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Hospital Capacity Management & Optimization in Covid-19

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Abstract

A hospital is an institute in the healthcare system that provides us with services like patient treatment focusing on specialized medical staff, including doctors, nurses and other healthcare workers, medical equipment, and procedures. The hospital is the first line of defence against any type of illness or a pandemic; it is the sector that has been the most devastated and is the most vulnerable. There are now more than 513 million reported cases of covid worldwide since the epidemic began in December 2019, with even more than 6.2 million casualties. The tremendous rise in cases, which quickly outpaced the restricted infrastructure of many of these hospitals, is among the most serious issues encountered throughout the epidemic. This led to a hospital capacity crisis due to the huge difference in the number of patients and the limited hospital resources.

The purpose of this dissertation is to examine all elements and propose advice for dealing with healthcare capacities issues, with a particular emphasis on the covid-19 epidemic. That the very first section of the study is a comprehensive review of literature on healthcare strategic planning. The literature survey includes the challenges faced during the pandemic and the optimization models and techniques related to hospital capacity management. It is followed by analytical research with a data-driven simulation package. It includes picking a resource planning tool most suitable for hospital capacity management. The resource management tool's difficulties and prospects are also highlighted. This would point the way toward incorporating the capacity project management tool into healthcare facilities.

KEYWORDS

SARS-CoV-2, COVID-19, Hospital Capacity Management, Resource Planning Tool, Guidelines.

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Finally, I would want to dedicate my thesis to my late Aunt, who is not at all here with me today however is always in my heart and prayers. Despite her devotion and prayers, I would not have made it this far. May her soul attain enlightenment.

Table of Contents

List Of Tables

List of Figures

List of abbreviations

Sars-Cov-2	Severe Acute Respiratory Syndrome Coronavirus
WHO	World Health Organization
CDC	Centre for Disease Control
ED	Emergency Department
PPE	Personal Preventive Equipment
ICU	Intensive Care Unit
CPAS	Covid-19 Capacity Planning & Analysis
SMBO	Surrogate Model Based Optimization
DES	Discrete Event Simulation
CPAP	Continuous Positive Airway Pressure
EC	Elliptic Curve

1 INTRODUCTION

Merriam-Webster defines a hospital as an institution that offers medical or surgical care to the sick or disabled. The process of ensuring that a company's superior capabilities and productivity gains are maximised at all times and in all conditions is referred to as resource management.

A company's potential refers to how much it can achieve, develop, or offer in a certain amount of time. The number of beds, medical staff availability, and operating theatre and diagnostic equipment hours in use are all examples of hospital capacity, while Healthcare capacity planning is defined as maximising a hospital's unit accessibility to provide the required ability for swift, safe clinical evaluation, medicine, and evacuation to meet consumption demands.

A new coronavirus SARS-CoV-2 now identified as different from other coronaviruses that commonly infect humans. COVID-19 is an acute respiratory infectious illness that is spread mostly through the lungs. In late 2019, the first pneumonia case caused by this new coronavirus was reported.

One of the biggest challenges to face during the pandemic was the sheer number of patients that were coming to the hospital. Due to the limited capacity of the hospitals, they were soon filled with the maximum number of patients that leads to crisis situation.

The thesis is going to address the capacity management problems faced during the pandemic. It will include a detailed literature review of the hospital capacities before the start of the pandemic & during the later phase of the pandemic.

We will collect & analyze the data and provide a working model of the challenges faced. Based on the data collected, we will try to find different optimization techniques and analyze them to find the best, most effective technique to address the capacity management problem during the pandemic.

1.1 Background & Overview

1.1.1 Covid-19 Background

On December 31, 2019, the World Health Organization issued a public notice about a spike in immunocompromised pneumonia cases in Wuhan City, which has a population of 11 million citizens and is the social and artistic heartland of China.

On January 5, 59 cases had indeed been discovered, most of which ultimately led to death. 1 WHO received 282 confirmed cases ten days later, four of which were in Japan, South Korea, and Thailand. 2 In Wuhan, six people died, 51 people were seriously ill, and 12 people were in critical condition.

The virus in question was discovered on January 7, and its genome was released on January 12. 3 A new coronavirus, SARS-CoV-2, was responsible for the severe acute respiratory disease that became known as COVID-19[1].

The World Health Organization (WHO) designated this etiological agent as COVID-19 on February 11, 2020. (Coronavirus Disease, 2019).

After then, the illness continued to spread, infecting the remainder of Asia, the Middle East, and Europe, despite the deployment of elaborate containment efforts. COVID-19 was designated a pandemic on March 11 at an international news conference hosted by Tedros Adhanom Ghebreyesus, the WHO's General Director[2].

1.1.2 Past Influenza Pandemics Response & Preparedness

Influenza pandemics originate whenever a new virus emerges with limited protection among humans, culminating in the fast worldwide spread. Associated with outbreaks are characterized by diverse landscape spread rather than disease or fatalities; nonetheless, concerns regarding expansion and seriousness are typically linked that's because an absence of immunization can enhance both dissemination and morbidity.

The H5N1 influenza virus was generally identified as a growing pandemic danger in 2005-2006. As a result, several hospitals began preparing for the worst. 4 Throughout the next six years; meanwhile, no consistent inter-human transmission of this virus has been observed. [3].

A previously undiscovered variant of influenza A, the pandemic 2009 influenza, emerged in March 2009 A (H1N1). The virus emerged quickly in Mexico and then was quickly known to possess catastrophic possibilities. 5,6 Aviation industry helped spread this virus, and the Organization for Disease Prevention and Control announced a global medical emergency barely a week after the first individual incidence was discovered in the United States.

During the following nine months, this unusual virus infected about 57 million people in the United States. 7 Children were disproportionately afflicted, unlike in regular seasonal influenza epidemics. 8,9 Children under the age of 18 accounted for almost one-third of hospitalized patients and one-tenth of flu-related fatalities between April 2009 and mid-January 2010.

Only 16% of patients admitted to hospitals with normal seasonal influenza are under the age of 50. 8 Consequently, a significant number of children needed healthcare services and hospitalization, and also the inflow of individuals had a particularly adverse influence on paediatric medical practitioners and institutes.

Furthermore, researchers have posited that emergency departments (EDs) were a primary source of care for sick people or children with influenza-like illness (ILI))[3].

In April 2009, the first infants diagnosed with the new H1N1 influenza virus were discovered in Philadelphia. Over 2500 people were shown in the Children's Hospital of Philadelphia (CHOP) emergency department over the next ten weeks, the corresponding period in 2008. In the autumn, hospital management expected that the next wave of 2009 H1N1 might produce that much more sufferers, so they began interdisciplinary planning efforts to prepare for an influx of pediatric patients[3].

The following list tells us the responses that were used in preparedness for past influenza pandemics:

1 Patient Surge Planning

2 Inpatient Capacity Expansion

3 Patient care resources

4 Infection Control

5 Tabletop Exercises

The unprecedented H1N1 epidemic sparked a substantial growth in primary care for patients. The primary healthcare infrastructure was able to completely adapt to the problems posed by the outbreak thanks to transdisciplinary and planned teamwork.

2 Literature Review

This section aimed to perform an extensive literature review on hospital capacity management with a special focus on the COVID-19 pandemic. Moreover, it was to review the relevant methods for the prediction of epidemic dynamics and hospital capacity optimization. And lastly, it was to identify and address any & all literature gaps or research questions that arise after the completion of our review.

2.1 Hospital Capacity Management during Covid

COVID-19 has had quite a significant impact on almost all elements of many of these sectore however, the majority of the issues that medical institutions all through the world have confronted stem from a shortage of resources.

Throughout many circumstances, personal protective equipment for medical personnel was just in increasingly scarce. Based on one study, just 37.4% of Pakistani caregivers had availability to N95 respirators, 34.5 percent to gloves, 13.8 percent to mask screens or spectacles, and 12.9 percent to full attire.[4].

Additionally, roughly 7% of physicians reported they were forced to care for COVID-19 patient's lack of sufficient Personal Protective Equipment, and more than 80% indicated they reused sections of their Personal Protective Equipment. According to one study[8], just 18.5 percent of doctors in Jordan reported they had availability to all needed personal protective equipment.

Even just the United States, whose medical model is normally tied to nearly unlimited supplies, had Personal Protective Equipment shortages. Nearly 15% of doctors claimed they didn't have access to N95 respirators, over 20% said they didn't possess gloves, over 12% said they didn't have face coverings, and nearly half said they didn't possess full suites. [4].

A number of health care services across the globe lost all ability to conduct a thorough analysis, finding it challenging to detect and isolate infections. Quarantines all throughout the globe disrupted production processes, worsening shortfalls.

Various hospitals from around the state made a plea for donations of personal safety equipment, and creative people were coming up with imaginative ways to build PPE out of commonplace items. Consequently, ICU units and ventilation systems were already in low supply in clinics throughout the planet. [5].

Due to the obvious pandemic's intense focus, non-COVID-19 sickness care has deteriorated. As shown in a World Health Organization study, diagnostic and intervention programs for non - communicable diseases have been considerably disrupted because of the COVID-19 epidemic. Because as the virus spread, healthcare professionals who dealt with them were reassigned to assist with the COVID-19 treatment. Additionally, non-urgent or reactive surgeries and procedures were rescheduled in compliance with the appropriate of numerous health departments.

Numerous individuals found it extremely difficult to go out to their doctor's appointments leading to decreased public transit access. Individuals with serious mental chronic diseases such as cancer, hepatitis, and cardiovascular diseases were regularly reluctant to acquire the procedures and drugs they needed.

Such effects were particularly visible in baltic states, which were forced to devote extremely insufficient budgets to tackling the epidemic[9, 10]. In an assessment of 7 settlements in Bangladesh, Kenya, Nigeria, and Pakistan, lower appropriate support, including maternity and immunization programmes, monitoring for hypotension, tuberculosis, HIV, and vector-borne illness was observed, which received significant emphasis before the pandemic. In addition, medical costs have increased while the median wage has decreased.[6].

2.2 Effect of Covid on Healthcare workers

The following list gives us an overview of the major challenges that were faced by the healthcare workers during covid:

1 Infection

2 Shortage of PPE & other preventive equipment

3 Deaths

4 Understaffing

5 Psychological impact

2.2.1 Infection

As per the World Health Organization, one out of every ten health practitioners in some regions is diagnosed with Covid-19[7]. Healthcare professionals made up 9% of the population sick in Italy in March 2020. ACCORDING TO THE INTERNATIONAL COUNCIL OF NURSES, the COVID-19 outbreak sickened at least 90,000 clinical staff and killed approximately 260 nurses. In March 2020, one out of every four doctors in the UK was ill, secluded, or caregiving for a sibling who had been affected.

2.2.2 Shortage of PPEs

The shortage of Personal Preventive Equipment was reported almost all over the world. Despite differences in various nations, all states experienced serious deficits in personal protective equipment for protection in highly infectious environments. In China, insufficient staff training, a lack of personal protective equipment (PPE), a lack of knowledge of PPE use, and a lack of clear PPE advice resulted in illnesses and deaths among healthcare professionals[8]. Many hospitals in the United States have reported a scarcity of personal such types of equipment for hospital employees. As the number of cases grew, it was predicted that the US would require many more surgical masks than it already had[9].

2.2.3 Deaths

The deaths of healthcare professionals, including nurses and doctors, were reported in several countries. In Italy, the death toll has continued to rise. By April 2020, it is anticipated that 119 doctors and 34 nurses will have died [10].

2.2.4 Understaffing

Another major reason that the hospitals were faced with was the understaffing of healthcare professionals. Although understaffing was a serious issue even before the pandemic, it was amplified in Covid.

Nursing duties were incredibly high, according to Lasater and some other experts, with 50% of the nurses experiencing exhaustion in an observational research study. "Unfavorable patient and nurse outcomes are highly related to inferior nurse staffing," researchers observed. Nurses can't deliver the greatest treatment to patients if they don't have enough employees to handle the inflow of Covid patients. They just lack the personnel to keep track of all of the patients[11].

2.2.5 Psychological Effect

As shown in a Singapore study, care providers caring for COVID-19 patients reported panic, despondency, and pressure[12]. Rising employment demands for medical personnel collide against their obligations to respective friends and relatives, producing mental distress. Clinical staff shared their fears of just being compelled to personality, isolate, or just become ill. Quarantining was associated with limiting contact with the patient and failure to disclose to employment for medical professionals[13, 14].

Distress, sadness, and inadequate sleep plagued medics, physicians, and other healthcare officers in its front areas in China. Panic afflicted 46.04 percent, sadness afflicted 44.37 percent, and sleeplessness afflicted 28.75 percent[15].

2.3 Effect of Covid on Patients

The most affected risk group apart from that of healthcare workers was general patients. When the epidemic began, due to lack of knowledge mainly, hospital admissions fell drastically, with several reports of hospitals operating at 50% capacity in the US[16-18]. Hospitals purposely shortened medical surgeries and other non-critical treatments, resulting in a dramatic drop in volume. However, healthcare facilities observed a perplexing decrease in hospitalizations for severe health illnesses, such as microvascular complications.[19-23]. The impact of the very first generation of the Covid outbreak on hospitalized patients in the United States has so far been restricted to specific community hospitals[23].

Despite the overwhelming unpredictability, community fear remained home instructions and other restrictions placed during the initial disease stage in April 2020; this one was hypothesized that so many people with metastatic illnesses, whether life-threatening or not, won't seek medical treatment out of anxiety of the viral disease or issues about direct connections at congested healthcare institutions.[16].

A better comprehension of COVID-19's impact on healthcare hospitalizations over the period will aid healthcare service executives and authorities in selecting features of vulnerable patients of immediate medical condition prevalence and severity[16].

Figure 1 compares hospital admittance patterns in 2019 and 2020 to February benchmark admittance numbers. In 2020, overall medical admissions and non-COVID-19 admissions began to decline sharply in March, hitting bottom in April and then levelling out in June/July. As non-COVID-19 admissions flattened, a secondary upsurge in alleged COVID-19 admissions (the gap between the "total admissions 2020" and "non-COVID-19 admissions 2020" lines) began in numerous states by late June[16].

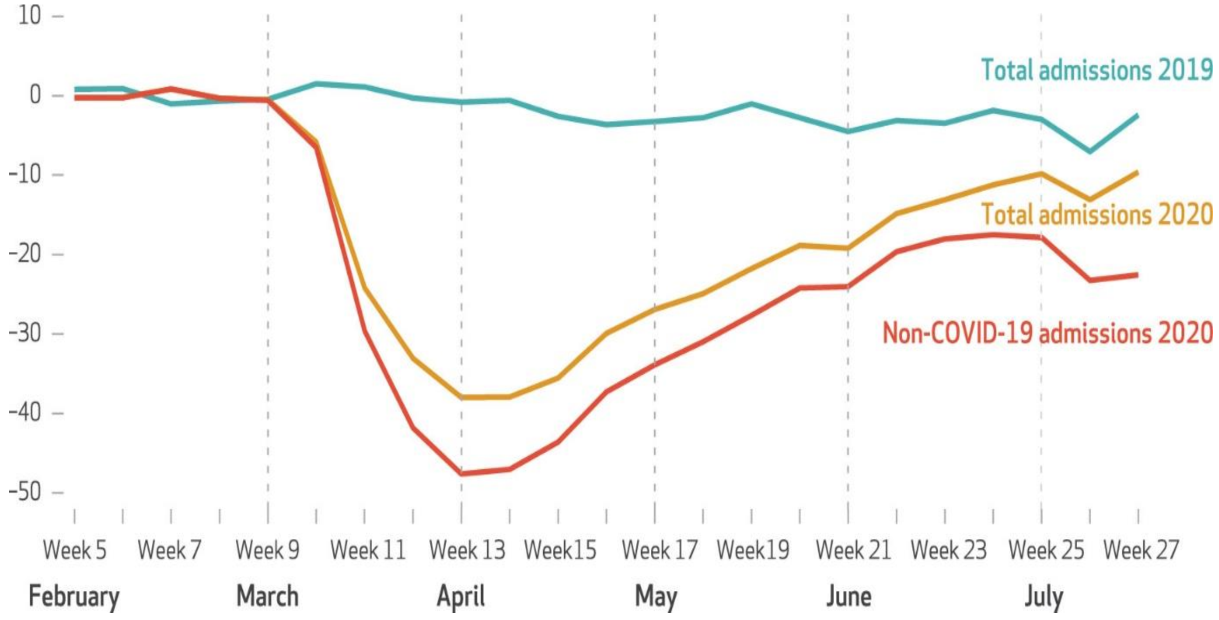

Figure 1 Total medical admissions in 2019 and 2020 and non-COVID-19 medical admissions in 2020 in a group of US hospitals by week[16]

SOURCE Hospital admissions data from Sound Physicians NOTES Data from 201 hospitals in 36 states represent 1,056,951 admissions. Non-COVID-19 entries are defined as all symptoms suggestive of COVID-19 admittance dependent on doctors' replies to a particular query in the medical record upon admitting commencing in week ten that correlates to the commencement of the outbreak. When looking at the average weekly admittance in February (weeks 5–8), the proportion decreases. The dates for weeks 5 and 27 are February 2–8 and July 5–11, 2020, correspondingly[16].

2.4 Effect of Covid on Organ Transplant

COVID-19's emergence has had a global impact on transplantation. The impact has been felt not just in terms of donor or recipient concerns and also in relation to health utilization since the proportion of cases in some areas exceeds limits[24].

Between March 24, 2020, and March 31, 2020, a nationwide assessment was carried out to analyze the influence on transplantation practice all across the United States, along with central variance in diagnostics, healthcare delivery, and policy.

71.8 % of people said they had stopped receiving live donor kidneys, and 67.7% said they had stopped getting live donor livers. Increased limits were connected to more rigorous restrictions on COVID-19 incidence.

COVID-19 recipients ranged in age from one to ten years after transplantation, with 69.6% being kidney recipients and 25.0 percent being seriously ill[25].

2.5 Effect of Covid on ERs & ICUs

2.5.1 Effect of Covid on ICUs

From its very discovery in December 2019, the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) has wreaked havoc on ICUs all across the globe. COVID-19 has caused more than 24 million confirmed diagnoses and also more than a quarter of a million mortality globally as of August 28, 2020.[26].

Despite increased ICU assistance, the number of fatalities for severely sick patients with COVID-19 ranged from 40% to 61% in early case series[32-34]. This rate of death is far greater than in previous viral pneumonitis pandemics, such as the 2009 H1N1 influenza pandemic, when mortality rates ranged from 10% to 30%.[27, 28].

During the present pandemic, the occurrence of extreme COVID-19 has put a strain on the typical provisioning of ICU class service, with accounts of long Intensive stays[29]. Relatively subsequent ICU series from locations with lower COVID-19 populace distribution have reported ICU death rates of roughly 15%[30].

2.5.2 Effect of Covid on Emergency Departments

During the first generation of the epidemic, daily ED participation fell by 37%, healthcare admittance fell by 30%, and medical bed utilization fell by 27%; within a year, everything was back to business as usual. ED appointments and clinical admittance reduced among all age categories, with younger generations seeing the biggest decrease in Emergency department visits and older people experiencing the highest decrease in healthcare hospitalization.

There had been reduced limited ED appointments and inpatient stays of all levels of severity as during the epidemic. COVID-19 has been the most prevalent indication during the initial surge of clinical procedures. Standards had rebounded a year later, with a tendency favouring greater stroke rates than before the epidemic. Within the first wave of the outbreak, ED visits increased 1-week fatality, while non-COVID-19 admissions did not[31].

2.6 Covid-19 mitigation strategies

Several of the biggest obstacles in the face of the COVID-19 epidemic was coming up with more effective measures to stop it from spreading anymore. The generation of comprehensive strategies, quick and timely actions, as well as adequate management of human resources favouring interdisciplinary work would prove pivotal in containing & mitigating the COVID-19 outbreak[32].

The mitigation strategies are divided into three categories for their better comprehension. Figure 2 shows a flowchart of the mitigation strategies used against covid-19:

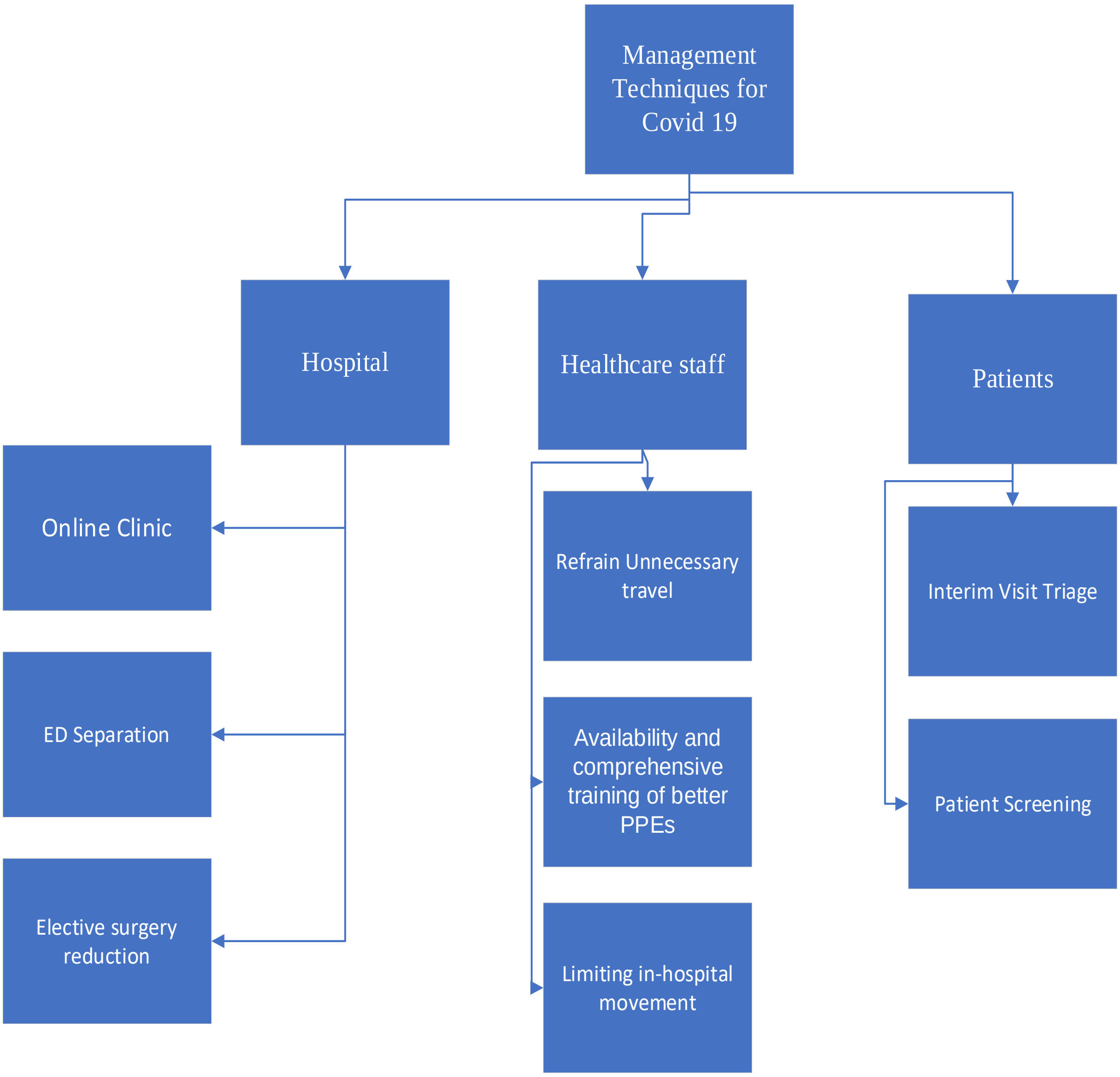

Figure 2 Mitigation Strategies

The management techniques have been divided into three categories:

1. Hospital management strategies
2. Healthcare staff management strategies
3. Patient management strategies

2.6.1 Hospital management strategies

Figure 3 shows the subcategories of hospital management strategies. Given below are some of the most effective hospital strategies:

1. Establishment of Online Clinics
2. Emergency Department (ED) separation
3. Elective Surgery reduction

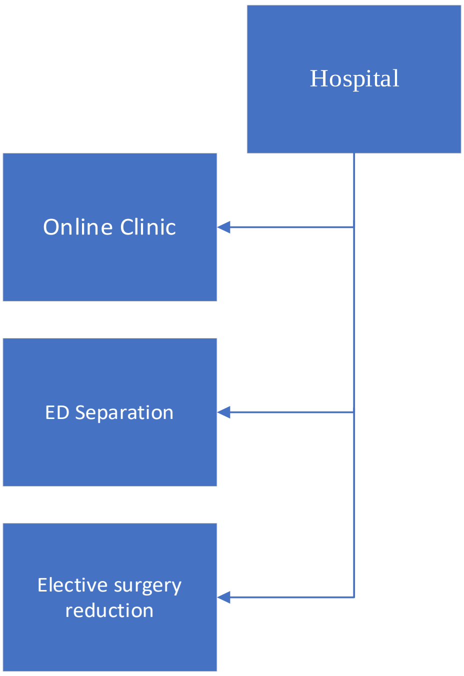

Figure 3 Hospital management strategies

To begin, internet clinics were established to help with patient triage in order to decrease visitor overload. Next, to stop the occurrence of covid-19, intermediate visit screening and ED segregation were implemented. Lastly, elective surgeries were reduced to give priority to patients with more serious conditions and stop the rapid growth of Covid-19.

2.6.2 Healthcare staff mitigation strategies

Some of the most effective strategies are given below:

1. Refrainment from unnecessary travel
2. Availability & training of better PPEs
3. Limiting the in-hospital movement

To begin, medical personnel were urged to avoid needless visits to only certain locations to lessen their chances of contracting the covid-19.

Secondly, they were provided with better PPEs for the same reason. Comprehensive and informative training programs were introduced to inform them of the proper use of PPEs.

And lastly, To decrease their travel throughout the hospitals, regular appointments were halted and supplanted with phone conversations where possible.

2.6.3 Patient mitigation strategies

Patients were screened thoroughly using comprehensive and detailed questionnaires to separate the patients with serious illnesses.

The patients with mild or curable diseases were asked to consult the healthcare workers using online clinics or phone calls.

Interim visit triage was also introduced to facilitate the patients and reduce the overall influx of patients.

2.7 Optimization Strategies

Given below is a list of different optimization strategies used:

1. Clinical Predictive Models
2. Data-driven optimization models
3. Improvement models using simulation
4. CPAS (Covid-19 Capacity Planning & Analysis)
5. Adaption of resource Planning Tool

2.7.1 Clinical Predictive Models

Clinical predictive models that accurately anticipate who might just require testing, hospitalization, and critical care depending on retrospective cohort medical studies might minimize peak load by ensuring resources are allocated to those at most threat.

For instance, a prognosis system that clearly describes people who would be predicted to test positive for SARS-CoV-2 beforehand might help prioritize SARS-CoV-2 diagnostic infrastructure.

Moreover, given the recent emergence of SARS-CoV-2, developing a standard diagnostic forecasting model for SARS-CoV-2 is difficult as solid connections involving trial information, hospitalization, and ICU admittance still have to be established.[33].

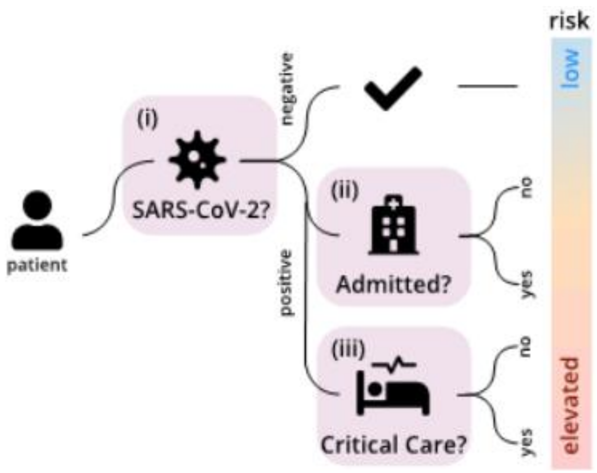

Figure 4 Clinical Predictive Model[33]

Based on medical, demographics, and blood testing statistics, modelling techniques (light purple) are used. Efficient diagnostic forecast models distinguish individuals based on their unique risk, prioritising health care resources like diagnostics, hospitalization, and critical care capacity [33].

The following steps are ivolved in this process:

1. Setting the problem
2. Setting up methodology
3. Preprocessing
4. Developing a Model
5. Choosing a Model
6. Model Assessment and evaluation

2.7.2 Data-driven optimization models

Given below is a list of different optimization models:

1. An optimization model for timing social distancing
2. An optimization model for forecasting ICU occupancy
3. An optimization model for patient allocation

2.7.2.1 An optimization model for timing social distancing

In the lacking of prevention and treatment treatments, nonpharmaceutical interventions are the only approach to minimize catastrophic illness and death.

Closure of universities and colleges and non-essential businesses, forbidding large gatherings, mandating interpersonal distancing, and limiting transport, along with mandating face veil, regular wash hands, surface treatments, and working at home once sick, could really decrease the incidence and potential dangers of people infected interacting with vulnerable individuals.[34].

In this sense, the goals of this optimization model are clear. Initial, a conceptual and quantitative architecture for COVID-19 policy solutions for mitigation strategies following the first epidemic wave is presented.

Second, the framework is being used to establish the optimal mechanisms for initiating and terminating shelter-in-place procedures in order to minimize the number of expensive social isolation periods while maintaining that COVID-19 treatments do not reach national capacities.

Finally, the indisputable importance of providing shelter to vulnerable persons is highlighted to lessen COVID-19's impact. Such a method is used as a reference for implementing quick closings depending on local hospitalization patterns in data in place to evade excessive emergency influx while reducing socioeconomic inconvenience.[34].

2.7.2.2 An optimization model for forecasting ICU occupancy

Predicting and forecasting modelling that portrays the elements influencing actions might be a valuable way to make sure the protracted sustainability. Throughout actuality, such models can also be used to visualize patient flows and patient care methods, modelling mechanisms and their interactions in a stochastic environment, determine the efficacy of current practises, and conduct what-if evaluations to estimate the impact of resourcing, asset, and process activities on health system performance.[35].Fuzzy Self-Tuning Particle Swarm Optimization for this logistic model[35].

2.7.2.3 An optimization model for patient allocation

This optimal model provides several effective solutions for patient placement. It depends on the following four important determinants:

1. No. of patients
2. Bed capacity
3. Distance between cities
4. Intercity cooperation

It begins by constructing a compartmental model for describing viral transmission. The regions particularly afflicted by Covid-19 are then identified using Pareto analysis and allocation performed. Finally, to test the durability of our decision model, we do a sensitivity analysis.[36].

2.7.3 Improvement model using simulation

The purpose of the improvement model is to reduce the overall stress on hospitals by improvement of patients' workflow using simulation. It involves the following steps[37]:

1. Identify the bottlenecks
2. Reduce waiting time by proposing optimization scenarios
3. Using discrete event simulation to find best -a case scenario for the reduction in patient waiting time

2.7.4 CPAS (Covid-19 Capacity Planning & Analysis)

To deal with the pandemic's extraordinary ICU needs, we'll require a nationwide coordinated effort based on data to estimate hospital demand a Capacity Planning and Analysis System (CPAS) used in hospitals throughout to help in the management of ICU beds, supplies, and personnel, was created for this purpose.

This system is meant to give insights for ICU capacity planning for many stakeholders; it accomplishes this goal by generating credible projections for ICU needs over varying intervals, spans and intensities. It draws inferences from a vast reservoir of heterogeneous data sources using cutting-edge machine learning algorithms.

CPAS uses an intuitive and interactive interface to display its predictions and insights, allowing the user to explore scenarios under various assumptions[38].

CPAS is designed to ensure that ICU runs smoothly by anticipating the resources needed in numerous places ahead of time and allowing for timely resource management. Though the planning process is still most beneficial during the pandemic's height, it is indeed valuable well after the crest since it may help facilities manage the shift from COVID-19 urgency to daily operations.

The vast bulk of health resources was allocated to serving COVID-19 patients during the pandemic, resulting in a considerable decline in the capability to treat various ailments. In conclusion, when the COVID-19 pattern continues to deteriorate, it will be necessary to reassess and reallocate resources. As the pandemic spreads, this system considered one of very few management information setups to be introduced across the nation to optimize ICU resources[38].

2.7.5 Adaption of resource planning tool

BABSIM.HOSPITAL is an open-source hospital capacity management programme that takes into account the complications caused byCovid-19. It offers several benefits to crisis teams, including comparisons to their own local preparation, simulations of local events, and simulations of multiple scenarios.

There are advantages for medical practitioners, such as pandemic analysis at the local, regional, state, and federal levelsand particular risk groups consideration.. Furthermore, there may be administrative and managerial gains, including analyzing the state of specific facilities in consideration of local events, taking into consideration sufficient means such as bedrooms, ventilators, spaces, and protective clothes, and scheduling people such as healthcare personnel[39].

Models based on discrete event simulation (DES) are useful for estimating resource utilization and capacity planning[40]. They're utilized to simulate the difficulty of hospital capacity management . This system mimics the passage of hundreds of thousands, if not millions, of patients through hospitals.

This simulation demands a significant amount of computing power. As an outcome, because only a restricted number of simulations can be performed in an adequate duration of time, an extremely effective simulator is necessary. The DES package "Discrete-Event Simulation for R", which enables high-level process-oriented modelling, was used[41]. The code for running the simulations is free and open R-Package.[42].

The DES software application includes hospital data and is based on the notion of a route. It enables you to simulate the progression of the pandemic in relation to the availability and utilized hospital core competencies.

This system combines two powerful approaches: Lawton and McCooe's modelling technique and a Surrogate Model-Based Optimization approach, i.e., our system combines two powerful approaches: Lawton and McCooe's modelling method and a Surrogate Model-Based Optimization McCooe and Lawton's[43] modelling approach and a Surrogate Model-Based Optimization (SMBO) approach[44]:

- **Discrete event simulation:** The'simmer' R-package is used to construct a simulation using 29 default settings developed in collaboration with healthcare professionals. These factors are critical to the simulation's accuracy and must be carefully optimized.

- **Model-based optimization:** The Sequential Parameter Optimization Toolbox (SPOT) R-package is used to execute SMBO to quickly and accurately discover the optimal values for the 29 parameters, resulting in an optimization-via-simulation strategy.

2.8 Literature Gaps

The main purpose of our literature review was to review the relevant methods for the prediction of epidemic dynamics and hospital capacity optimization.

Even though there have been significant efforts in hospital capacity management, there are still some gaps. These gaps are identified below:

1. The COVID-19 caused new problems for effective hospital capacity management, e.g., hospital surge, fatigue of healthcare workers, and lack of proper PPEs. These challenges cannot be well tackled by the existing methods.
2. There is still room for improvement in exploring the strengths of both optimization and simulation in hospital capacity management.
3. The interactions among different influencing factors in hospital capacity management, e.g., hospital size, Bed availability etc., have not been thoroughly investigated.

To address these shortcomings, a simulation-based strategy combining optimizing and dynamic simulation is being developed to enhance healthcare sustainability practices.

For this purpose, a dynamic state of the art resource planning tool by the name of Bab-Sim.Hospital is going to be used.

3 Introduction of Resource planning Tool

BABSIM.HOSPITAL is an open-source resource-planning tool for hospitals that may be used to prepare for the future, in addition to addressing issues raised by the COVID-19 pandemic. It allows for comparisons with their own local planning, modelling of local happenings, and simulation of a range of situations.

There are benefits for medical practitioners, such as examining the pandemic at the local, regional, state, and federal levels, taking into account distinct risk classes, techniques for certifying the period of hospitalizations, and the chance of transferring from one state to another.

Furthermore, there are potential benefits for administration and management, such as assessing individual hospitals' situations in light of local events, planning and allocating resources such as beds, ventilators, and rooms, protective clothing, and making preparations and allocating patient care personnel.[39].

For resource utilization prediction and capacity planning, discrete event simulation (DES) models may be quite useful[40, 41]. Modelling the hospital resource planning issue is accomplished via the use of these tools.

This simulation necessitates the use of significant computing resources. A highly efficient simulator is necessary because only a restricted number of simulations may be run in an appropriate duration of time beneath normal operating conditions.

The DES package "Discrete-Event Simulation for R" (simmer), which enables high-level process-oriented modelling, was chosen[2]. It is included in the R programming language. It is now accessible as an open-source R-package[42], which contains the code necessary for executing the simulations.

This is founded on the simulation model's concept of a trajectory shared route for items or more of the same and takes into account healthcare data that is presently accessible to it.

The model provides a mechanism for modelling the trajectory of an epidemic in relation to the availability and utilized health care resources, along with ability. Surrogate Model-Based Optimization (SMBO) is a strategy for optimizing surrogate models[44] and is used to augment the modelling approach, which is based on Lawton and McCooe [43]. Thus, our system integrates two strong approaches: modelling and Surrogate Model-Based Optimization (SMBO).

DESCRIPTION: The'simmer' R-package is used to create a simulation with 29 parameters set to their default settings, which have been determined via collaborative efforts with medical specialists [41].

These parameters play an important role in the simulation's accuracy and, therefore, must be precisely tuned to ensure accuracy. Although domain knowledge, such as that obtained from medical practitioners, is useful in performing realistic simulations, more fine-tuning is necessary.

In this study, the Sequential Parameter Optimization Toolbox (SPOT) R-package is used to execute SMBO in order to discover the optimal values for the 29 parameters in a quick and accurate way, which results in an optimization-by-simulation technique [45]. But the comparatively large number of factors makes it difficult to get high-quality results from the optimization process.

4 Automated Data Collection & Curation

This simulator simulates resource use in hospitals, such as the number of ICU beds (y) in relation to the number of infected persons, using a mathematical formulation (x). Additionally, information on age and gender may be utilized as input for the simulation and the number of infections. Extract, Transform, and Load techniques combine data from various sources into sophisticated collections [46].

Following the successful extraction of data, the following step is to alter the information obtained. Many ways are used in this stage to get reliable data that is correct, comprehensive and consistent across all of the data sources.

The final step is to transfer the modified data into a data collector of the data analyst's choice, which will then be available for future usage.

Germany: The BABSIM.HOSPITAL simulator online uses an ETL procedure to examine data from the Robert Koch Institut (RKI) and the Deutsche interdisziplinare Vereinigung für Intensiv- und Notfallmedizin (DIVI) . Germany: An ETL procedure is used to examine the Robert Koch Institut data in the online edition of the BABSIM.HOSPITAL simulator(RKI In the accompanying data sets, you can find anonymized information about every case that has been documented in Germany.

A total of 780,065 observations were collected from the RKI data set, which included 18 different variables like age, gender, infection information, and so on. The data set was updated on a daily basis and was automatically imported into BABSIM.HOSPITAL. The DIVI can provide you with information on intensive care units in Germany. DIVI makes available an API as well as a daily report. Digital information from DIVI and RKI is used in the official simulator, which can be viewed atofficial website. Its specifications have been developed via consultations with German professionals, particularly intensive care unit physicians and healthcare administrators. The online version is discussed in further detail in the following sections.

UK: An expansion of the interface is detailed in this study that enables the statistics gathered that are not based on DIVI and RKI data, i.e., an interface to Comma-separated Value (CSV) files and Excel files may be used to process, simulate, and optimize any sort of field and simulation data.

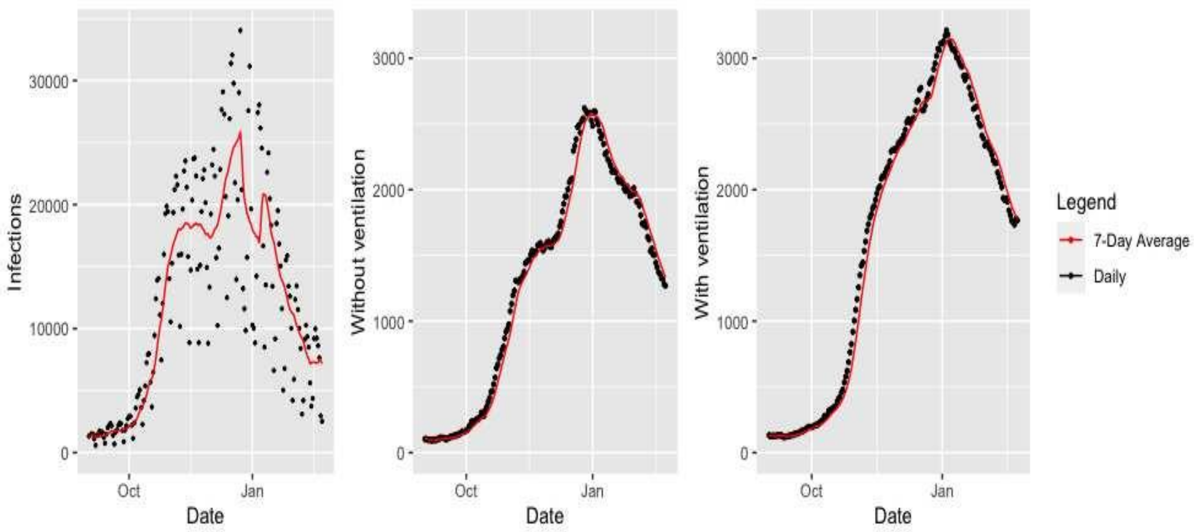

Figure 5 The current German COVID-19 is visualized. Data taken from BABSIM.HOSPITAL.

From top to bottom: The number of occupied critical care beds in hospitals , and the number of intensive care beds with invasive ventilation, as reported by the Robert Koch Institute.[39].

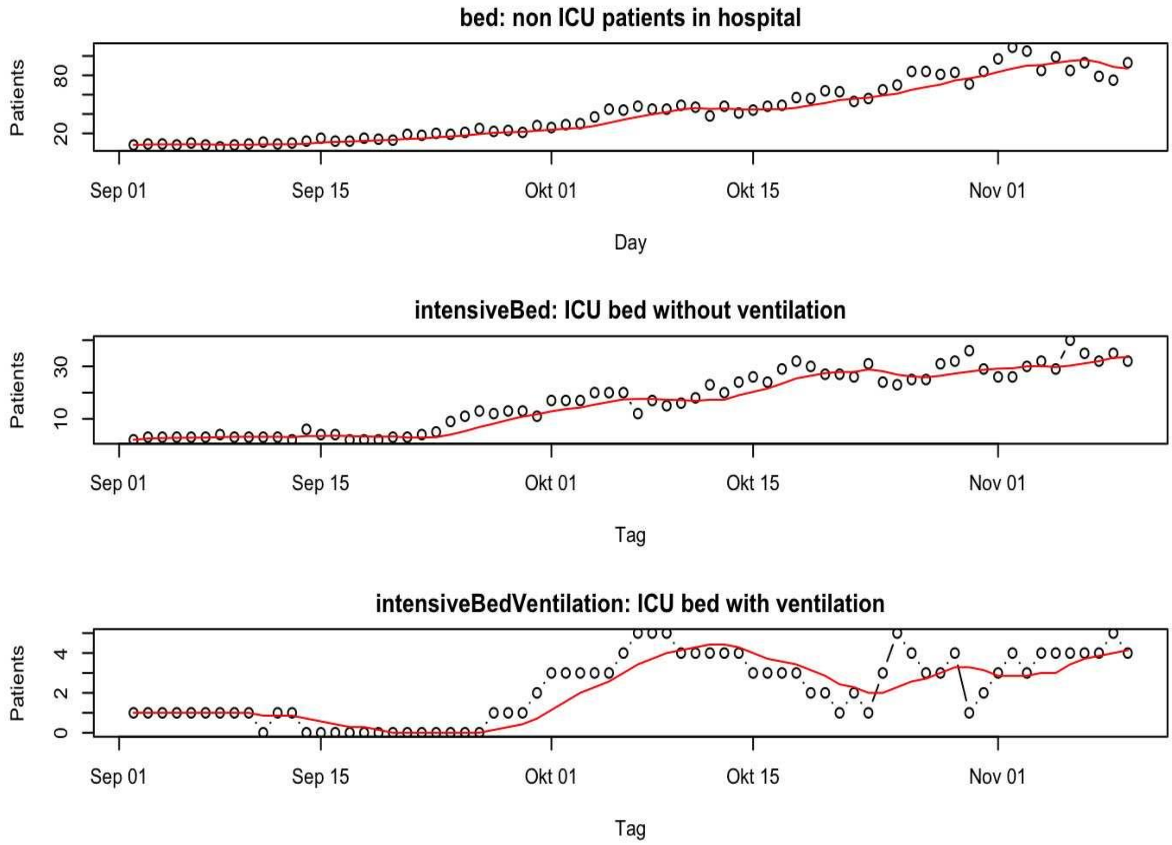

Figure 6 Data from the United Kingdom

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Real-world data is represented by dots, while the weekly average is represented by red lines. The last row shows ICU beds with ventilation. In comparison to Germany, the United Kingdom has much fewer ICU ventilator beds [39].

Anonymized data from an area in the United Kingdom was utilized to demonstrate our technique. A Microsoft Excel file containing the following items (columns) was used to read the information:

• the day of the week

• bed: the total number of COVID-19 patients admitted to a hospital

A number of patients are using non-invasive ventilators in the intensive care unit (ICU) (CPAP). They would normally be in intensive care or something similar; however, in the United

Kingdom, this has not always been available. On the critical care unit, the number of patients intubated and ventilated with COVID-19 was the highest.

The field data, which was based on UK data, was divided into three-bed categories:

1) bed: non-intensive care unit (ICU) patients in the hospital

2) intensiveBed: Intensive Care Unit (ICU) bed without ventilation

3) intensiveBedVentilation: An intense care unit bed with ventilator.

The data set from the United Kingdom that was utilized in this analysis is seen in Fig. 5. The whole data collection contains information spanning 240 days. We are relying on data collected after September 2020.

5 The Simulations

5.1 Discrete Event Simulation

When COVID-19 individuals are hospitalized, BABSIM.HOSPITAL mimics the usual pathways that they take while in the hospital. The DES processes every single infection that have been documented till the patient has recovered or died. In other words, After a transition-specific period, patients shift with a probability pij from state Si to state Sj, dij after following a trajectory, which is defined as follows: The model's parameters are the durations and probabilities associated with each condition. This kind of behaviour may be shown graphically. Fig. 7 depicts the transition probabilities and discusses the states in further detail[39].

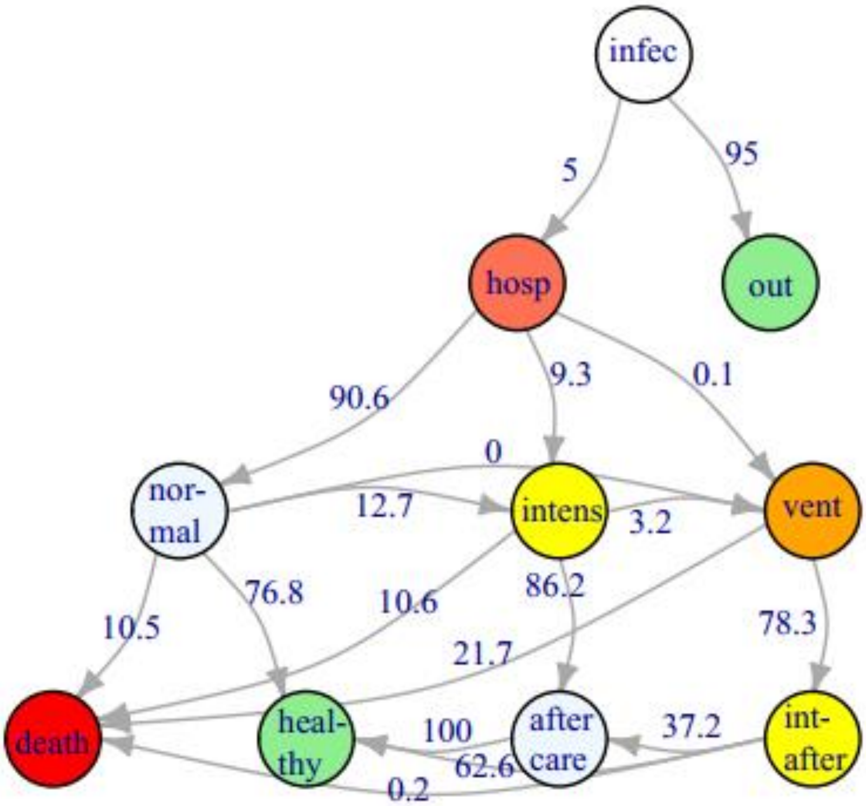

Figure 7 Patient flow full model

It can be noted that in the above figure, Nodes represent the states of a system (S_i). Edges reflect state transitions and the probability associated with them (p_{ij}).

The following are the labels for the nodes: RKI has produced a report on the number of persons who have been found to be positive for Covid-19 Non-hospitalized infected people, hosp: Infected people who are hospitalized, normal: Isolation ward, intensive: 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: Aftercare isolation ward, healthy: Death: Deceased, and discharged as recovered. Intensive care unit that does not require invasive ventilation. The nucleus of this figure is BABSIM.HOSPITAL. This distinguishes BABSIM.HOSPITAL from other hospital simulators. It makes it possible to conduct a thorough investigation of the underlying circumstances. It may be customized to meet the specific needs of those who are interested upon their request[39].

An infected patient (state S_1) is admitted to the hospital (state S_2) with a probability p_{12} after 12 days in the community (state S_1). She recovers (state S_7) after d_{17} days if the probability of recovery is p_{17}. The probability of departing nodes add up to one, for example, p_{17} = 1 p_{12} = 1 p_{17}. Transition probabilities, such as the likelihood that an infected individual will have to go to the hospital; durations, such as the time span until an infected individual goes to the hospital (in days); distribution properties, such as truncated and translated gamma distributions; and risk factors based on demographic groups, such as age and gender, are all included in the modelling process.

There are four sorts of parameters in the modelling process: Probabilities of transition, such as the likelihood that an inf In the online version of the BABSIM.HOSPITAL simulator, each new patient is assigned a unique risk score based on risk data. Despite the fact that the "risk" factor is a critical determinant of the length and severity of a COVID-19 infection, it was not investigated.

Table I provides a high-level summary of the parameter ranges for the 29 parameters that make up the BABSIM.HOSPITAL simulation model, as well as their respective values[39].

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**	**7**	**10**	**18**	**5**	**9**
$\mathbf{X_7}$	**AmntDaysIntensiveToVentilation**	**4**	**6**	**10**	**3**	**5**
$\mathbf{X_8}$	**AmntDaysIntensiveToDeath**	**5**	**6**	**14**	**3**	**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**	**0.01**	**0.001**	**0.004**	**0.005**	**0.02**
X_{17}	FactorPatientsNormalToIntensive	0.1	0.07	0.13	0.07	0.13
$\mathbf{X_{18}}$	**FactorPatientsNormalToVentilation**	**0.001**	**2e − 05**	**0.0004**	**0.0001**	**0.002**
X_{19}	FactorPatientsNormalToDeath	0.1	0.08	0.12	0.08	0.12
$\mathbf{X_{20}}$	**FactorPatientsIntensiveToVentilation**	**0.3**	**0.05**	**0.07**	**0.25**	**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

Table 2 Default (DE) & adapted (UK) ranges of the 29 parameters

A Bold font indicates parameters that have been adjusted for the United Kingdom option. The prefix amntDays* denotes duration (measured in days), whereas FactorPatients* denotes proportions or probability (measured in percentages or probabilities).

The default column displays expert advice from German experts; minUK and maxuk imply adapted ranges from the United Kingdom, whereas minDE and maxde denote parameter ranges from Germany. It is critical to fine-tuning these parameters in order to produce reliable forecasts that are based on current and local information.

Because of the time-dependent changes, it is necessary to re-fit the model parameters to the present condition on a regular basis. Because of this, each German area undergoes a daily parameter tweaking operation that ensures an accurate prognosis. In collaboration with medical specialists, an initial estimate for each of the supplied metrics was developed and documented.

For example, between the first and second waves of COVID-19 infections in Germany, the proportion of patients who received effective therapy increased dramatically. Additionally, political actions at the national and municipal levels may have a considerable impact on the situation. While restricting access to nursing homes may help prevent infections in high-risk segments of the population, opening schools may result in many illnesses among the community's younger members.

The following is a description of the optimization problem: The BABSIM.HOSPITAL simulator needs two input parameters (vectors): $\vec{x}_t$, which represents the model parameters, and $\vec{u}_t$, which represents the number of infections (infection rate). BABSIM.HOSPITAL calculates the needed resources based on these two inputs—in our example, the number of beds, ICU beds, and ICU beds with ventilators—and then allocates them. The simulation's outcome, i.e. the resource required on each day t, will be designated as $\vec{y}_t$, i.e., the required resources on each day t[39].

$$\hat{y}t = (\hat{R}_{bed}(t), \hat{R}_{icu}(t), \hat{R}_{vent}(t)) \qquad 1$$

The DES produces reliable findings and allows for the development of projections that are useful for hospital capacity planning. The simmer program provided a solid foundation for implementation and was able to manage more than half a million data points in a short period of time under very tight deadlines.

5.2 Online version

An online version of BABSIM.HOSPITAL that includes a graphical user interface and makes the simulator open and accessible to the public may be found at https://covid-resource-sim.th-koeln.de/app/babsim.hospitalvis.A snapshot of this program is shown in Figure 8.

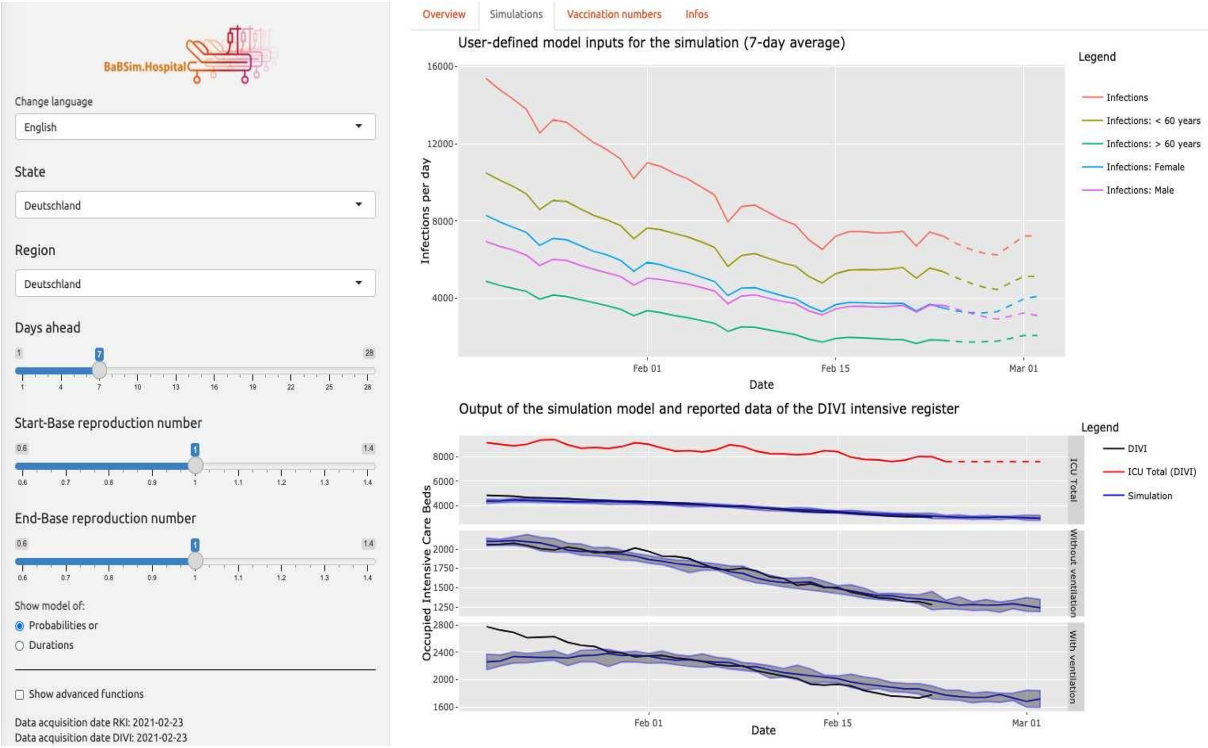

Figure 8 Online version of BabSim[39]

Users have the option of selecting various nations and areas to simulate, as well as some very broad parameters for the simulation.

BABSIM.HOSPITAL is an open-source and free project. It's written in the R programming language and may be downloaded for free. Using the online version of the BABSIM.HOSPITAL simulator process the RKI data set, which comprises approximately 750,000 observations of 18 variables that are updated daily and are automatically included in the BABSIM.HOSPITAL simulator.

The Continuous Integration / Continuous Deployment (CI/CD) strategy eliminates the need for human engagement, resulting in simulations and optimizations that begin immediately as the data is retrieved from the source system.

6 Optimization

Optimization runs may be performed based on the simulation findings in order to optimize the parameter values advised by the experts. The Root Mean Squared Error (RMSE), as specified in Eq. 2, is used to assess the model's error in the simulator. The following is how we frame the minimization problem:

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

There are three separate bed types in this equation, with T being the number of days simulated. A weighted average of the root mean square error (RMSE) for each bed category is employed as a final error metric due to the fact that not all beds are equally essential. In [47], you can find a more in-depth explanation of the process.

The large quantity of data that the tool must handle, along with the high complexity of the issue and the high level of accuracy needed, makes simplifying the modelling process in order to enhance performance a significant undertaking.

Because of the restricted amount of time available for each optimization run, it is necessary to apply efficient optimization techniques to maximize performance.

The state-of-the-art optimization methodologies that were reviewed included::

• Stand-alone, standard optimization algorithms, such as BOBYQA [48], CMA-ES [49], Simulated Annealing [50],

• Surrogate model-based optimizers and response surface methods [51],

• Combinations of global and local optimizers that are parallelized[52],

• single-iteration optimizers with enormous parallelism[53, 54], and

• SMBO approaches [55].

First and foremost, the applicability of these various techniques was investigated. Outcomes from the preliminary experiments suggested that only SMBO techniques achieved satisfactory results. Due to the implementation in SPOT [56, 57], we chose to adopt SMBO as the basis for our design. To be more specific, we chose a SPOT setup that follows the steps listed below.

It all begins with a space-filling design (in this case, the Latin hypercube design [58]), which is used to generate and evaluate a collection of initial solutions.

• After that, the produced data is used to train a surrogate model. [59]A Gaussian process regression model is used to train this model. The hyperparameters of the model are established via maximum likelihood estimation, and a search method from Evolutionary Computation (EC), namely Differential Evolution[60], is used to find the values of the parameters.

• Following that, based on the surrogate model, SPOT identifies the candidate solution that has the highest promise in terms of performance.

• The real, costly simulation is used to assess the potential solution that has been identified.

• Following the SMBO stage, a model-free search is used to refine the solution that was discovered. Instead of using the surrogate model, the same Algorithm (ISRES) as previously described is applied to the actual error measure of the simulator rather than the surrogate model.

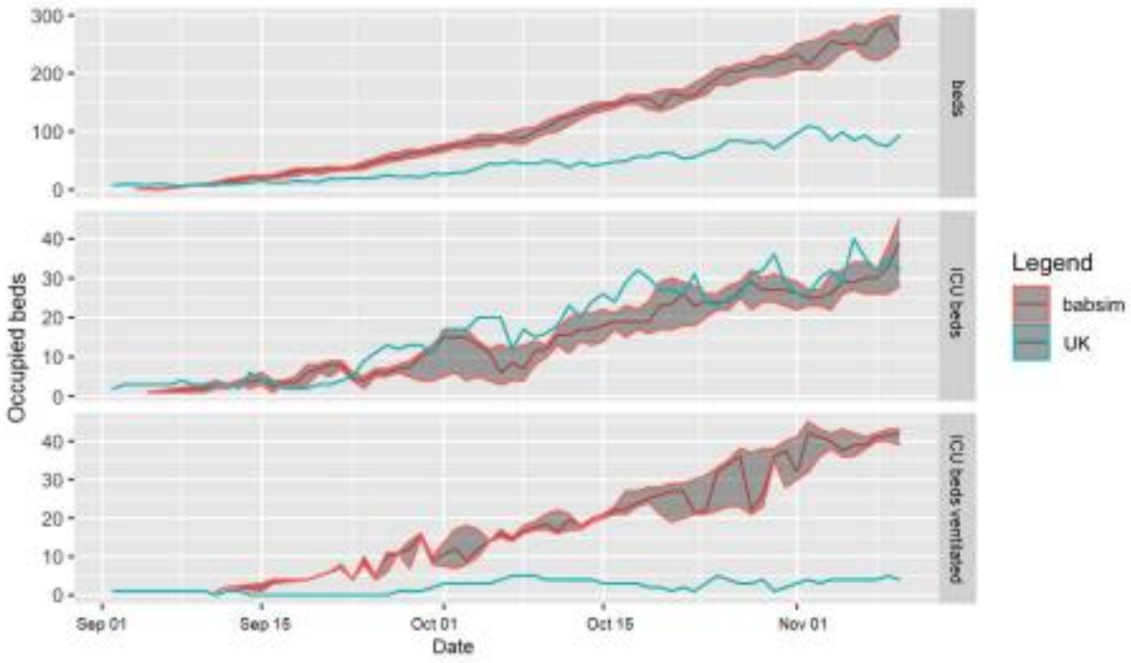

Figure 9 Real Data Compared to simulation results with default parameters

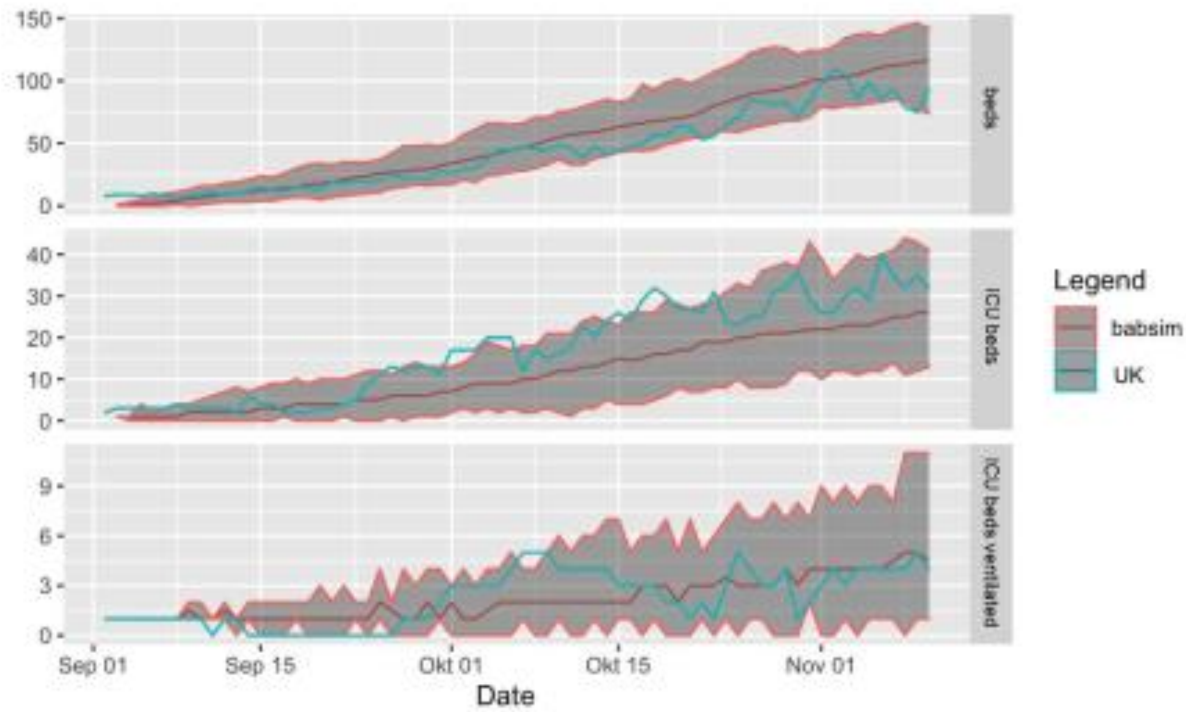

Figure 10 Real Data compared to simulation results with optimized parameters

As it can be seen from the figures above, It is possible to see large residuals (errors), notably for standard beds and ICU beds with ventilation, in the data. The default parameter settings are used by BABSIM.HOSPITAL. German domain expertise (in the form of physician recommendations) has been used to develop these. The value of c1 was fixed to be 0.2. The disparity between the genuine data from the United Kingdom and the simulated data remains when just normal ICU beds (category II) are taken into consideration. As a result, an additional adaptation was required.

7 Adaptation of Search Boundaries

The United Kingdom has much fewer intensive care units (ICUs) than Germany (6.6 per 100,000 against 29.2 per 100,000 in 2011 [22]). As a result, patients may be handled differently in various countries: in certain countries, The clinical criterion for admission to an intensive care unit (ICU) in the United States may be higher than in Germany. We can change the search space's boundaries to reduce the chances of patients being referred to the critical care unit.

First Adaptation—Decreasing the Probability of Failure: To accommodate the differing settings, we made the following modifications to the parameter bounds (see Table III-A): There are three incoming edges to vent (Fig. 7: in orange), and they come from nodes normal, hospital, and intensification.

We were able to reroute patients to other bed categories by providing a reduction factor, such as c1 R+, that simply doubles the default probability of patients reaching the ICU ventilated node, as described above. The fact that the total of the probabilities of the outgoing edges must equal one means that changing the probability of one edge will alter the probabilities of all of its connected edges in the model as well (see Fig. 3).

Making the decision to use c1 = 0.2 resulted in enhanced simulation outputs and more accurately represents real-world disparities in the provision of intensive care units (ICUs) in the United Kingdom and Germany. Remember that c1 does not directly impact the probabilities; rather, it affects the search bounds that the optimizer uses to find the best solution[39].

There has been a reduction in the range of the parameter x16, which indicates how many patients are admitted to the intensive care unit (ICU) with ventilation, from [0.01; 0.02] to [5.0e 04; 0.004]. The metric x18, which reflects the percentage of patients who are transferred from regular beds to intensive care units with ventilation, has also been narrowed from [0.1; 0.2] to [0.02; 0.04].

Furthermore, the range of the parameter x20, which reflects the percentage of patients who are transferred from the intensive care unit to the intensive care unit with ventilation, was lowered from [0.1; 0.2] to [0.02; 0.04][39].

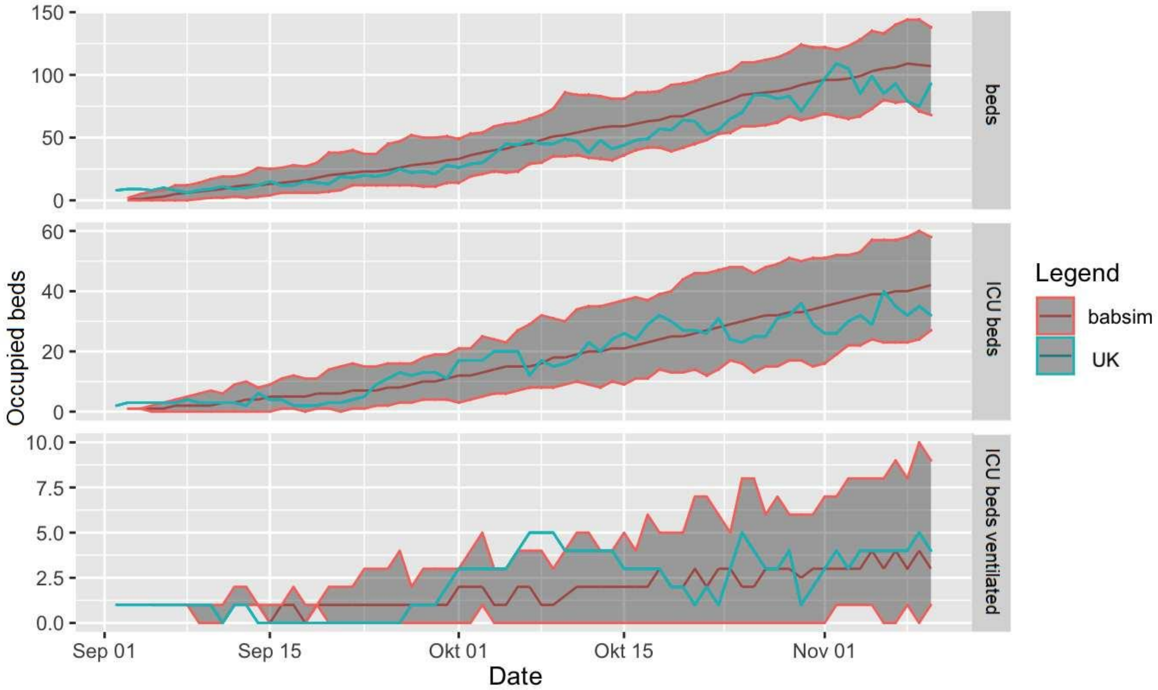

Figure 11 Real data compared to results from simulations with optimized parameters

When comparing the data from Fig. 5, it is clear that there has been a major improvement. Because the simulation model parameters were tailored to the conditions seen in UK hospitals, the residuals were significantly reduced. Additionally, the outcomes of simulations for category II beds have improved.

There has been a reduction in the range of the parameter x16, which indicates how many patients are admitted to the intensive care unit (ICU) with ventilation, from [0.01; 0.02] to [5.0e-04; 0.004]. The parameter x18, which reflects the fraction of patients who are transferred from standard beds to intensive care units with ventilation, has also been narrowed from [0.1; 0.2] to [0.02; 0.04] in range. The metric x20, which defines the percentage of patients who go from intensive care to intensive care unit with ventilation, was also narrowed from [0.1; 0.2] to [0.02; 0.04] in the study.

When search intervals for ventilated ICU beds were reduced by a factor of 16, 18, and 20, the simulation results were significantly improved: the numerical root means square error (RMSE) decreased from 184.10 to 46.94. Visual examination, as shown in the right panel of Fig. 9, confirms that the improvement has occurred.

Increased Durations in Second Adaptation (2nd Adaptation) However, even if the use of ventilated intensive care unit beds (bed category III) were to increase, the simulation of the second bed type would still be unsatisfactory. There are more ICU beds than we anticipate.

According to some estimates, this is due to the higher threshold for ICU admission in the United Kingdom, resulting in an average UK ICU patient who is more ill than the typical German ICU patient. This difficulty was resolved by increasing the search intervals for these metrics and decreasing the time of patients in intensive care units. The durations were multiplied by another factor, denoted by c2 R+, in order to get this result. In our studies, we used the value c2 = 2.0 as a starting point.

In order to broaden the range of the parameter x6, which indicates the number of days patients spend in the intensive care unit with ventilation before being transferred to intensive aftercare, the range was expanded from [5; 9] days to [10; 18].

The range of the parameter x7, which governs the number of days before ICU patients are admitted to the intensive care unit with ventilation, has been expanded from [3; 5] days to [6; 10] days, according to the researchers. The interval of the parameter x8, which sets the number of days patients spend in intensive care before dying, was also raised from [3; 7] to [6; 14] days[39].

8 Results

A large decrease in the root mean square error (RMSE), as specified in Eq. 2, is achieved by the adaption of parameter constraints based on domain knowledge.

Under these conditions and by using the default BABSIM.HOSPITAL parameter bounds, which were derived from the current situation in Germany, the simulation error is 0 = 184.10.

As a result of the first adaptation, which decreases the percentage of patients treated in ICU beds with ventilation, the simulation error is 1 = 46.94, whereas as a result of the second adaptation, which increases the number of time patients spend in an ICU bed, there is an additional reduction in the simulation error to 2 = 29.0.

In summary, it has been shown that the modification may minimize simulation errors by about 70%. Figures 10 and 11 provide a good visual representation of the improvements.

9 Discussion & Outlook

A discrete event simulation-based tool for capacity planning, the BABSIM.HOSPITAL simulator has been created over the past year to assist physicians, administrators, health authorities, and crisis teams in Germany. It is available as an open-source download. BABSIM.HOSPITAL's enormous size and computational cost make it a difficult simulator to optimize for performance.

Solving this job for a large number of locations in Germany, each with its own set of local characteristics, necessitates the development of effective ways to deal with the ever-increasing number of infections and, therefore, the ever-increasing number of simulation run times. For every state and area in Germany, an SMBO technique yields findings that are stable and reliable throughout time.

A significant deal of interest is being shown in estimating the work involved in migrating the simulator to other places. According to the data from the United Kingdom, we proved that a modification to the related optimizer's search ranges (bound restrictions) leads to suitable results.We successfully presented the simulator using real-world data from the United Kingdom, and the results were satisfactory.

As mentioned above, the move from the German healthcare system to the United Kingdom healthcare system may be performed by changing the optimizer's search ranges rather than the simulator's absolute parameter values. Because ranges are easier to express than point values, it is far simpler to modify these ranges than it is to modify single values inside them.

The first adaptation was made possible by using the same factor as the relative number of ICU beds (c1 was chosen as 1/5, which reflects the difference in the number of ICU beds in the UK versus Germany[61]), which was surprising (as even c1 = 1/5 seems extreme until you realize how different the two countries are! According to the findings of our investigation, simulations using BABSIM.HOSPITAL is not limited to the German healthcare system[39].

Furthermore, this demonstrates the need for domain expertise in producing reliable and valid simulation results. Seven hundred thirty-four optimizers are especially useful in high-dimensional search spaces, where they might yield theoretically perfect but practically useless answers. This conversation provides critical information about the issue[39].

Because it replicates a tough real-world problem that can be handled using EC approaches, the BABSIM.HOSPITAL simulator may also be used as an intriguing simulation and optimization benchmark for EC algorithms. It provides a benchmark problem that is quite noisy, moderately high-dimensional, has many inequality constraints, and is computationally time-consuming. It is freely distributed as open-source software, making it accessible to the whole scientific community.

Furthermore, as proven in prior research, this study shows how DES may benefit from EC techniques and vice versa. This is critical to understand since DES simulation may be applied to a wide range of real-world circumstances.

As well as the probability of each transition occurring, is important to doctors in real-world applications. It's likely that it'll help with treatment comparisons in cases when hospitals have behaved differently.

For example, some hospitals used a lot of continuous positive airway pressure, whereas others used less and had to convert to ventilation sooner. The simulator may be used to assess how much extra capacity is available in hospitals for continuing elective treatments, such as planning cancer surgery, which is a particularly valuable aspect of using it to evaluate UK data.

10 Conclusion

Merriam-Webster defines a hospital as an institution that offers medical or surgical care to the sick or disabled. The process of ensuring that a company's superior capabilities and productivity gains are maximised at all times and in all conditions is referred to as resource management.

A company's potential refers to how much it can achieve, develop, or offer in a certain amount of time. The number of beds, medical staff availability, and operating theatre and diagnostic equipment hours in use are all examples of hospital capacity, while Healthcare capacity planning is defined as maximising a hospital's unit accessibility to provide the required ability for swift, safe clinical evaluation, medicine, and evacuation to meet consumption demands.

During the epidemic, one of the most difficult difficulties was dealing with the massive influx of patients. Due to the hospitals' low capacity, they were quickly filled to capacity with the maximum number of patients, resulting in a crisis scenario. We look at the capacity management issues that arose during the epidemic.

Prior to the onset of the pandemic and throughout the latter stages of the epidemic, a literature study is conducted for hospital capacity. We gather and evaluate data and create a functioning model of the problems encountered. We also strive to identify several optimization approaches and examine them based on the data obtained in order to determine the best, most effective technique to handle the capacity management challenge during the pandemic.Before beginning the thesis study, a definite plan of action was established. The following is a list of the objectives established during that time:

- Conduct a comprehensive review of literature of the issues that hospitals confront during a pandemic, with a specific attention on hospital capacity management and the approaches used to address such issues.
- Conduct a thorough and in-depth investigation of the hospitals' capacity management issues.
- Research several optimization methods that handle hospital capacity concerns and determine the most effective strategy for addressing the hospital's capacity management difficulties.
- Examine the literature and identify any gaps.

- Identify the best resource planning tool and conduct a thorough analysis based on the calculations and analytical study conducted during the second phase.

Phases I and II of our thesis were separated into two sections. A full literature analysis on hospital capacity management and challenges encountered in hospitals during the pandemic epidemic was completed at the end of phase I.

Phase I identified the following gaps in the literature:Coronavirus pandemic has brought on new obstacles for effective hospital capacity management e.g., lack of sufficient PPEs, lack of hospital beds, lack of ICUs etc.

- The full potential of optimization and simulation approaches in hospital capacity management has yet to be exploited, leaving space for improvement.
- Various factors that influence hospital capacity, such as bed availability and hospital size, have not been adequately examined.

In phase two, an ideal open-source resource planning tool was selected to conduct an analytical study using data-driven simulation methodologies. Bab Sim Hospital is the name of the open-source resource planning tool stated above. It was intended to aid physicians, administrative personnel, healthcare authorities, and crisis response teams in Germany.

Although it was designed to help German hospitals, it may be used to help hospitals all over the world with a few tweaks to the specifications. Hence our job was to moodify its parameters in such a way that it can be accessible to a wider variety of people. For that purpose we took UK hospital data as a case study and modified the parameters to its specifications. The modified parameters for UK case study were discussed in detailed in previous chapters.

It may readily be updated, adjusted, and moulded into the particular demands of any individual or institution on a municipal, state, or national level due to its open source nature. It considers 29 variables, the most important of which are hospitalised non-ICU patients, ICU patients with ventilator equipment, and ICU patients without ventilation equipment.

After meticulous optimization and result analysis using the resource planning tool Bab Sim, a 70% reduction in simulation mistakes was seen, allowing the system's productivity and efficiency to grow.

10.1 Future Scope and Suggestions

The potential of a corporation relates to how much it can achieve, develop, or offer in a certain period. Hospital capacity is defined as achieving maximum a hospital's unit availability to provide the required ability for swift, safe clinical evaluation, medicine, and evacuation to meet consumer demands,

Although there is a mechanism in place for hospital capacity management, there is always room for improvement.

The following suggestions for future additions and improvements can be considered based on all of the research and analysis completed during the thesis: First and foremost, Personal Protective Equipment (PPE) should be readily available.

- To minimise the number of patients in hospitals, elective operations and minor accidents should be postponed or handled over the phone or online.
- There should be emergency protocols in place to deal with the rapid influx of patients so that there is a minimum shortage of resources and personnel in case of another pandemic.
- In the event of a sudden viral epidemic, places should be set aside to be utilised as treatment rooms, with appropriate equipment on hand; and resource planning systems should be updated to better analyse and manage resources and staff.
- To anticipate the number of cases and determine the quantity of equipment and manpower needed to cope with the pandemic, predictive algorithms should be employed.
- A countrywide adaptation of the aforementioned resource planning tools and algorithms should be established so that they are linked and resources or persons may be moved from one location to another in the event of an emergency.

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