Designing an Agent-Based Model for a City-Level Simulation of COVID-19 Spread in Cyprus

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Abstract: To date, several epidemiological agent-based models have been developed to study the spread of the highly infectious coronavirus (SARS-COV) disease in different countries. However, no extensive effort has been implemented for the Republic of Cyprus. In this research, we present the design framework of the EPIMO-LCA agent-based model that respects the SEIR epidemiological model and attempts to simulate human mobility to predict the spread of COVID-19 at a city-level of detail. More specifically, we fully describe the three main model components (agents, environment and interactions) and explain all anticipated functionalities, processes, input and output elements. The agent-based model envisaged is expected to contribute to a better understanding of the interactions between intervention measures and disease spread for the city of Larnaca, the Republic of Cyprus, and beyond.

1 INTRODUCTION

A pressing need for understanding the behaviour of epidemiological diseases has emerged in light of the recent COVID-19 (SARS-CoV-2) experience. Having spread all over the world, leaving millions of human losses behind, coronavirus 2 has posed significant challenges to humankind at every level. Cyprus was no exception, counting more than 1,500 deaths and 600,000 (>50% of the total population) infections (World Health Organization, 2023). The particularly high human-to-human inapparent transmission rate in combination with the severe implications that COVID-19 may have on human health, and especially the vulnerable group of people, have led to an urgent need of seeking ways to limit the virus spread. Intermittent non-pharmaceutical interventions (NPIs) have proven able to reduce the infection spread rate (Buhat et al., 2020) but may, on the other hand, have significant impact on the socioeconomic aspects of human life in the medium- and long-term (Novakovic & Marshall, 2022). The above highlight the importance of forming effective policies and taking better-informed and timely decisions in regard to prevention, control and mitigation of COVID-like viruses spread (Cui et al., 2006). In this context, radical advances on epidemiological (disease spread) modelling have marked the aftermath of the recent pandemic to support scientists and decision makers in understanding the underlying mechanisms driving the spread of the infection.

Intricate relationships between social and physical processes, including the transmission of infectious diseases, have recently been at the focal point of spatial sciences and geography. Indeed, modelling of human-environment interactions enables insights into the spatial dynamics of these relationships, leading to

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improved decision making and addressing of complex challenges. Mathematical models, representing simple or complex abstractions of mobility and interactions among individuals and populations, have been central to infectious disease response and decision-making process (Bachar et al., 2021; Hethcote, 1989, 2000; Kifle & Obsu, 2022; Vytla et al., 2021). This is particularly useful in the case of infectious diseases towards increasing our understanding on the drivers of transmission (Crooks & Hailegiorgis, 2014; Merler et al., 2015; Willem, 2015) and non-linear causal effects and providing the ability to simulate future scenarios (Gomez et al., 2021; Kerr et al., 2021; Kyriakidis et al., 2021; Shastry et al., 2022; Silva et al., 2020). Among the most widely used computational models, agent-based models (ABMs) have become popular due to their inherent ability to model and simulate mobility transitions of autonomous agents within complex systems (Mehdizadeh et al., 2022) based on a set of behavioural rules guiding their interactions (Bonabeau, 2002). This particular modelling architecture is widely applied in fields where simplifying complexity is crucial, like economics (Heckbert et al., 2010), mobility (Loraamm, 2020) and supply chain (Chen et al., 2013). Therefore, it is only fitting that such modelling approach be utilised in the field of epidemiology. In relative terms, agents can be individuals, groups, organizations, or even non-human entities able to interact with each other and their environment in various ways, depending on the specific model. Consequently, each agent can be described by individual properties but also given a certain status at each discrete time step, as described in the following section. The bottom-up approach of ABMs allows for the realistic simulation of interactions among individuals both in space and time which in turn could give insights to population-scale patterns (Tracy et al., 2018) of the phenomenon under study.

A plethora of ABMs, drawn from the extensive data gathered for the needs of modelling COVID-19 transmission, has been developed during the last two years. The majority is built upon dynamic equations linking compartments; those being susceptible (S), exposed (E), infected (I), and recovered (R). As the letters S, E, I, R represent, the health status of a given human population within a dynamic infectious disease context, health experts and scientists should always regard any pandemic situation within a tight temporal context so as to accomplish its minimum possible spread, while achieving better forecasts (Yang et al., 2021) for the future.

Different variations of the so called SEIR model, have been extensively used in an ABM context to assess planned interventions used to combat COVID-19 (Altun et al., 2021; Kim & Cho, 2022; Taghizadeh & Mohammad-Djafari, 2022). A systematic review on agent-based social simulation of Covid-19 is given by Lorig et al. (2021) while Kong et al. (2022) provide a scoping review of the compartmental structures used in the dynamic models developed for COVID-19 spread. Application examples include Covasim (Kerr et al., 2021), an ABM model to project COVID-19 dynamics and interventions, COVID-ABS (Silva et al., 2020) developed in an attempt to simulate health and economic effects of interventions and CityCOVID (Ozik et al., 2021), incorporating behavior and social interaction in a real-case scenario in Chicago.

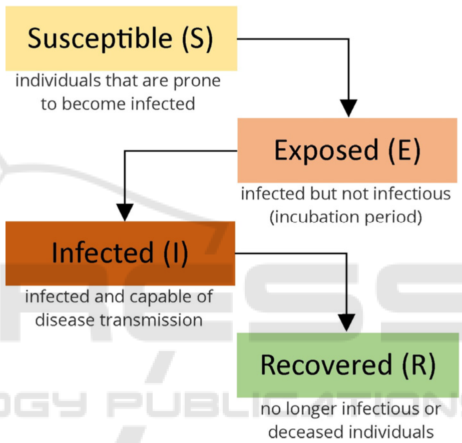

Figure 1: Diagram of a typical S.E.I.R Model.

In cases where the adoption of SEIR models is needed to allow health stakeholders and officials to extract concrete conclusions and make predictions, proper model calibration is imperative in order to understand both the static and dynamic nature of the phenomenon under study. Towards that end, Ajbar et al. (2021), answering to the critical -for such understanding and for the model calibration as well- inverse modelling problem, identified their model parameters using real time data of Saudi Arabia and subsequently used the computed values to analyse the behavior of the model. Over time, SEIR models showcased their advantages rendering them important tools for policy makers and governments when coupled with network-driven dynamics being capable of predicting with high accuracy any epidemic peaks taking into account external factors such as the virus transmission over air (Liu et al., 2020). Although, SEIR models might be considered adequate for modelling and forecasting other diseases, as far as COVID-19 is concerned, Moein et al. (2021) showed that a more complex approach that takes into account mortality rates and hospital capacity as well should also be considered when attempting to make a pandemic forecasting feasible.

Building upon the need for a more complex approach to COVID-19 modelling, the present study introduces an ABM to simulate the spread of the disease based on human mobility and evaluate the impact of governmental countermeasures, with a focus on the Republic of Cyprus as the study area. In addition to simulating the distribution of future cases and deaths, the model is designed to be able to predict the possible outcomes after the implementation of strong governmental countermeasures, thus, allowing the evaluation of such actions in preventing COVID-19 spread locally.

To the best of the authors' knowledge, no similar studies have been conducted for the particular region of interest (Larnaca, Cyprus) that utilise agent-based modelling to study the spread of COVID-19. Spatial behavior is based on the Human Mobility Schedule (HMS) and is designed to be incorporated to the model through a questionnaire survey that represents the human mobility of Cypriot citizens after each iteration of the ABM simulations.

2 METHODOLOGY

To simulate the spread of COVID-19 using the agent-based approach, we identify NetLogo software as the most widely used open-source solution capable to represent and analyse a model of this capacity. This section describes the main logic of EPIMO-LCA agent-based model and explains its functionalities, processes, properties, input and output elements.

The Human Mobility Schedule (HMS) is a crucial component of the model as it contains all the necessary information regarding mobility behavior (how and when the agents move based on age group) on an hourly basis. The aim of the HMS is to describe the main mobility activities of individuals in Cyprus according to their age during a typical day. It is based on the analysis of real data resulted from a two-part questionnaire survey addressed to Cypriot citizens. In the first part of the questionnaire, demographic information (gender, age, region of residence and occupation) as well as mobility characteristics (means of transport, mobility type, frequency and distance) are requested. The second part asks for the completion of a mobility schedule indicating the person's indicative location/activity per hour within a typical day.

2.1 Agents

Based on their age, there are three principal types (breeds) of agents in the EPIMO-LCA model. Each bread describing a specific group of people, moves differently according to the HMS: 1) Mostly-out agents (age: 18-64) represent the group of people that mainly move from-to their work office, 2) Students (age: 6-24) represent the group of people that mainly move from-to educational institutions and 3) Mostly-at-home agents (age: 18+) represent the group of people that stay mostly at home (unemployed, elderly and work-from-home individuals).

Table 1: Agent properties.

No	Property	Type	Function
1	Age	numeric	Initial setup of population % by age group
2	Chronic disease	True/ False	Initial setup of population % with increased chance of mortality
3	Mask wear	True/ False	Initial setup of population % that respect the mask-use measure
4	Social distance	True/ False	Initial setup of population % that respect the social distance measure
5	Immune	True/ False	Initial setup of population % that are immune (natural, vaccination or medicine)
6	Healthy	True/ False	Initial setup of population % that are healthy
7	Infected	True/ False	Initial setup of population %, and later after being exposed
8	Susceptible	True/ False	Agents that are in close proximity with an infected agent
9	Exposed	True/ False	Agents at high risk to be infected (incubation period)
10	Recovered	True/ False	After the pass of 14 days being infected
11	Deceased	True/ False	After being infected and if at high risk

Agents are defined by a set of eleven properties (table 1). Properties 1 to 7 are set ahead of model initialization (model parameters), while properties 6 to 11 are dynamic and change as the agents are interacting with each other, describing the state of the agent.

2.2 Actions and Behaviours

At the start of the simulation, agents are assigned one of the 3 states (Healthy, Immune or Infected) depending on the parameters initially set. After model initialization, agents move using the road network interacting with each other and gradually evolve to 4 more states (Susceptible, Exposed, Recovered, Deceased). Depending on their state, agents behave as follows. Healthy, Immune, Susceptible, Exposed and Recovered agents continue to move based on their breed and according to HMS. Immune and Recovered agents stay in this state forever and cannot transmit the virus nor get infected. Therefore, re-infection is not possible. Infected agents can also continue to move (according to HMS) or implement the stay-at-home quarantine rule, depending on the initial parameter set.

Moving progressively from one state to another, there are five intermediate stages where agents evolve 1) from Healthy-to-Susceptible, after being in close proximity and in contact with an infected agent, 2) from Susceptible-to-Exposed, after in direct contact with an Infected agent and if at high risk of infection (no mask use, no social distancing, no immunity), 3) from Exposed-to-Infected, after the pass of n days (incubation period), 4) from Infected-to-Recovered, after the pass of 14 days being infected and, lastly, 5) from Infected-to-Deceased, after the pass of three days and if at high risk of mortality (age group, chronic disease).

2.3 Environment

Agents interact in a spatial environment using the road network of the city of Larnaka, Cyprus. Each time-step (tick) represents one hour of human activity. Moreover, buildings are also mapped and used as origin - destination for moving agents. More specifically, these buildings correspond to high-risk areas for virus transmission and are represented as points (centroids) in space with different colours based on building type (residential, offices, health centers, educational institutions, shopping centers, etc) and represented with various buffer sizes depending on crowd capacity.

Having one of the highest car ownership rates in the world (629+ cars per 1000 inhabitants), Cyprus' residents rely heavily on private car commuting (Obrien, 2022). Based on this fact, in our simulation we don’t include any public transportation parameters assuming all agents use private cars with an average speed of 50km/h (speed limit in urban areas).

2.4 The Proposed ABM

Initially, the agents are randomly distributed in residential buildings and as the model starts, they begin to move (according to HMS) to other buildings. As a result, while respecting each building crowd capacity, agents are continuously gathering in closed limited areas and interact with each other. Thus, the virus begins to spread and emerge. The simulation continues until all agents are either Healthy, Immune, Infected, Deceased or Recovered. In our proposed model, the simulation of COVID-19 spread adheres to the following process (figure 2):

1. Agents are created according to setup parameters (Initialization of the model).
2. Agents are assigned with a colour based on their initial state (Healthy - green, Immune - grey and Infected - red).
3. Agents are allocated randomly in space, initially within residential areas while respecting crowd capacity.
4. Healthy and Immune agents move according to HMS. Infected agents also move depending on preset rule (if 14-day home quarantine parameter is disabled).
5. Non-immune and non-infected agents that are in close proximity to infected agents turn to yellow colour (susceptible).
6. Susceptible agents at low risk of infection turn green colour (healthy).
7. Susceptible agents at high risk of infection turn orange colour (exposed).
8. Exposed agents turn red colour (infected) after n days (n*24 ticks).
9. Infected agents at high risk of mortality turn black colour (deceased).
10. Infected agents at low risk turn blue colour (recovered) after 14 days (336 ticks).
11. The Simulation stops when all agents are either healthy, immune, infected, deceased or recovered.

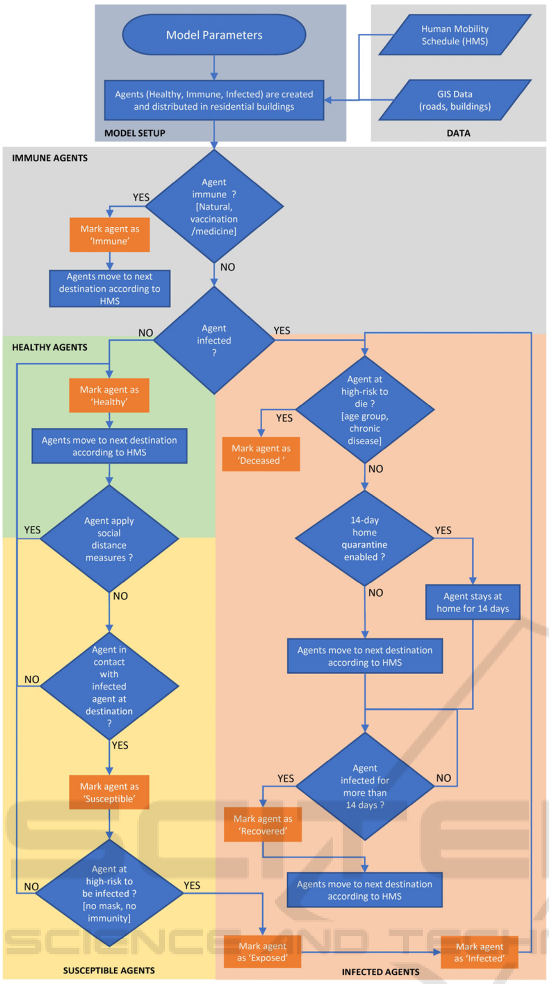

Figure 2: The EPIMO-LCA model flow chart.

Through NetLogo's user interface, specific demographic and epidemiological input parameters can be easily adjusted and countermeasure policies can be enabled or disabled (mask use, vaccination, lockdown, etc.) in the simulation. More specifically, the user using a slider can define the number of: a) the total population size (ranging from 10-600), b) people initially infected (% of total population), c) immune people (% of total population), d) people with chronic diseases (% of total population), e) people in each age group (% of total population), f) mortality rate, g) recovery rate, h) hospital capacity/beds (ranging from 10-600), i) people that adhere to social distancing (% of total population), j) people vaccinated or on medication (% of total population). Additionally, the user using a switch can enable or disable important parameters regarding: k) mandatory mask use, l) shops closure (entertainment, restaurants, bars, shopping) and m) full lockdown enforcement.

2.5 Data

All the required data are obtained from freely available open repositories (OpenStreetMap and National Open Data Portal of Cyprus - data.gov.cy) and from local governmental authorities (Department of Land and Surveys and Statistical Service of the Republic of Cyprus). Additionally, the latest CORINE Land Cover (CLC2018) product by the Copernicus Land Monitoring Service is considered an important dataset for the determination of land use areas at an 100m spatial resolution using Sentinel-2 and Landsat-8 satellite data. All these data are necessary for the development of the agent-based model and additionally will be also used for the purposes of data analysis and model validation.

2.6 Expected Results and Validation

The proposed ABM is expected to contribute to the better understanding of the emergence and course of the dangerous virus in the community while considering the effects of important coping policies as well as human mobility behaviours for the simulation of the disease spread at a city-level. It aims to help experts and decision makers to combat future epidemic and pandemic events. By showcasing all the critical statistics and graphs (number of healthy, immune, susceptible, exposed, infected, recovered and deceased people) in real time, the model aims to be an efficient tool for the prediction of virus spread, the evaluation of the important coping measures and the estimation of the possible consequences.

To validate the effectiveness of the model, four different case scenarios will be simulated for comparison with real data. The case scenarios concern specific key time periods (lockdown, mandatory mask use, etc) during the COVID-19 (2020-2022) pandemic in Cyprus. For each simulation, the coping policies as well as demographic and epidemiological data will be simulated using real data as input parameters. Simulation results will be then compared with the actual situation (real number of infections, people immune, deaths, etc) that the Republic of Cyprus experienced. In this way, we can evaluate the effectiveness of the model.

3 CONCLUSIONS

Respecting the concept of the SEIR epidemiological model, in this research we presented the design framework of an ABM for COVID-19. The "EPIMO-

LCA" model is designed with the goal to simulate human mobility behavior in order to predict future outcomes (spatial distribution of cases and deaths) at a city-level of detail, while also considering important governmental countermeasures (like mandatory mask use, lockdown enforcement, etc.). In our proposed design we specified the types and properties of the agents, their actions as well as the environment that they will interact during the simulation. Additionally, we identified the need for data concerning human spatial mobility behavior as such data does not exist for Cyprus. This is why we suggest the implementation of a questionnaire survey. The results of this survey will be analysed and lead to the development of the HMS with the scope to be integrated in the model as an immediate future step. In this way we can produce a representative activity schedule that describe the mobility of the Cypriot citizens (per age group) during a typical day. Thus, the HMS is a critical component as it defines the way that the agents will move during the ABM simulations. After the actual development of the model, the validation process will follow using real data and specific case scenarios. Once the methodology and all parameters are finalized, the model can be expanded and parameterized for the rest of the districts of Cyprus (Limassol, Nicosia, etc.).

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