals under special consideration of the COVID-19 pandemic, called babsim.hospital. 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. babsim.hospital combines simulation, optimization, statistics, and artificial intelligence processes in a very efficient way. The core is a discrete, event-based simulation model.

Keywords  Statistics · Applications, Computer Science · Computers and Society

1 Introduction

Resource and capacity planning with respect to the COVID-19 pandemic is a challenging task for hospitals. This paper describes BaBSimHospital, a resource planning tool that was developed in cooperation with ICU experts, crisis teams, and health administrations. babsim.hospital combines simulation, optimization, statistics, and artificial intelligence processes in a very efficient way. The core is a discrete, event-based simulation model. Sequential parameter optimization (SPOT) is used to optimize the parameters (status transition probabilities, length of stay, distribution properties) Bartz-Beielstein, Lasarczyk, and Preuss (2005). For modeling purposes, distributions (including a truncated and translated Gamma distribution) were specially developed by us in order to realistically simulate the length of stay. babsim.hospital takes into account different risks for individual groups of people (age and gender-specific) and can be used for any resources beyond the planning of bed capacities.

Using BaBSimHospital provides the following advantages for crisis teams:

• comparison with your own local planning,
• simulation of local events,
• adaptation to your own situation,
• simulation of any scenario (worst / best case),
• simulation of any pandemic scenario, considering the local situation,
• standardized approach.

And, there are benefits for medical professionals, e.g.,
• analysis of the pandemic at local, regional, state and federal level,
• consideration of special risk groups,
• validation of the length of stay,
• validation of the 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: beds, ventilators, rooms, protective clothing,
• personnel planning: medical and nursing staff.

The ideas used in the \texttt{babsim.hospital} implementation are based on the paper by Lawton and McCooe (2019). \texttt{babsim.hospital} is implemented in the statistical programming language R, see R Core Team (2020). It uses a discrete-event simulation, which uses the \texttt{simmer} package (Ucar, Smeets, and Azcorra 2019).

This paper describes practical aspects (“how to use”) of the \texttt{babsim.hospital} package. Although this paper focuses on the situation in Germany, it can be used for different settings. For example, we have used data from UK to model a local configuration. Even, if there are no real-world data available, the user can perform simulations based on synthetic data. How to use synthetic data and the theoretical background of \texttt{babsim.hospital} is described in Bartz-Beielstein et al. (2020).

This paper is structured as follows. Section 2.2 describes the data, which are necessary for the simulation. How to run a simulation is described in Section 3. The visualization of simulation results is illustrated in Section 4. Section 4 also presents the error measure, which is used for the optimizations. The optimization procedure is introduced in Section 5. How to visualize the optimized parameter settings is discussed in Section 6. Section 7 describes how data for future simulations can be generated. \texttt{babsim.hospital} provides tools for a deeper understanding of the simulation parameters. The corresponding tools from statistics and sensitivity analysis are described in Section 8.

2 Packages and Data

2.1 Packages

A clean start and loading the required packages can be performed as follows:

```r
rm(list=ls())
suppressPackageStartupMessages({
  library("SPOT")
  library("babsim.hospital")
  library("simmer")
  library("simmer.plot")
  library("plotly")
  library("rpart")
  library("rpart.plot")})
```

We need at least version 2.1.8 of \texttt{SPOT}.

```r
packageVersion("SPOT")
%> [1] '2.1.10'
```
2.2 Simulation and Field Data

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 will be used as simulation input.

In general, the simulator requires two types of data: simulation data that describes the spread of the pandemic over time and field data that contains daily resource usage data. Included in the package are tools to generate synthetic data, e.g., you can generate simulation and field data to run the simulations. This procedure is described in Bartz-Beielstein et al. (2020).

To demonstrate the usage of real-world data, we have included two sample datasets from Germany.

- **Simulation data**, i.e., input data for the simulation. We have included a data sample from the German [Robert Koch-Institute](https://www.rki.de) (RKI). Please take the copyright notice, which is shown in Section 10 (Appendix) under advisement, if you plan to use the RKI data included in the package.

- **Field data.** We have included a data sample from the German [DIVI Register](https://www.intensivregister.de/). The field data is used to validate the output of the simulation. Please take the copyright notice, which is shown in Section 10 (Appendix) under advisement, if you plan to use the RKI data included in the package.

2.2.1 Simulation Data

First, we will take a closer look at the simulation data. Here, we will use the data from the RKI Server. `babsim.hospital` provides a function to update the (daily) RKI data.

```r
updateRkidataFile("https://www.arcgis.com/sharing/rest/content/items/f10774f1c63e40168479a1feb6c7ca74/data")
```

Users are expected to adapt this function to their local situation. The downloaded data will be available in the package as `rkidata`. Due to data size limits on CRAN, the full dataset is not included in the `babsim.hospital` package. Instead, we provide a subset of the Robert Koch-Institut dataset with 10,000 observations in the package.

```r
str(babsim.hospital::rkidata)
```

The `rkidata` can be visualized as follows (here `region = 0` is Germany, `region = 5` is North Rhine-Westphalia, `region = 5374` Oberbergischer Kreis, etc.):

```r
p <- ggVisualizeRki(data=babsim.hospital::rkidata, region = 5374)
print(p)
```
After downloading the rkidata set, these data will be preprocessed. Not all the information from the original rkidata data set is required by the babsim.hospital simulator. The function getRkiData() extracts the subset of the raw rkidata required by our simulation, optimization, and analysis:

```r
rki <- getRkiData(rki = rkidata)
str(rki)
```

As illustrated by the output from above, we use the following simulation data:

1. 'Altersgruppe': age group (intervals, categories), represented as character string
2. 'Geschlecht': gender
3. 'Day': day of the infection
4. 'IdBundesland': federal state
5. 'IdLandkreis': county
6. 'time': number of days ('0' = start data). It will be used as 'arrivalTimes' for the 'simmer' simulations.
7. 'Age': integer representation of 'Altersgruppe'

### 2.2.2 Field Data

Next, we will describe the field data, i.e., the real ICU beds (or other resources). Similar to the rkidata, which is available online and can be downloaded from the RKI Server, the field data is also available online. It can be downloaded from the DIVI Server as follows, where YYYY-MM-DD should be replaced by the current date, e.g., 2020-10-26.
updateIcudataFile("https://www.divi.de/joomlatools-files/docman-files/divi-intensivregister-tagesreports-csv/DIVI-Intensivregister_YYYY-MM-DD_12-15.csv")

Note, the data structures on the DIVI server may change, so it might be necessary to modify the following procedure. Please check the hints on the DIVI web page. Contrary to the updateKidataFile() function, which downloads the complete historical dataset, the updateIcudataFile() function only downloads data for a single date. The downloaded data will be available in babsim.hospital as icudata. As described in the Appendix (Section 10) the DIVI dataset is not open data. Therefore, only an example data set, that reflects the structure of the original data from the DIVI register, is included in the babsim.hospital package as icudata:

```r
str(babsim.hospital::icudata)
> 'data.frame': 40470 obs. of 9 variables:
$ bundesland : int 1 1 1 1 1 1 1 1 1 1 ...
$ gemeindeschluessel : int 1001 1002 1003 1004 1051 1053 1054 1055 1056 1057 ...
$ anzahl_meldebereiche : int 3 5 2 1 1 2 3 3 2 1 ...
$ faelle_covid_aktuell : int 0 1 0 0 0 0 0 0 0 0 ...
$ faelle_covid_aktuell_beatmet: int 0 0 0 0 0 0 0 0 0 0 ...
$ anzahl_standorte : int 2 3 2 1 1 2 3 3 2 1 ...
$ betten_frei : int 24 116 103 9 13 11 15 17 9 7 ...
$ betten_belegt : int 31 113 114 16 41 13 24 35 28 5 ...
$ daten_stand : Date, format: "2020-09-01" "2020-09-01" ...
```

The icudata can be visualized as follows (region = 0 is Germany, region = 5 is North Rhine-Westphalia, region = 5374 is the Oberbergischer Kreis, etc.). Based on the icudata, two plots can be generated. The first plot shows the ICU beds without invasive ventilation. ICU beds without ventilation can be calculated as faelle_covid_aktuell - faelle_covid_aktuell_beatmet.

```r
p <- ggVisualizeIcu(region = 5374)
print(p[[1]])
```

![](image1)

The second plot shows ICU beds with ventilation:
The `icudata`, i.e., the field data or real data, will be preprocessed as follows. The function `getIcuBeds()` converts the 9 dimensional DIVI ICU dataset `icudata` (bundesland,gemeindeschluessel,..., daten_stand) into a data.frame with two columns:

1. ‘intensiveBedVentilation’
2. ‘Day’

These are the two bed categories introduced above.

```r
fieldData <- getIcuBeds(babsim.hospital::icudata)
str(fieldData)

%> 'data.frame': 102 obs. of 3 variables:
%> $ intensiveBed : int 103 103 96 97 97 92 94 100 94 104 ...
%> $ intensiveBedVentilation: int 132 125 127 128 126 126 134 130 133 129 ...
%> $ Day : Date, format: "2020-09-01" "2020-09-02" ...
```

Now that we have introduced the required data, we can perform the first simulations.

### 3 Performing Simulations

To run a simulation, the setting must be configured (seed, number of repeats, sequential or parallel evaluation, variable names, dates, etc.). `babsim.hospital` uses a list to store information related to the configuration. We will describe the components of this list first. The configuration list contains information about the simulation and field data.

```r
region = 5374
seed = 123
simrepeats = 2
parallel = FALSE
percCores = 0.8
resourceNames = c("intensiveBed", "intensiveBedVentilation")
resourceEval = c("intensiveBed", "intensiveBedVentilation")
```
We can specify the field data based on icudata (DIVI) for the simulation as follows:

```r
FieldStartDate = "2020-09-01"
icudata <- getRegionIcu(data = icudata, region = region)
fieldData <- getIcuBeds(icudata)
fieldData <- fieldData[which(fieldData$Day >= as.Date(FieldStartDate)),]
rownames(fieldData) <- NULL
icu = TRUE
icuWeights = c(1,1)
```

Next, simulation data (RKI data) can be selected. The simulation data in our example, depend on the field data:

```r
SimStartDate = "2020-08-01"
rkidata <- getRegionRki(data = rkidata, region = region)
simData <- getRkiData(rkidata)
simData <- simData[which(simData$Day >= as.Date(SimStartDate)),]
simData$simData$simData$Day <= max(as.Date(fieldData$Day)),]
simData$time <- simData$time - min(simData$time)
rownames(simData) <- NULL
```

Finally, we combine all field and simulation data into a single list() called data:

```r
data <- list(simData = simData, fieldData = fieldData)
```

Configuration information is stored in the conf list, i.e., conf refers to the simulation configuration, e.g., sequential or parallel evaluation, number of cores, resource names, log level, etc.

```r
conf <- babsimToolsConf()
conf <- getConfFromData(conf = conf,
simData = data$simData,
fieldData = data$fieldData)
```

In addition to the configuration list, a second list, which stores information about the simulation model parameters, is used. The core of the babsim.hospital simulations is based on the simmer package. It uses simulation parameters, e.g., arrival times, durations, and transition probabilities. There are currently 29 parameters (shown below) that are stored in the list para.

```r
para <- babsimHospitalPara()
str(para)
```

%> List of 29
%> $ AmntDaysInfectedToHospital : num 9.5
%> $ AmntDaysNormalToHealthy : num 10
%> $ AmntDaysNormalToIntensive : num 5
%> $ AmntDaysNormalToVentilation : num 3.63
%> $ AmntDaysNormalToDeath : num 5
%> $ AmntDaysIntensiveToAftercare : num 7
%> $ AmntDaysIntensiveToVentilation : num 4
%> $ AmntDaysIntensiveToDeath : num 5
%> $ AmntDaysVentilationToIntensiveAfter : num 30
%> $ AmntDaysVentilationToDeath : num 20
%> $ AmntDaysIntensiveAfterToAftercare : num 3
### 3.1 Simulation Runs

The `babsim.hospital` simulator requires the specification of:

1. ‘arrivalTimes’
2. configuration list ‘conf’
3. parameter list ‘para’

for the simulation. Arrival times were not discussed yet. `babsim.hospital` provides the function `getRkiRisk()` that generates arrivals with associated risks. The Risk is based on age (Altersgruppe) and gender (Geschlecht):

```r
rkiWithRisk <- getRkiRisk(data$simData, para)
head(rkiWithRisk)

| Altersgruppe | Geschlecht | Day       | IdBundesland | IdLandkreis | time | Age |
|--------------|------------|-----------|--------------|-------------|------|-----|
| A15-A34      | M          | 2020-09-01| 5            | 5374        | 0    | 25  |
| A15-A34      | M          | 2020-09-01| 5            | 5374        | 0    | 25  |
| A15-A34      | M          | 2020-09-01| 5            | 5374        | 0    | 25  |
| A35-A59      | M          | 2020-09-01| 5            | 5374        | 0    | 47  |
| A35-A59      | W          | 2020-09-01| 5            | 5374        | 0    | 47  |
| A35-A59      | W          | 2020-09-01| 5            | 5374        | 0    | 47  |
```

To perform simulations, only two parameters are required:

1. ‘time’: arrival time
2. ‘Risk’: risk (based on age and gender)

A data.frame with these two parameters is passed to the main simulation function `babsimHospital`. Output from the simulation is stored in the variable `envs`. The simulation run is started as follows:
4 Visualize and Evaluate Simulation Output

4.1 Simmer Plots

First, we illustrate how to generate plots using the `simmer.plot` package (Ucar, Smeets, and Azcorra 2019). In the following graph, the individual lines are all separate replications. The smoothing performed is a cumulative average. Besides `intensiveBed` and `intensiveBedVentilation`, `babsim.hospital` also provides information about the number of non-ICU beds. The non-ICU beds are labeled as `bed`. Summarizing, `babsim.hospital` generates output for three bed categories:

1. ‘bed’
2. ‘intensiveBed’
3. ‘intensiveBedVentilation’

To plot resource usage for three resources side-by-side, we can proceed as follows:

```r
resources <- get_mon_resources(envs)
resources$capacity <- resources$capacity/1e5
plot(resources, metric = "usage", c("bed", "intensiveBed", "intensiveBedVentilation"), items = "server")
```

Note, each resource can be plotted separately. For example, the following command generates a plot of non icu beds.

```r
plot(resources, metric = "usage", "bed", items = "server", steps = TRUE)
```
4.2 Evaluation of Simulation Results

babsim.hospital provides functions for evaluating the quality of the simulation results. Simulation results depend on the transition probabilities and durations, i.e., a vector of more than 30 variables. These vectors represent parameter settings. babsim.hospital provides a default parameter set, that is based on knowledge from domain experts (doctors, members of COVID-19 crises teams, mathematicians, and many more). We can calculate the error (RMSE) of the default parameter setting, which was used in this simulation, as follows:

```r
fieldEvents <- getRealBeds(data = data$fieldData, resource = conf$ResourceNames)
res <- getDailyMaxResults(envs = envs, fieldEvents = fieldEvents, conf=conf)
resDefault <- getError(res, conf=conf)
print(resDefault)

%> [1] 9.412271
```

The error is 9.4122709.

4.3 Generating babsim.hospital Plots

In addition to the original simmer plot, babsim.hospital provides functions for visualization. Here, we illustrate how babsim.hospital plots can be generated. Before we deescribe these plots, readers should be aware of the fact, that we do not use the full data, simulation results are completely wrong and do not represent any real-world situation! The following figures are included to demonstrate the working principles of the visualization procedures.

```r
p <- plotDailyMaxResults(res)
plot(p)
```
5 Optimization

As discussed above, \texttt{babsim.hospital} provides a default parameter set, which can be used for simulations. The function \texttt{babsimHospitalPara()} provides a convenient way to access the default parameter set:

\begin{verbatim}
para <- babsimHospitalPara()
\end{verbatim}

\texttt{babsim.hospital} provides an interface to optimize the parameter values of the simulation model. The following code is just a quick demo. To run the following code, the complete \texttt{rkidata} and \texttt{icudata} data sets must be available. Please download the data from RKI and DIVI or provide your own simulation and field data! Note: results are stored in the directory \texttt{results}.

\begin{verbatim}
%> [1] "2020/09/01 00:00:00" "2020/12/11 00:00:00"
%> [1] "2020-09-01" "2020-12-11"
%> [1] "trainDataSim: 2020-10-05" "trainDataSim: 2020-12-11"
%> [1] "trainDataField: 2020-11-02" "trainDataField: 2020-12-11"
%> [1] "Starting optimization loop:
%> [1] "##########################################################
%> [1] "Repeat: 1##########################################################
%> [1] "trainConfSim: 2020-10-05" "trainConfSim: 2020-12-11"
%> [1] "trainConfField: 2020-11-02" "trainConfField: 2020-12-11"
%> [1] "Warning cutting some x0 parameters as there are too many"
%> [1] "Starting Surrogate Optimization"
%> [1] "##########################################################
%> 60% completed.
\end{verbatim}
The code from above was shown for didactical purposes. It starts a short optimization run to illustrate the underlying optimization procedure. Results from real the runoptDirect() runs are stored in the paras.rda file. babsim.hospital provides results from several regions (towns and counties in Germany), e.g.:

- 'getParaSet(5374)': Oberbergischer Kreis
- 'getParaSet(5315)': City of Cologne
- 'getParaSet(5)': North-Rhine Westphalia
- 'getParaSet(0)': Germany

5.1 Use Optimized Parameters

Results, i.e., parameter settings, of the short runoptDirect() optimization from above can be used as follows:

```r
ey <- resDemo$best.df
para <- getBestParameter(xy)
res <- modelResultHospital(para=para,
                          conf=conf,
                          data = data)
resOpt <- getError(res, conf=conf)
print(resOpt)
%> [1] 6.566367
```

These results show that even a very short optimization improves the error: The improved is 6.5663677, which is smaller than 9.4122709. This improvement can also be visualized.

```r
p <- plotDailyMaxResults(res)
print(p)
```
6 Visualize Parameter Settings

Besides using the optimized parameters for simulations, which allows improved simulations, the optimized parameters can be used for analysing the parameter settings. `babsim.hospital` includes several tools to analyze parameter settings. You might recall that parameter settings consist of

- transition probabilities, e.g., the probability that an infected individual has to go to the hospital.
- durations, e.g., the time span until an infected individual goes to the hospital (in days).

The following plot illustrates the transition probabilities. It uses the following states:

1. ‘infec’: infected
2. ‘out’: transfer out, no hospital required
3. ‘hosp’: hospital
4. ‘normal’: normal station, no ICU
5. ‘intens’: ICU (without ventilation)
6. ‘vent’: ICU ventilated
7. ‘intafter’: intensive aftercare (from ICU with ventilation, on ICU)
8. ‘aftercare’: aftercare (from ICU, on normal station)
9. ‘death’: patient dies
10. ‘healthy’: recovered

The transition matrix, that stores the probabilities, is shown below:
```r
para <- babsimHospitalPara()
getMatrixP(para = para)
%>
[,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10]
%> [1,] 0 0.9 0.1 0.0 0.00 0.000 0.0 0.00000 0e+00 0.000
%> [2,] 0 1.0 0.0 0.0 0.00 0.000 0.0 0.00000 0e+00 0.000
%> [3,] 0 0.0 0.0 0.9 0.09 0.010 0.0 0.00000 0e+00 0.000
%> [4,] 0 0.0 0.0 0.0 0.10 0.001 0.0 0.00000 1e-01 0.799
%> [5,] 0 0.0 0.0 0.0 0.00 0.300 0.0 0.60000 1e-01 0.000
%> [6,] 0 0.0 0.0 0.0 0.00 0.000 0.7 0.00000 3e-01 0.000
%> [7,] 0 0.0 0.0 0.0 0.00 0.000 0.0 0.32999 1e-05 0.670
%> [8,] 0 0.0 0.0 0.0 0.00 0.000 0.0 0.00000 0e+00 1.000
%> [9,] 0 0.0 0.0 0.0 0.00 0.000 0.0 0.00000 1e+00 0.000
%> [10,] 0 0.0 0.0 0.0 0.00 0.000 0.0 0.00000 0e+00 1.000
```

This matrix can be visualized as follows:

```r
visualizeGraph(para=para, option = "P")
```

### Wahrscheinlichkeiten (Prozent)

![Probability Graph]

Similar to the probabilities, durations can be visualized:

The corresponding probabilities matrix is shown below:

#### 7 Extend RKI Data

*babsim.hospital* can be used to simulate several scenarios, i.e., possible developments of the pandemic. To simulate these scenarios, arrival events must be generated. The function `extendRki()` adds new arrival events. To generate new arrivals, three parameters must be specified:

1. `data`: an already existing data set, i.e., the history
2. `EndDate`: last day of the simulated data (in the future)
3. `R0`: base reproduction values (R0) at the first day of the scenario and at the last day of the scenario. A linear interpolation between these two values will be used, e.g., if `R0 = c(1,2)` and ten eleven days are specified, the following R0 values will be used: (1.0, 1.1, 1.2, 1.3, ..., 1.9,2.0).

```r
data <- getRkiData(babsim.hospital::rkidata)
%> getRkiData(): Found days with negative number of cases. Ignoring them.
n <- as.integer( max(data$Day)-min(data$Day) )
```
To illustrate the `extendRki()` data extension procedure, a short example is shown below:

```
visualizeRkiEvents(data = data, region=5374)
```

The following plot shows the result of the data extension:

```
visualizeRkiEvents(data = dataExt, region = 5374)
```
8 Sensitivity Analysis

We will describe only a very quick parameter analysis. A detailed analysis will be presented in a forthcoming paper. Here, we demonstrate how machine learning tools (regression trees) can be used to visualize the most important parameters of the simulation model.

```r
param <- getParaSet(5374)

n <- dim(param)[2] - 1

y <- param[,1]
x <- param[,2:dim(param)[2]]

fitTree <- buildTreeModel(x=x,
                         y=y,
                         control = list(xnames = paste0('x', 1:n)))

rpart.plot(fitTree$fit)
```
Several additional tools are available, e.g., to perform a sensitivity analysis, because babsim.hospital uses the R package SPOT (sequential parameter optimization toolbox) to improve parameter settings. SPOT implements a set of tools for model-based optimization and tuning of algorithms (surrogate models, optimizers, DOE). SPOT can be used for sensitivity analysis, which is important under many aspects, especially:

- understanding the most important factors (parameters) that influence model behavior. For example, it is of great importance for simulation practitioners and doctors to discover relevant durations and probabilities.

- detecting interactions between parameters, e.g., do durations influence each other?

The fitness landscape can be visualized using the function plotModel. Again, we would like to mention that these results are only shown for didactical purposes. They are not a valid statistical analysis, because the optimization via simulation runs are too short and do not produce sufficient results. Here, the interaction between the first two model parameters, i.e., AmntDaysInfectedToHospital, and AmntDaysNormalToHealthy, is shown.
A regression-based parameter screening can be performed to discover relevant (and irrelevant) model parameters:

```r
fitLm <- SPOT::buildLM(x=res$x,
                        y=res$y,
                        control = list(useStep=TRUE))
summary(fitLm$fit)
```

```r
Call:
  lm(formula = y ~ x.12 + x.13 + x.14 + x.15 + x.24 + x.25 + x.26,
      data = df)

Residuals:
   Min     1Q    Median     3Q    Max
-3.7513 -1.2679  -0.1442  1.0313  6.1996

Coefficients:
            Estimate Std. Error t value  Pr(>|t|)
(Intercept)  16.9509    2.0349   8.330 2.14e-13 ***
x.12        -0.2486    0.1004   2.475  0.0148 *
x.13        -0.5088    0.3603   1.412  0.1606
x.14       -31.8801    5.6697  -5.623  1.38e-07 ***
x.15       -30.2948    5.6697  -5.344  1.48e-07 ***
x.24      -0.4782    0.2884  -1.658  0.1000
x.25       -0.5521    0.5214   2.973  0.0036 **
x.26        22.1438    9.3273   2.374   0.0193 *

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.785 on 113 degrees of freedom
Multiple R-squared: 0.3807, Adjusted R-squared: 0.3423
F-statistic: 9.924 on 7 and 113 DF,  p-value: 1.307e-09
```
9 Summary

Based on ideas presented by Lawton and McCooe (2019), we developed a resource planning tool for hospitals that considers the specific situation of the COVID-19 pandemic. babsim.hospital is implemented in the statistical programming language R, see R Core Team (2020), and uses a discrete-event simulation model. The simmer package (Ucar, Smeets, and Azcorra 2019) was used to implement the simulation model.

babsim.hospital was developed in cooperation with ICU experts, crisis teams, and health administrations. It combines simulation, optimization, statistics, and artificial intelligence processes in a very efficient way.

Sequential parameter optimization (SPOT) is used to optimize the parameters (status transition probabilities, length of stay, distribution properties) Bartz-Beielstein, Lasarczyk, and Preuss (2005). For modeling purposes, distributions (including a truncated and translated Gamma distribution) were specially developed by us in order to realistically simulate the length of stay. babsim.hospital takes into account different risks for individual groups of people (age and gender-specific) and can be used for any resources beyond the planning of bed capacities.

Using babsim.hospital provides many advantages for crisis teams, e.g., comparison with your own local planning, simulation of local events, adaptation to your own situation, simulation of any scenario (worst / best case), simulation of any pandemic scenario, considering the local situation, and enables a standardized approach. And, 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: beds, ventilators, rooms, protective clothing, and personnel planning, e.g., medical and nursing staff.

babsim.hospital is open source and will be available on CRAN, see (https://cran.r-project.org).

10 Appendix

10.1 Copyright Notices

10.1.1 RKI Data

Please take the following copyright notice under advisement, if you plan to use the RKI data included in the package:

Die Daten sind die „Fallzahlen in Deutschland“ des Robert Koch-Institut (RKI) und stehen unter der Open Data Datenlizenz Deutschland Version 2.0 zur Verfügung. Quellenvermerk: Robert Koch-Institut (RKI), dl-de/by-2-0
Haftungsausschluss: „Die Inhalte, die über die Internetseiten des Robert Koch-Instituts zur Verfügung gestellt werden, dienen ausschließlich der allgemeinen Information der Öffentlichkeit, vorrangig der Fachöffentlichkeit“.

Taken from https://npgeo-corona-npgeo-de.hub.arcgis.com/datasets/dd4580c810204019a7b8eb3e0b329dd6_0

10.1.2 DIVI Data

We have included a data sample from the German DIVI Register: https://www.intensivregister.de/. Please take the following copyright notice under advisement. The DIVI data are not open data. The following statement can be found on the DIVI web page:

Eine weitere wissenschaftliche Nutzung der Daten ist nur mit Zustimmung der DIVI gestattet.
Therefore, only an example data set, that reflects the structure of the original data from the DIVI register, is included in the babsim.hospital package as icudata.

11 References

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