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FACS-CHARM: A HYBRID AGENT-BASED AND DISCRETE-EVENT SIMULATION APPROACH FOR COVID-19 MANAGEMENT AT REGIONAL LEVEL

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ABSTRACT

Pandemics have huge impact on all aspect of people's lives. As we have experienced during the Coronavirus pandemic, healthcare, education and the economy have been put under extreme strain. It is important therefore to be able to respond to such events fast in order to limit the damage to the society. Decision-makers typically are advised by experts in order to inform their response strategies. One of the tools that is widely used to support evidence-based decisions is modeling and simulation. In this paper, we present a hybrid agent-based and discrete-event simulation for the Coronavirus pandemic management at regional level. Our model considers disease dynamics, population interactions and dynamic ICU bed capacity management and predicts the impact of various public health preventive measures on the population and the healthcare service.

1 INTRODUCTION

The Coronavirus pandemic is arguably the worst pandemic event in the 21st century. It has posed unparallel challenges to almost all sectors in all countries across the whole world. At the date of writing (May 2022) the World Health Organization (WHO) recorded more that 500 million cases world-wide and more than six million recorded deaths (WHO 2022a). The impact of COVID-19, a disease caused by SARS-CoV-2, however is estimated to be higher. In a recent report, WHO estimated that the excess mortality associated with COVID-19 during the first two years of the pandemic (January 2020 to December 2021) has reached almost 15 million worldwide (WHO 2022b).

One of the interesting aspects of the response to COVID-19 is its local nature. National and local governments have implemented various measures at various points in time according to the severity of the disease in that location, the economic constraints and inputs from experts. Moreover, similar sets of

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measures can vary in their ability to contain the spread of infection in different locations. Arguably, this is due to the differences among the regions in terms of demographics, the economy, the density and behaviour of the population, as well as the degree of compliance to public health preventive measures. Further, healthcare resources as well as health needs vary significantly between districts. Therefore, it is essential to evaluate the efficiency of these measures for a given region.

Modeling & simulation (M&S) has been used widely to support decision-making for COVID-19. Early on in the pandemic Currie et al. (2020) discussed the use of M&S in the context of reducing the impact of COVID-19. They identified key decisions that M&S can support and they suggested M&S methods for each key decision based on the focus of the study. For example, ABM is identified as an appropriate method when individual behaviour is considered important. On the other hand, DES is most suited for studying operational matters. Hybrid simulation (HS) is also identified as the method that is used when a single approach cannot capture the complexity of the system.

Arguably, dealing with a crisis of that scale is complex. It is unlikely that a single model can encompass the multiple dimensions of a pandemic. Some of the reasons behind that maybe that attempting to include all of the aspects of such a crisis can lead to unmanageably complex models or that different modeling methods are better suited to model different dimensions of the crisis, among others (Mustafee et al. 2017). Many modeling efforts emerged in the past two years. There are many models that focus on the epidemic dynamics of the disease. Some examples are discussed in Kerr et al. (2021), Hinch et al. (2021) and Wang et al. (2021). There are also numerous models with emphasis on resources allocation. Examples include Zhu, Hen and Teow (2012), Melman, Parlikad and Cameron (2021) and Saidani, Kim and Kim (2021). However, few studies attempt to tackle both and investigate the impact of prevention measures at a local scale.

In this paper we present a hybrid agent-based and discrete-event simulation approach that aspires to provide a comprehensive manner for managing COVID-19 at a regional level. Our hybrid model consists of the Flu and Coronavirus Simulator (FACS), an agent-based simulation (ABS) model that predicts the spread of infections in specified area, and the dynamiC Hospital wARd Managemt (CHARM) model, a discrete-event simulation (DES) of intensive care unit (ICU) patient flow that caters for reconfiguration of ICU wards in runtime. Details of both models are described in Section 3.

The Hybrid FACS-CHARM model can be used to explore questions regarding public health interventions and their impact on the local hospital facilities. Example questions are:

- What would the impact of public health intervention be on the case numbers?
- What would the impact of public health intervention be on the local hospitals?
- When would COVID-19 bed surge be needed?
- What would the impact of elective cancelation strategies be on bed capacities?

The purpose of this paper is to present our approach in using hybrid ABS-DES for COVID-19 management at a regional level and discuss its potential. It is therefore not in the scope of this manuscript to study specific use cases and present experimental results. Within the STAMINA project, our approach is trialed in three use cases across Europe and neighboring countries. In later publications, we will discuss these in detail and present the experimental results.

The paper is structured as follows. Section 2 presents an overview of the literature in the field. In Section 3, the materials and methods of this study are discussed. This includes detail of the FACS and CHARM models. The hybrid FACS-CHARM model is discussed in Section 4. Section 5 concludes the paper.

2 BACKGROUND

Hybrid simulation, in general terms, means the combination of two or more simulation methods. In the context of this study, we follow the definition of Brailsford et al. (2019) where HS is defined as a modeling approach that combines two or more of the following methods: DES, system dynamics (SD), and ABS. Typically, DES is most commonly used to model the process and operations of a system, SD is most commonly used for strategic decision and aggregated populations, and ABS is mainly used to model individuals and their interactions.

Due to the complexity of emergency situations and healthcare systems, HS is gaining in popularity in the field. For example, Ruiz-Martin et al. (2016) that used DEVS and ABS HS for modeling information spread in emergency situations. Viana et al. (2017) modeled the home hospital health delivery in Norway using ABS and DES. Their model was implemented in a single simulation package. Fakhimi et al. (2014) used hybrid ABS-DES to study sustainability in emergency medical services. Bell et al. (2016) discussed an HS whole system modeling approach in healthcare using system dynamics (SD) and DES.

There are also many HS studies that modeled various aspects of the Coronavirus pandemic. For example, Cimini et al. (2021) used HS to assess the impact of containment measured for COVID-19. Their HS consists of an ABS virus contagion model and a DES people flow model in indoor environments. The authors conducted a case study at the University of Bergamo and their experiments shown the results of different class size examples. They reported that the use of HS allowed for more flexibility and insight gaining. Bouchnitaa and Jebranea (2020) used multi-agent systems with social force modeling to study how the movement of people affect the transmission of COVID-19 and tested different non-pharmaceutical interventions in a case study in Morocco.

Arguably, DES is the most popular simulation method in the area of hospital bed capacity management and other pandemic related operations such as testing. Several studies have been conducted to estimate ICU bed capacity (Zhu, Hen and Teow 2012), to balance hospital resources for COVID-19 (Melman, Parlikad and Cameron 2021). Saidani, Kim and Kim (2021) developed a DES to study COVID-19 testing capacity on a University campus. ABS has been used widely to model the spread of infectious diseases. Examples include Kerr et al. (2021) where the authors used ABS to model disease dynamics within social networks and the effect of preventive measures. The model includes hospitalizations and hospital bed capacity as input parameters. Similar study was conducted by Hinch et al. (2021). The authors developed their ABS in Python and with R interfaces. Wang et al. (2021) used the Unity game engine (https://unity.com/) to develop an ABS of COVID-19. They reported that the visualization of their simulation contributed to a better user experience.

Most of the ABS disease spread models consider bed capacities in an aggregated level but, usually, they do not include the operations of a hospital. We argue that a hybrid approach where hospitals are explicitly modeled as well as the population interactions in the community is beneficial in gaining insight of the progress of a pandemic and the impact of public health preventive measures on the community and the healthcare system. This is particularly interesting at a regional level where the character of an area can be captured in the model.

Moreover, in a panel discussion where Aleman et al. (2021) debated different modeling approaches for COVID-19, it was highlighted that availability and reuse of existing models could have resulted in faster modeling efforts and therefore better support to decision-makers, especially at the early stages of the Coronavirus pandemic. To support this effort, it is important to have well-documented models using standard reporting methods such as the ODD protocol (Grimm et al. 2020) and the STRESS guidelines (Monks et al. 2019). Also, Lather and Eldabi (2020) discussed the benefits of a HS hub for pandemic situations where models can be easily found and accessed.

In the next section we discussed our FACS and CHARM models and how they are used as HS. Both models are publicly available as well as their interfaces.

3 MATERIALS AND METHODS

This section details the ABS and DES models that constitute out hybrid simulation. It discusses the structure of the models, the input and output data as well as their user interface.

3.1 Flu and Coronavirus Simulator (FACS)

The Flu and Coronavirus Simulator (FACS) is an ABS model that uses geospatial, demographic and disease-specific data to model the temporal and spatial progression of COVID-19 in a specified geographical location (e.g., city or borough). It identifies the amenities and houses in the location and creates a local spatial network of people (agents) and amenities. It then simulates the movement of population across the amenities according to their needs which results in the spread of infection. The needs are specified based on an agent's age. For example, school age population go to school, working age population go to offices, etc. All agents spend most of their day at home and a proportion of their time in shopping, outdoor and indoor leisure facilities. Infected agents self-isolate and if the disease is severe, they are hospitalized. FACS has the capability to simulate the effects of various preventive measures such as lock-downs and vaccination strategies as well as the impact of emergence of new variants of the virus and the impact of distribution of amenities in the region. FACS can be easily adapted to model other similar air-borne diseases.

FACS consists of three main modules, these are the FACS pre-processing module, the FACS core module and the FACS post-processing module.

FACS pre-processing module. This module is used for the preparation of input data using CSV and YAML files, the parsing of different buildings types from the OpenStreetMap (https://www.openstreetmap.org/) files and preparing the geospatial location graphs. The input data can be categorized into three types, that is population data, disease data and location data. *Population data* includes the age distribution of agents in the area and is obtained from openly published demographic information, it also includes data that determine the behavior of the population i.e., its needs based on age. *Disease data* contains the disease parameters and prevention measures data, including pharmaceutical (e.g., vaccination) and non-pharmaceutical (e.g., social distancing, lockdowns, etc.) intervention. The disease parameters are the infection rate, the mortality rate, hospitalization probability, incubation period, time to hospitalization, length of stay in ICU, and time to recovery. Prevention measures data is in the form of a schedule. For each time period there are several pharmaceutical and non-pharmaceutical measures related parameters that are defined in a YAML file. With regard to vaccinations, these are the number of vaccinations administered per day, eligible age group, efficacy in terms of disease severity and ability to transmit the virus while vaccinated and booster doses administered per day. With regard to non-pharmaceutical measures, the parameters are the facilities under lockdown, mask wearing and uptake, track and trace efficiency and social distance advice. *Location data* includes the type of amenities and their coordinates as well as their size in square meters and all facilities of a specific type, i.e., a school type amenity incudes schools, colleges and universities, an office type amenity includes all work spaces, i.e., office, industrial area, construction site, etc.

FACS core module. This module contains the rules that govern the behaviour of the population and the disease as well as the impact the prevention measures have on the disease outcome. The population follows daily routines, e.g., they go to school or work, they stay in their household, they visit shopping and leisure amenities, etc. Based on these routines, they spend time in outdoor or indoor facilities of a certain size where they come into contact with other people. The size of the area, the air quality in this area, the time spent within as well as their immunity, the infection rate and the number of infected people they come into contact are the factors that affect the probability of getting infected. The infection probability is calculated by equation (1).

$$P_{inf} = M \, x \, \frac{IR}{SF} x \, LS_S \left(\frac{NI_{Avg} \, x \, A_{per}}{A_{loc} \, x \, Max_{per}} \right) x \, \frac{LS_{Inf}}{OD_{loc}} \qquad (1)$$

Where,
P_{Inf} is the probability of a susceptible person to become infected
M is a static contact rate multiplier

IR is the infection rate
SF is a scaling factor
LS_s is the length of stay of susceptible person in an area in minutes
NI_{Avg} is the average number of infectious contacts per day;
A_{loc} is the size of the location in m^2
A_{per} is the physical area of a single standing person
Max_{per} is the maximum number of persons that can fit in 4m^2
LS_{Inf} is the length of stay of an infectious person in the area in minutes
OD_{loc} is the opening time of a location on a given day

In the core module, the attributes of the agents are updated. These attributes indicate whether the agents are susceptible, infected, recovered, or dead. If infected, agent attributes indicate whether the symptoms are mild or severe and in the latter case whether they are admitted to hospital. Other attributes include an agent's immunity, vaccination status, geolocation at a given time its needs and household (size and geolocation).

The prevention measures rules are essentially the implementation of the measures as these are described in the input parameters. Each agent, based on its age and history follows the respective prevention measures with a given uptake probability.

FACS post-processing module. This module processes the raw simulation outputs. It is used to collate all replication outputs, plot the output graphs and visualize the disease progression on an interactive map. Output results include the daily number of agents in each compartment, i.e., susceptible, infected, recovered and dead, daily hospitalizations, and a history log of the behaviour of each agent, e.g., places visited, where an infection occurred, etc. Example of a FACS output is shown in Figure 1, where the number of daily cases (b) and hospitalizations (b) for the London borough of Brent is plotted. The graph shows experiments ran in the first year of the COVID-19 pandemic. The shaded area indicates 95% confidence intervals. The green line plots actual validation data and the vertical red lines denote key lockdown interventions. FACS is described in detail in Mahmood et al. (2020).

3.2 dynamiC Hospital wARd Management (CHARM)

Hospitals across the globe face capacity challenges due to the Coronavirus pandemic. Large numbers of COVID-19 patients require admission to ICU and very often for a long period of time. Another big challenge is the highly infectious nature of the virus. Hospitals make huge ward rearrangements in order to prevent nosocomial infections as well as create surge bed capacity for the anticipated COVID-19 admissions. During the first wave, hospitals cancelled all elective surgeries and were able to deal with only

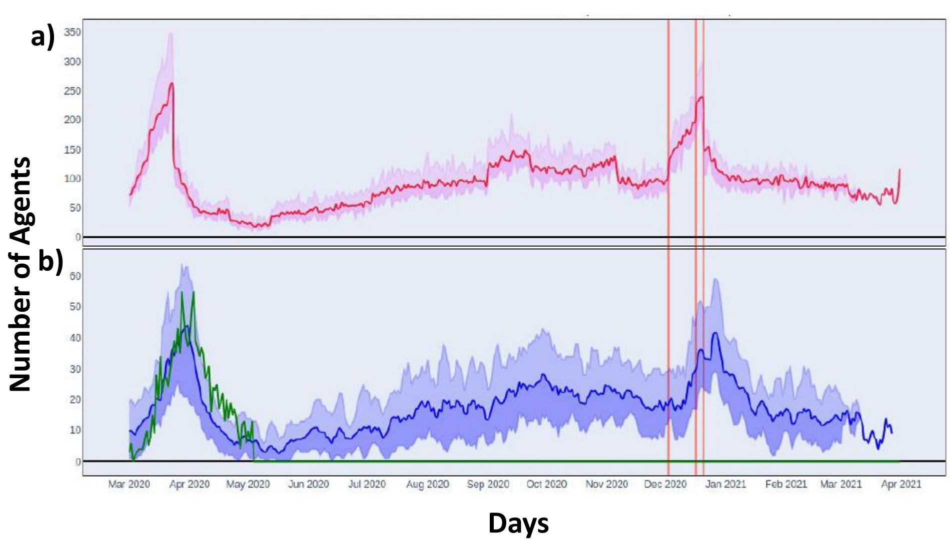

Figure 1: FACS example output daily cases (a) and daily hospitalizations (b).

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a small number of emergency incidents. When the first crisis started to ease, hospitals main question was how to manage future COVID-19 outbreaks, or other highly infectious diseases, and at the same time continue normal operation? Arguably, cancellation of all scheduled surgeries is not a viable strategy. The backlog of elective operations has a massive impact on the care that healthcare systems can provide to the population. Consequently, this has a negative impact on the quality of life and the economy.

In an attempt to support hospitals in planning their ICU bed capacity, we developed the dynamiC Hospital wARd Management (CHARM) model. CHARM is a DES model of the ICU patient flow process that allows for dynamic reconfiguration of hospital wards. It considers three types of admissions for emergency, elective and COVID-19 arrivals. A routing logic allocates the patients to the respective wards. COVID-19 capacity can be pooled from elective and emergency capacity when there is a surge of COVID-19 admissions. The resources are reversed to their original configuration when the surge eases. Hospital wards in CHARM are allocated in zones that represent six types, i.e., COVID-19 (C) and COVID-19 recovery (CR), emergency (EM) and emergency recovery (EMR), and elective (EL) and elective recovery (ELR). These zones are the pool of bed resources for each type. Each ward is dynamically recharacterized as of different zone type according to bed occupancy.

The model logic is shown in Figure 2 and applies on every patient that enters the model. There are three types of arrivals for C, EM and EL patients. When there is a new arrival, the model checks whether there is bed availability in the respective wards. If there is no bed available, the patient is moved out of the specific facility. If a bed is available, the patient stays in the ICU ward for the designated length of stay (LoS). A mortality check takes place at the end of this stay. If the patient does not die, the patient will attempt to move to a respective recovery ward. Similarly, to ICU, if there is no recovery bed available, the patient will move to another facility. If there is recovery bed available, the patient will occupy this resource and stay for a designated LoS. Mortality check takes place in the recovery wards too. Patients that do not die, are being discharged.

At every simulation time unit, the model performs some calculations and checks. The 7-day average of bed occupancy for type C beds is calculated to account for ward change setup time. Based on the bed occupancy, ward reconfiguration occurs. If COVID-19 bed occupancy is greater than a set threshold, emergency and elective zones are converted to COVID-19 zones, respectively. If COVID-19 bed occupancy falls below a set threshold, elective and emergency zones converted back to their original type.

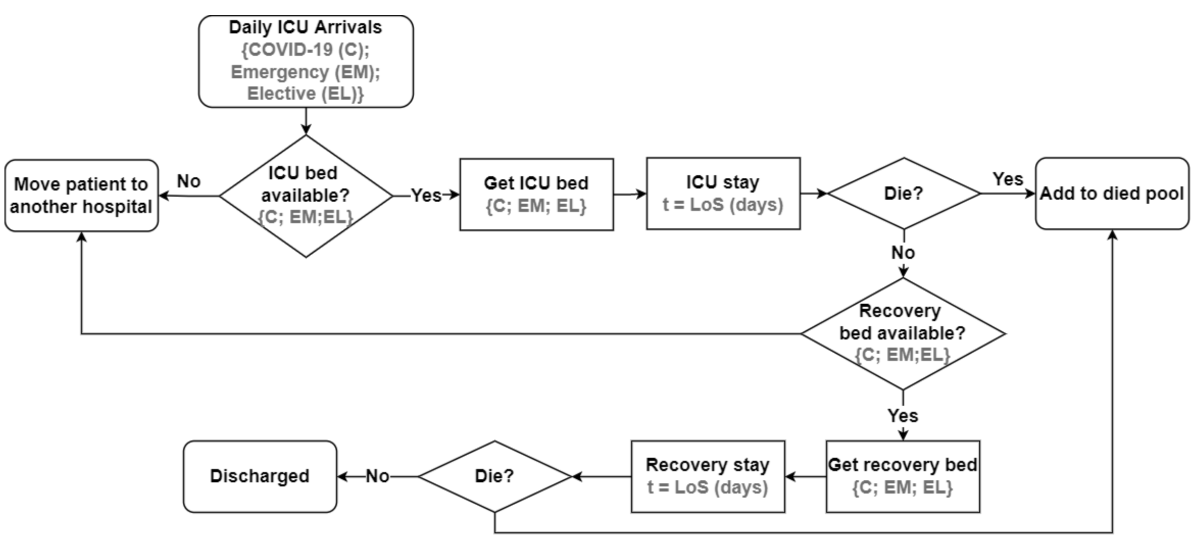

Figure 2: CHARM patient flow diagram.

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CHARM is built in Python using the SimPy libraries (https://gitlab.com/team-simpy/simpy). It takes two types of input data, that is daily COVID-19 patient arrivals and input parameters data.

COVID-19 arrivals, for the time horizon of the simulation, are read from a CSV file. This file in our hybrid FACS-CHARM is generated by a FACS simulation. However, CHARM can run independently too using retrospective primary COVID-19 ICU arrival data or predicted from other models. The input parameters data is also read from CSV files. These include daily emergency and elective arrivals, LoS for each zone type, mortality probability, the upper and lower thresholds of COVID-19 ICU bed occupancy and the number of replications that we wish to run the simulation for. Input parameters also include the initialization of zones with their types and capacities.

Patient arrivals and LoS are sampled by triangular distributions. Mortality rate is a probability (a number between 0-1) and occupancy thresholds are percentages (a number between 0-100). Example input parameter values can be seen in Table 1. The values derived from Simpson et al. (2005) and Melman, Parlikad and Cameron (2021).

Table 1: CHARM example input parameters.

	Arrivals (number of patients per day)	**Length of Stay (LoS) in days**	**Mortality (probability)**
Emergency (EM)	Triangular (min=0, mode=1, max=5)	Triangular (min=1, mode=6, max=9)	0.07
Emergency recovery (EMR)		Triangular (min=1, mode=9, max=12)	0.008
Elective (EL)	Triangular (min=0, mode=1, max=4)	Triangular (min=3, mode4, max=6)	0.02
Elective recovery (ELR)		Triangular (min=1, mode=7, max=9)	0.004
COVID-19 (C)	Fixed (read from file)	Triangular (min=1, mode=21, max=80)	0.39
COVID-19 recovery (CR)		Triangular (min=1, mode=16, max=60)	0.28

At the end of the simulation run the model outputs are written to CSV files. These include outputs of every replication as well as averages and 95% confidence intervals of the simulation run. Output data includes beds availability and capacity per type, beds availability and capacity per zone, 7-day moving average COVID-19 occupancy, cumulative number of patients moved due to bed shortages for each type, cumulative number of patients discharged per type, cumulative patients died per type. Example output graphs are shown in Figure 3. In these graphs we can see elective and COVID-19 bed availability and capacity. We can observe that on day 3 elective beds were requisitioned for COVID-19 and on day 15 where COVID-19 occupancy dropped to safe levels, the beds were available again for elective patients.

4 FACS-CHARM HYBRID MODEL

In a state-of-the-art review of the literature on hybrid simulation, Brailsford et al. (2019) identified four types of hybridization. These are: (a) sequential, where two or more distinct single-method models that are executed sequentially, so that the output of one becomes the input to another; (b) enriching, where there is one dominant method with limited use of other methods; (c) interaction, where distinct single-method submodels interact cyclically at runtime; and (d) integration, where there is one seamless model in which it is impossible distinguish the boundaries of the simulation methods.

Based on the above classification, the FACS-CHARM hybrid model can be described as of sequential hybridization with manual or automated interconnection. Our model has a single connecting variable. This is the daily COVID-19 ICU hospitalizations.

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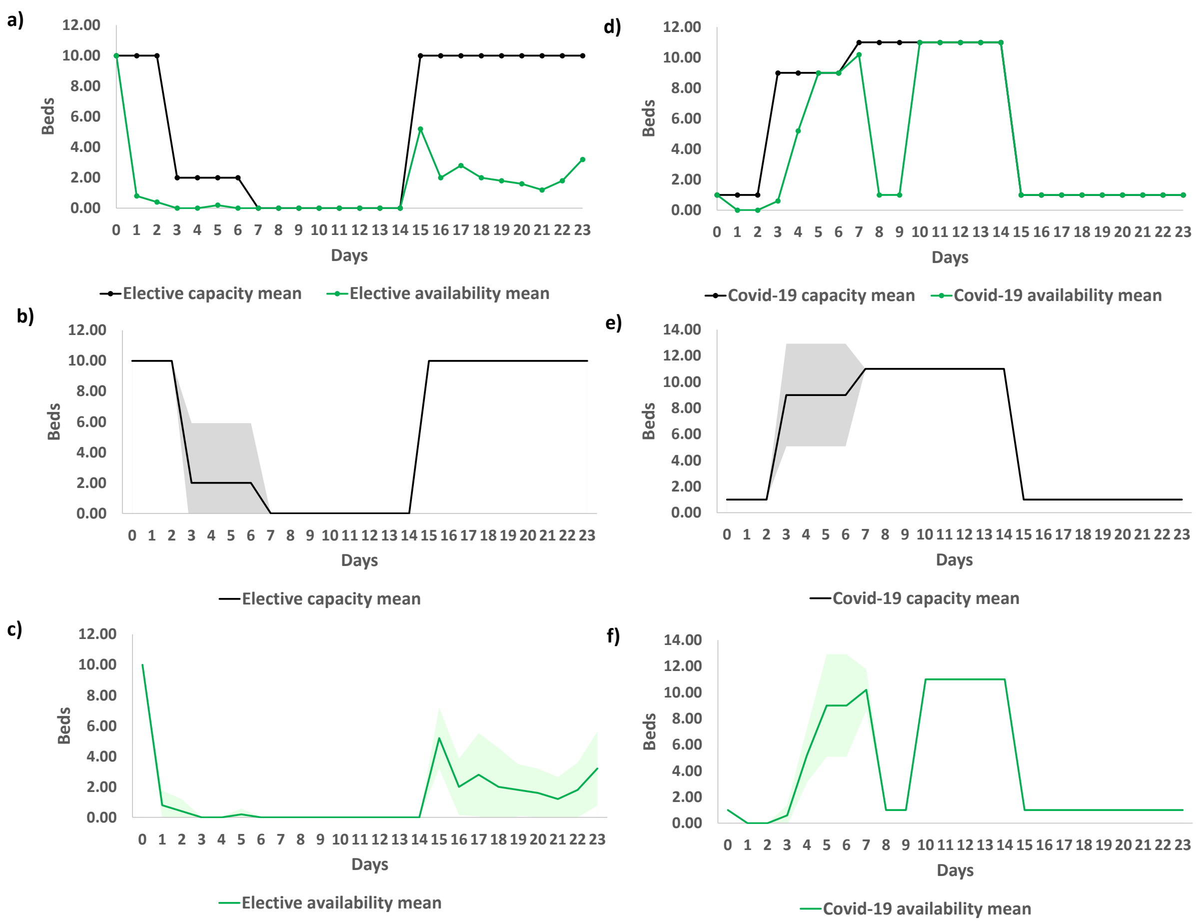

Figure 3: CHARM example output. Graphs a, b and c show the mean value of elective beds capacity and availability (a) and 95% confidence intervals (b) and (c), respectively. Graphs d, e and f show the mean value of COVID-19 beds capacity and availability (d) and 95% confidence intervals (e) and (f), respectively.

FACS predicts the daily COVID-19 ICU hospitalizations in the coverage area, among others. It also outputs geolocation information of the admitted cases. Using this feature, we can identify the total cases as well as the number of cases arriving at the individual hospitals serving the modeled region. CHARM in turn uses this information to predict ICU bed occupancy and whether surge capacity is likely to be needed.

FACS-CHARM can be used to study the COVID-19 impact on ICU capacity in the region as a whole and/or on individual hospitals within the region. For example, let's assume that the area modeled with FACS has three hospitals with ICU beds – hospitals A, B and C as shown in Figure 4. FACS records the temporal and spatial ICU hospitalizations. We therefore have information of the daily admissions in each of the hospitals in the area (Long = $X_{\{A, B, C\}}$, Lat = $Y_{\{A, B, C\}}$) and in the whole region. In this example, four CHARM instances can be run for analyzing ICU bed strategies in the region and/or in hospitals A, B and/or C. Input data for each case are daily ICU hospitalizations for the region, and/or for hospitals A, B and /or C, respectively.

The CHARM multiple instance option is denoted with a dotted line to indicate that this is optional. Each of the instances are independent and the choice to execute one or more depends on the scope of the study.

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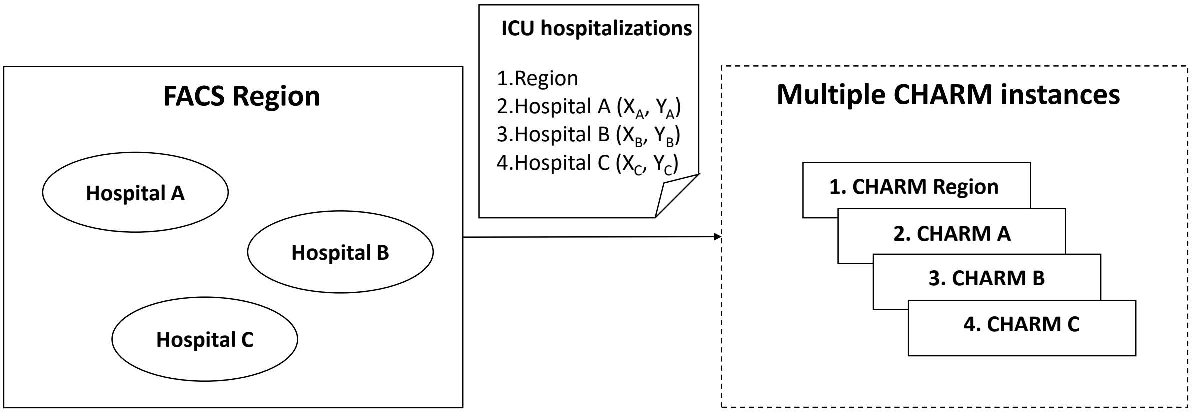

Figure 4: Hybrid FACS-CHARM data exchange.

The CHARM code is available on a public repository (https://gitlab.com/anabrunel/charm). We have also developed a dashboard CHARM that enables end users to enter input parameters in a user-friendly manner and visualize the output plots. This code is also publicly available at https://gitlab.com/anabrunel/charm-app. The CHARM dashboard is deployed on a demo server available at https://charm-des-app.herokuapp.com/. FACS is a parallelized software developed in Python and its code is available on a public repository (https://github.com/djgroen/facs). A dashboard has also been developed that enables end users to enter certain for preprocessed locations in a user-friendly manner and visualize the output plots. This code is also publicly available at https://github.com/arindamsaha1507/FADE_Dashboard. An instance of the FACS dashboard is deployed on a demo server available at https://facs-dashboard.herokuapp.com/lithuania. Figure 5 shows a screenshot of the CHARM and FACS dashboards.

It is worth noting that FACS-CHARM could be implemented as distributed simulation (DS). A FACS-CHARM hybrid distributed simulation model would fall into the DS mode B type as it is described in Taylor (2019). That is, FACS and CHARM are single models that run independently on remote compute nodes but are linked together via a communication network so they can interact. We envision that the most appropriate middleware between the models would be an implementation of a publish-subscribe protocol, such as a message broker (e.g. RabbitMQ (https://www.rabbitmq.com/), Kafka (https://kafka.apache.org/), etc.) or the high-level architecture (HLA) (IEEE-1516 2010). The FACS-CHARM DS implementation is

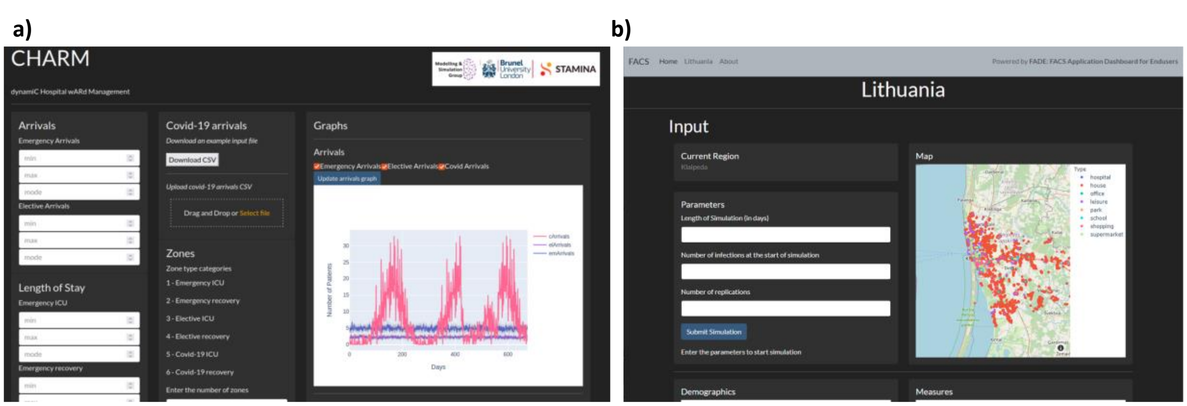

Figure 5: CHARM (a) and FACS (b) dashboards.

in our future plans the implementation of which follows the approach of our previous work in the area (Anagnostou and Taylor 2017; Anagnostou, Nouman and Taylor 2013).

5 CONCLUSIONS

The paper presented our hybrid ABS-DES model for COVID-19 management at a regional level. Our hybrid model consists of the FACS ABS model that is used to model the disease transmission in an area and its consequences (i.e., cases, ICU hospitalizations and fatalities) considering public health intervention measures, and the CHARM DES model that is used to model the ICU patient flow considering COVID-19 isolation beds and dynamic ward reconfiguration. We discussed the need for multiple simulation methods when tackling complex problems such as pandemics and we outlined both FACS and CHARM, their structures as well as the ways that they function together as a hybrid model. Currently, within the STAMINA project, we are developing three cases studies in Turkey, Romania and Lithuania. One of the limitations of the model is that we include only ICU bed resources. Nonetheless, staff shortages is a crucial factor as well in hospital capacity management. In our future work, we plan to extend the model to consider healthcare staff resources, too. Our future plans also include implementing the hybrid FACS-CHARM DS using a message broker interface.

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