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Identification of critical airports for controlling global infectious disease outbreaks: Stress-tests focusing in Europe

Paraskevas Nikolaou, Loukas Dimitriou *

Department of Civil and Environmental Engineering, University of Cyprus, 75 Kallipoleos Str, P.O. Box 20537, 1678, Nicosia, Cyprus

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ABSTRACT

As the global population increases and transportation connectivity improves in quality and prices, the demand for mobility increases, especially in long-haul services. According to the 2017 report of the European Commission in Mobility and Transport, the performance of all modes for passenger transport (roadways and airways) are reaching record highs. Although the benefits of the increased demand for mobility are substantial and welcome, an effort should be paid such as to ameliorate possible threatening side-effects that may also arise. As World Health Organization (WHO) denotes and as has been evident from the global COVID-19 epidemic outbreak, infectious diseases can be spread directly or indirectly from one person to another under common exposure circumstances such as air transportation (especially long-haul airline connections) that may act as the medium for transmitting and spreading infectious diseases. In this paper, analytical and realistic models have been integrated, for providing evidence on the spread dynamics of infectious diseases that may face Europe through the airlines system. In particular, a detailed epidemiological model has been integrated with the airlines' and land transport network, able to simulate the epidemic spread of infectious diseases originated from distant locations. Additionally, a wide set of experiments and simulations have been conducted, providing results from detailed stress-tests covering both mild as well as aggressive cases of epidemic spreading scenarios. The results provide convincing evidence on the effectiveness that the European airports' system offer in controlling the emergence of epidemics, but also on the time and extent that controlling measures should be taken in order to break the chain of infections in realistic cases.

1. Introduction

As the global population increases and transportation connectivity improves in quality and prices, the opportunities for people's mobility also are improving. According to the 2017 report of the European Commission in Mobility and Transport (European Commission - European Commission, 2019), the performance of all modes of passenger transport (e.g. roadways and airways) are reaching record highs. Although the benefits of the increased demand for mobility are substantial and welcome, an effort should be paid such as to ameliorate possible threatening side-effects that may also arise. As the World Health Organization (WHO) denotes and as has been evident from the global COVID-19 epidemic outbreak, infectious diseases can be spread directly or indirectly from one person to another under common exposure circumstances. Moreover, public health crises of the past decades, like SARS in 2003 or the H1N1 flu pandemic in 2009, have highlighted how easy it is for diseases to spread around the world very rapidly, leveraging the air transportation, especially nowadays that air-traveling allowed everyone to travel anywhere in the world within a day. As experienced with the ongoing outbreak of the coronavirus disease (COVID-19), it is of high importance the air transportation industry (airports, long-haul airlines, authorities, etc.), which services may act as the medium for transmitting and spreading infectious diseases, to be specifically prepared for addressing threats like global epidemics.

According to Routley (2019) Europe remains an important linchpin in international traveling. It must be also noted that 4 out of 10 internationally connected airports belong to European countries, which are Heathrow (United Kingdom), Frankfurt (Germany), Amsterdam Schiphol (Netherlands) and Charles de Gaulle (France). Therefore, there is an acute need to understand and predict the patterns that pathogens follow as they are highly possible to reach one of the European airports and though them to be spread in the European countries. Thus, the question raised here is: which airports (or complete network regions) are more sensitive/critical for controlling a possible disease spread?

* Corresponding author.
E-mail addresses: nikolaou.paraskevas@ucy.ac.cy (P. Nikolaou), lucdimit@ucy.ac.cy (L. Dimitriou).

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Subsequently, what are the methodological means that can be used for testing control policies for avoiding the spreading of such pathogens and where to apply quarantine or block measures for controlling a possible spread?

In order to study the phenomenon of disease spreading from in cases of global epidemics a four step process is applied here:

Step I: Network analysis of the global air transportation network
Step II: Epidemic simulation by integrating an epidemiological model with the air and land transportation model
Step III: Stress-test of alternative virus characteristics for validating and/or identify critical airports (or even complete regions or countries) that gating actions should be applied, and
Step IV: Estimating the most critical time instance that gating actions should be applied

Starting with the *Step I*, in the current paper network complexity analysis is conducted, which has proven important in controlling network epidemics (Loscalzo et al., 2017, Barabási, 2016). In particular, several centrality metrics are used and applied for identifying 'central' nodes of the air transport system (mainly airports), namely, Degree, Betweenness and Closeness Centrality. Each metric provided an indication of the airports' importance according to the type of connections these have with the rest of the European and non-European airports, a fact that suggest possible future facilitation of disease spreading within the European region through them. Additionally to the information on critical nodes (airports), policy-making also require additional information on the different effects that Europe may face in the case of different starting locations of infectious diseases. Moreover, in case of a global epidemic outbreak, it is important to know the epidemics dynamics related to transportation that European cities/countries will face.

Therefore, in *Step II* extensive stress-test scenarios were conducted for the investigation of the European airport system's robustness in protecting the European countries against possible global epidemic events. This concept was analyzed using the Global Epidemic and Mobility (GLEaM) epidemiological model and illustrated in the GLEAMviz software (Gleamviz.org, 2019). In detail, demographics and mobility data were incorporated with epidemic modeling, aiming to predict accurately the number of infections invaded by flight or by commuting. For this reason, several experiments have been analyzed using the GLEAMviz epidemic simulation model. The most frequently used epidemic models used in such cases are the Susceptible-Infected (SI) model, Susceptible-Infected-Susceptible (SIS) model (Song, 2017) and Susceptible-Infected-Recovered (SIR) model. The analytical approach followed in this paper, started by the implementation of three scenarios of SIR models for identifying disease-spreading dynamics at a continental level. Every scenario considered different values of recovery rate (μ) and transmission rates (β) parameters. The scenarios studied hypothetical disease outbreaks originated from the busiest airports of three continents, namely, Africa (Scenario 1), Asia (Scenario 2) and South America (Scenario 3). In detail, the airports that were concerned for each continent are listed below and presented in Fig. 1.

i. African airports: Cape Town, Durban, Johannesburg, Mauritius, Marrakech, East London Port Elizabeth, Mahe Island, Bloemfontein and Cairo,
ii. Asian airports: Singapore, Tokyo, Tokyo Narita, Seoul, Hong Kong, Nagoya, Shanghai, Delhi, Mumbai, Hyderabad, Bengaluru, Colombo, Chennai, Ahmedabad, Karachi, Chittagong and Amritsar, and
iii. South American airports: Lima, Quito, Bogota, Guayaquil, Sao Paulo, Rio de Janeiro, Santiago, Buenos Aires and Recife.

The purpose of developing these scenarios was the estimation of the possible disease outbreak dynamics within the European region when the outbreak originates from the three different continents. Based on the results, European countries are exposed more in possible diseases outbreaks originated from Africa and Asia. Besides this finding, this approach was able also to identify the parameters that may facilitate the disease spreading in the European region.

In *Step III*, in order to identify the critical nodes (or regions) for controlling an epidemic outbreak, extensive stress-test subject to the characteristics of hypothetical viruses are conducted, controlling the transmission rates, estimating the effects in European countries in terms of spreading dynamics. By performing such stress-tests, the control measures that should be taken for each type of contagious virus and virus starting location (continents) can be identified. Identifying the critical airports (or even large parts of the airline network like those of regions or countries) within Europe, combined with the popularity/criticality of the airports and the information obtained based on the continental analysis developed for a disease outbreak inside the European region, provide significant information on which European countries and airports are prone to a possible disease outbreak, an element crucial for supporting decisions for controlling phenomena of global disease outbreaks.

Finally, in *Step IV*, investigation on the most effective time that controlling actions should be applied is undertaken. By taking into account the dynamic nature of an epidemic, the time that controlling actions are applied in the transportation network stands for a crucial element for breaking the transmission chain and ultimately stop the spread of an epidemic incident. This investigation is based on an 'aggressive' type of virus (in terms of transmission rates) and focused on Italy under the conditions running since the beginning of 2020. Starting from January 2020 when Italy detected its first coronavirus cases, and based on the evolution of this virus after almost two months, it turned out that the COVID-19 virus spreading in Italy was extremely severe and thousands of people were infected and many of them lost their lives (Who.int, 2020). In this Step, the dramatic effect of the time that control measures taken is highlighted, since slight delays in necessary gating

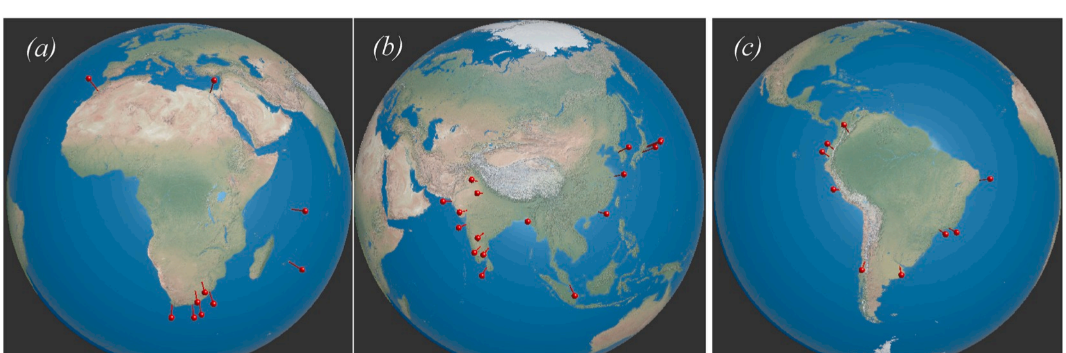


Fig. 1. Airports that were concerned in: a) Scenario 1-Africa; b) Scenario 2-Asia and; Scenario 3-South America.

decisions may result in uncontrolled spreading of an aggressive infectious virus throughout a large region.

Overall, this research provided a step-by-step approach for modelling future outbreaks spreading dynamics through the airlines network and identify critical nodes/airports (or even critical regions and countries) and the time that such actions should be applied in order to control infectious disease spreading. The rest of the paper is organized as follows. Section 2, provides an overview of related literature. Section 3 presents the analytical framework that was followed for the scoped of this research. Section 4, presents the overall outcome of the analytical framework for realistic settings. Conclusions are reported in the final section.

2. Literature review

The continuous growth of multimodal transportation has increased the volume of travel flows, on the global scale. Millions of peoples are crossing continents on a daily basis, a fact that has enhanced the speed of disease spreading, making the possibility of disease outbreak within days a realistic scenario. Air travel belongs to one of the means that can rapidly spread a disease to a global scale (Findlater and Bogoch, 2018). Therefore, there is a need for understanding and predicting the patterns that diseases follow as they spread on a regional or global scale. Consequently, spreading-control and quarantine-based actions remain the main tools for public health authorities in combatting epidemics. For this reason, several efforts have been conducted studying the dynamic disease spreading incorporating several factors, such as the distance between regional and human mobility behavior (e.g. Wu et al., 2018), network topologies, length of stay, etc. However, analyzing the dynamic spread of diseases on an international level may not be enough for concluding to the measures that will work as travel restrictions. Therefore, is critical to analyze the complexity of the networks for observing which vertices (airports) are more “sensitive” to a possible disease spread. In this scope, several studies have been implemented for analyzing the complexity of networks (Angeloudis and Fisk, 2006; Matamalas et al., 2018; Brockmann and Helbing, 2013). Additionally, Strona et al. (2018) studied the vulnerability of networks to epidemics and found that the density of infection pathways had a stronger effect on outbreak magnitude than the epidemic parameters when a broad range of network topology is considered. Furthermore, it is found that as the length of stay (an element of exposure to a possible threat) increases in highly connected locations the epidemic spread is expected to have an acceleration, depending also on the dominant role of the hubs either wise the spreading potential of the hubs is substantially reduced, delaying the epidemic spreading (Poletto et al., 2013). In Li et al., 2018 paper, they identified a weak relationship between population density and the death rate due to epidemics. Additionally, population density is closely dependent on the time and the rate of disease spreading. In Enright and Kao, 2018 work, the author defined methods based on network dynamics for modeling epidemic spreading among specialists, and thus highlighted the opportunities and difficulties in working within a disease-relevant network, while suggesting available software tools for conducting a similar analysis. Focusing on the meta-population epidemic dynamics, precautionary controlling actions has been proven critical to epidemic spreading. Therefore, several approaches have been proposed and tested in the real world, such as to reduce spreading rates (Gong et al., 2013).

The parameters of the epidemic dynamics modeling (e.g. transmission rate and diffusion rate) are critical while they compose the realistic component of epidemic spreading. Therefore, for accurately predicting epidemic spreading dynamics it is important to identify these parameters. For instance, Wang et al. (2013) estimated the transmission rate from the infected cases at the whole population level and have introduced a maximum likelihood estimator for estimating the diffusion rate (the probability that infected in a subpopulation diffuse to a neighbor susceptible subpopulation). In Merler and Ajelli, 2010 paper they studied the epidemic transmission rate in households, schools, workplaces and the general population of 37 European countries. In detail, they found that the cumulative attack rate in the different European countries had a range from 31.2% (Bulgaria) to 37.8% (Cyprus) and the average cumulative rate was 33.7%. Connectivity patterns between distant locations have a significant role in the epidemic spreading dynamics. No doubt, air transportation plays the main role of passengers' travel flows and thus it is important studying the role of the large-scale properties of the airline transportation network, which may act as a medium for spreading emerging disease, mainly due to exposure conditions evident in long hour flights (Colizza et al., 2006). Epidemic spreading forecasts aim to predict the real-time spread of a disease, i.e., the number of infected on a regional and international level and therefore to advocate policy-making measures in order to prevent a possible disease spreading. The allocation of limited resources in the identification of a potential bioterror attack is considered in the work of (Berman et al., 2012). Additionally, another study demonstrated how public health authorities could prioritize the allocation of response-resources in the U.S. at point of entry (Hwang et al., 2012). In detail, they examined the time-course for infectious air travelers to arrive in the U.S. from international cities. The exploration of the biopolitics of public health in the UK through an in-depth empirical analysis of the representation of H1N1 in UK national and regional newspapers was demonstrated in Warren et al. (2010) work.

Investigating a global phenomenon, such as disease spreading sometimes requires the use of powerful simulators that are given the demographic and mobility conditions of the population and therefore they can provide the dynamics of a possible disease outbreak. This description can be used for characterizing the capabilities of the GLEAMviz epidemic simulator. In detail, GLEaM simulator is a discrete stochastic epidemic computational model based on a meta-population approach (Balcan et al., 2010). Additionally (Broeck et al., 2011; Balcan et al., 2010; Nikolaou and Dimitriou, 2020), used the open-source epidemic spreading simulator, namely, GLEAMviz for emerging influenza-like illnesses diseases on a global scale. The study of Balcan et al. (2009) also developed a GLEaM meta-population model for the global evolution of the pandemic A (H1N1) and perform a maximum likelihood analysis of the parameters against the actual time infection of newly infected countries. Investigating and interpreting global epidemic phenomena can provide significant findings that can be used for demonstrating the impact of pandemic control measures' efficiency on airports (e.g. Chung, 2015). The effectiveness of different health screening strategies in air travelers was analyzed and compared from Gold et al. (2019). In detail, the case scenario was the air travelers from the disease affected countries to the United States.

In the following sections, the robustness of the European air transportation system under possible global epidemic outbreak is analyzed and results are provided on the effects that alternative gating actions may have for controlling the spreading of infectious diseases in the European area.

3. Simulation framework of an epidemic

As reported in recent global epidemic incidents and proved in the case of COVID-19, the risk for disease spreading became a realistic scenario. In order to study this dynamic disease spreading it is essential to understand the role of the transportation network (especially of the airlines network) and incorporate it in a generalized epidemiological model, detailed and realistic enough for providing meaningful quantitative support in managing authorities. Major airports globally, are becoming hubs in this disease spreading networks and from these nodes connecting alternative modes of transportation, may facilitate the further spreading of infectious diseases on a national and international level. Therefore, identifying critical nodes (airports) in the network of airports is essential, especially for designing and applying measures for preventing disease spreading. Essential information for developing epidemiological models stand for the demographic data of the countries in a fine-grained manner, human mobility patterns and stochastic models of disease transmission. Here, the framework for analyzing the European air and land transportation system against disease spreading is achieved by using GLEAMviz simulator software (Gleamviz.org, 2019; Balcan et al., 2009; Broeck et al., 2011). In detail, this simulation-based produce, process the global spread of infectious diseases by integrating through three layers: 1st layer-population data and geographic distributions (Sedac.ciesin.columbia.edu, 2019); 2nd layer-mobility data; and 3rd layer-epidemic model which can identify complex disease scenarios and respond strategies (e.g. emergency travel restrictions). The resulting forecasts and scenario analyses that such models provide, may help inform authorities and help designing policies/actions in order to address possible pandemic threats.

Starting with the identification of the critical airports, this was performed here using alternative centrality metrics, namely, Degree, Betweenness and Closeness Centrality. In particular, Degree Centrality is defined by the number of the links that one node has, i.e., the more a node has linked the more central it is. Betweenness Centrality showed how much a node have been involved between different groups of networks. Closeness Centrality showed the airports that have the shortest path to access to the other airports. Overall, the centrality metrics explained the airports that more or less are critical in the integration of European's airline network and, in these terms, critical in spreading infectious diseases.

The epidemic model that is used in the current experimental case, stands for the Susceptible-Infected-Recover (SIR) model, which is developed over the idea that healthy people (susceptible) become infected when they have sufficient contact infected people by a transmission rate (β) and then recovered with a fixed rate (μ). Ultimately, the recovered individuals are removed from the population as they become immune (or dead in case of fatal diseases) and they cannot be infected again or they cannot infect others. Fig. 2 shows the main features of the epidemic spread model from an initial location (airport) to the destination (also airport) based on a rate β. In particular, starting from a random location, the infections appear to spread to their neighbors with the same transmission rate. In the end when the "removal" situation occurs where the infected either becomes immune to the infection or the individual succumbs to the disease and pass, either way, the previously infected individual is removed from the population at risk. Equations (1)–(3) shows the time-dependent behavior of susceptible (s), infected (i) and recovered (r).

$$\frac{ds}{dt} = -\beta(k)i[1-r-i] \quad (1)$$

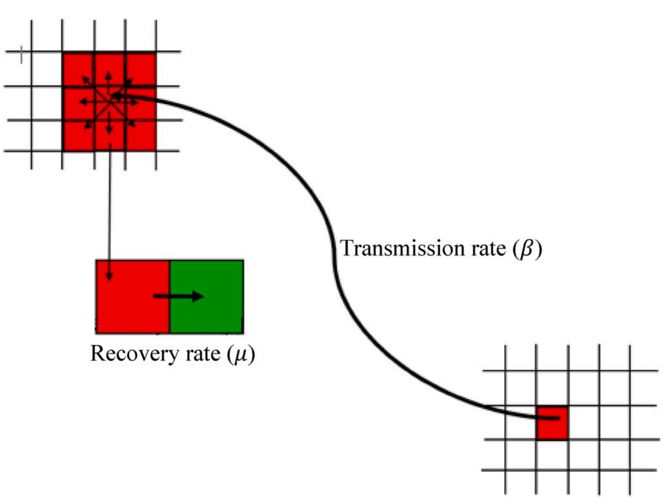


Fig. 2. Overall infectious diseases modeling approach.

$$\frac{di}{dt} = -\mu i + \beta(k)i[1-r-i] \quad (2)$$

$$\frac{dr}{dt} = \mu i \quad (3)$$

where k denoted the contacts of a typical individual.

Knowing the numbers of infected individuals by surveillance activities is not sufficient for identifying the probability of new infections. Therefore critical rates/parameters (e.g. transmission rate, β) should be selected by reasonable assumptions or by thorough experimental data. However, the question that arises is to find the values of the parameters of the SIR model (transmission and recovered rate) that may lead to a pandemic or severe disease spreading over a region.

In the current implementation, three scenarios were developed each one concerning the busiest airports of different continents as the initial location of the disease spreading, while the focus on the effects that each scenario has is in European countries. In detail, Scenario 1 concerned African airports, Scenario 2 Asian airports, and Scenario 3 South America airports. In each scenario, different variations of transmission rate values were tested in order to estimate the disease transmission patterns. Additionally, three different values of recovery rates were tested, this time for evaluating the seriousness of infection by testing a different number of days for recovery. In particular, we tested a 3-days recovery (no severely affected individuals by the infection while they recover in only 3 days), moderate-severe infection (it takes 5 days for an individual to recover) and severe infections (that take 10 days for an individual to recover). The recovery rate values that can express this approach are $\mu = 0.3$, $\mu = 0.2$ and $\mu = 0.1$, respectively. After the identification of the continents that have the highest influence of disease spreading inside the European region, and the implementation of the worst-case scenarios (i.e. choosing the transmission and recovery rate that appeared to produce the highest number of infections in Europe) a hypothesis for preventing these worst-case scenarios was tested by implementing countermeasures in (a) critical airports, (b) in countries where the critical airports are located and (c) in a particular country. The results from these implementations are presented in the following section.

4. Application and results

Before the implementation of the above described methodological framework, it is important first to observe how population and airports are distributed within the European region (Figs. 3 and 4). As it can be observed from both figures, the density of the population is correlated with the concentrations of airports. This observation highlights the importance of these airports on the transmission of a possible disease spreading to an epidemic.

The investigation of dynamic global epidemic phenomena (e.g. disease spreading) requires the analytical representation of the air network mobility which will provide a "picture" of the phenomenon's complexity. Fig. 5 shows the form of the global air transportation network, where it can be observed its scale and the complexity. As was described above, the experimental design adopted in this study starts with three centrality metrics (Degree, Betweenness and Closeness Centrality), which were able to identify popular-critical airports.

Tables 1–3 in the Appendix, present the results from the Degree, Betweenness and Closeness Centrality, respectively. It must be noted that in every centrality metric only the 20 most critical airports were depicted with a hierarchical order (from the highest metric number -most critical airport-to the lowest metric number –less critical airport). It appeared that critical airports were identified in Germany, United Kingdom, Belgium, Finland, Norway, and Estonia. There were also some airports that were identified from two centrality metrics either Betweenness and Closeness Centrality, or Betweenness and Degree Centrality or the combination of all centrality metrics (Fig. 6). As can be

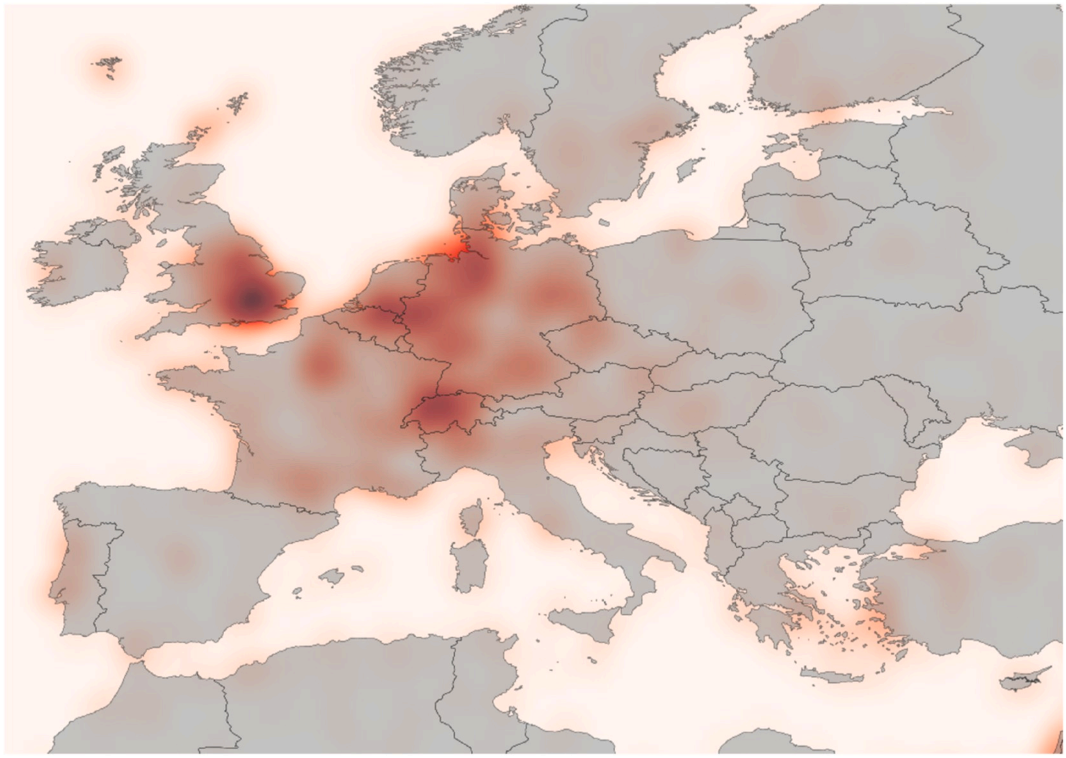


Fig. 3. Density of airports within the European region.

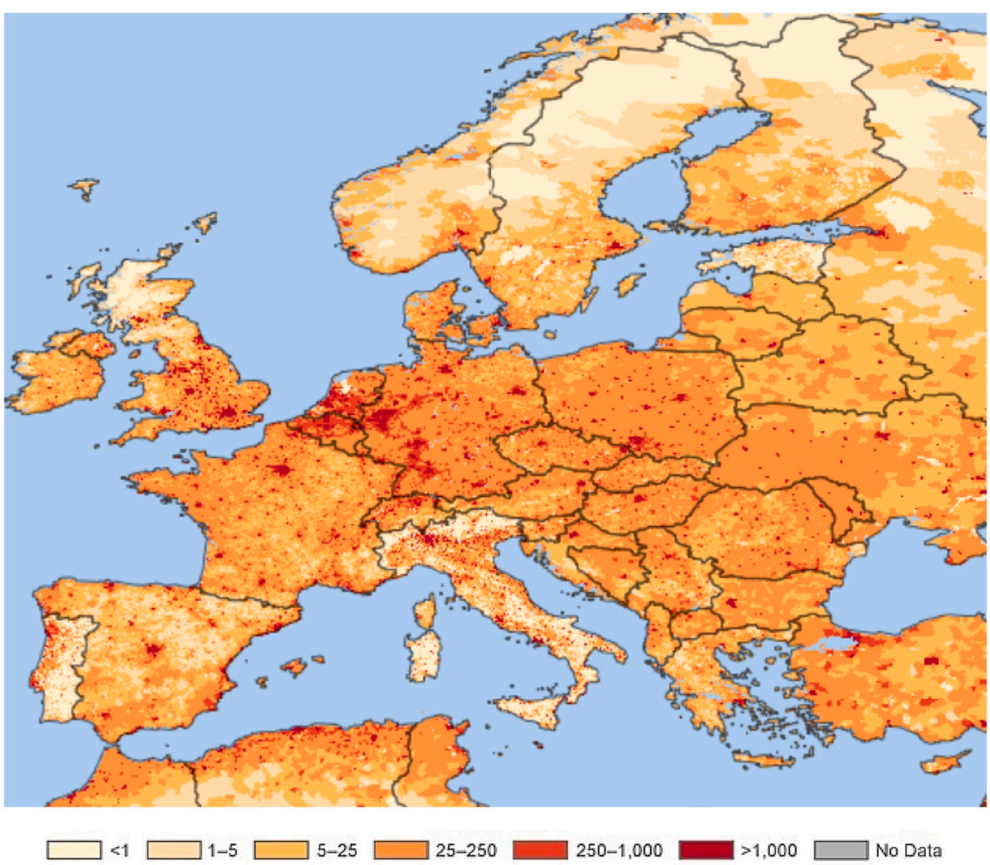


Fig. 4. European population density.

Fig. 5. Complexity of the global air transportation network.

seen from the airports map and the population map and from the results of the centrality metrics, highly populated areas with high concentrations of airports (such as Germany), appear to be critical in the entire air transportation network and thus vulnerable in a possible disease outbreak.

The next step was the development of three spreading scenarios, where it was considered that a disease of a different severity (expressed through recovery and transmission rates) starts from the busiest airports of three continents (Africa, Asia, and South America). In detail, with the disease spreading simulation it was able to predict the number of infected and recovered individuals for each region, country, or town in Europe. Fig. 7 presents the results from the simulation of the three scenarios (denoted in each line) and also presents the three recovered rates used (denoted in each column) with the 10 different transmission rates. As can be observed from the figure, when the disease starts from the African airports the most affected continents are Oceania and South America for transmission rates β equals 0.3, 0.4, 0.6, 0.7, 0.8, 0.9 and 1.0 respectivelly and for a recovered rate equal to 0.1. The other two recovered rates $\mu = 0.2$ and $\mu = 0.3$ showed a drop in the number of infected individuals and the continent that appeared to have the most infections in Europe and North America, respectively. Overall, in this scenario for every recovered rate and for transmission rate equal to 0.1 the continents did not record any infections.

As far as the second scenario is concerned, where the disease starts from the Asian continent (and airports) it appeared to have almost the same effect in the continents as in the first scenario with some differences, like when transmission rate equal to $\beta = 0.5$.In this scenario and for every recovered rate it appeared that when the disease starts from Asian airports the highest effect appeared to be on the same continent. Finally, yet importantly enough, in the third scenario the impact of the disease on the other continents when it starts with the busiest airports in South America is tested. For the case where the recovered rate is equal to

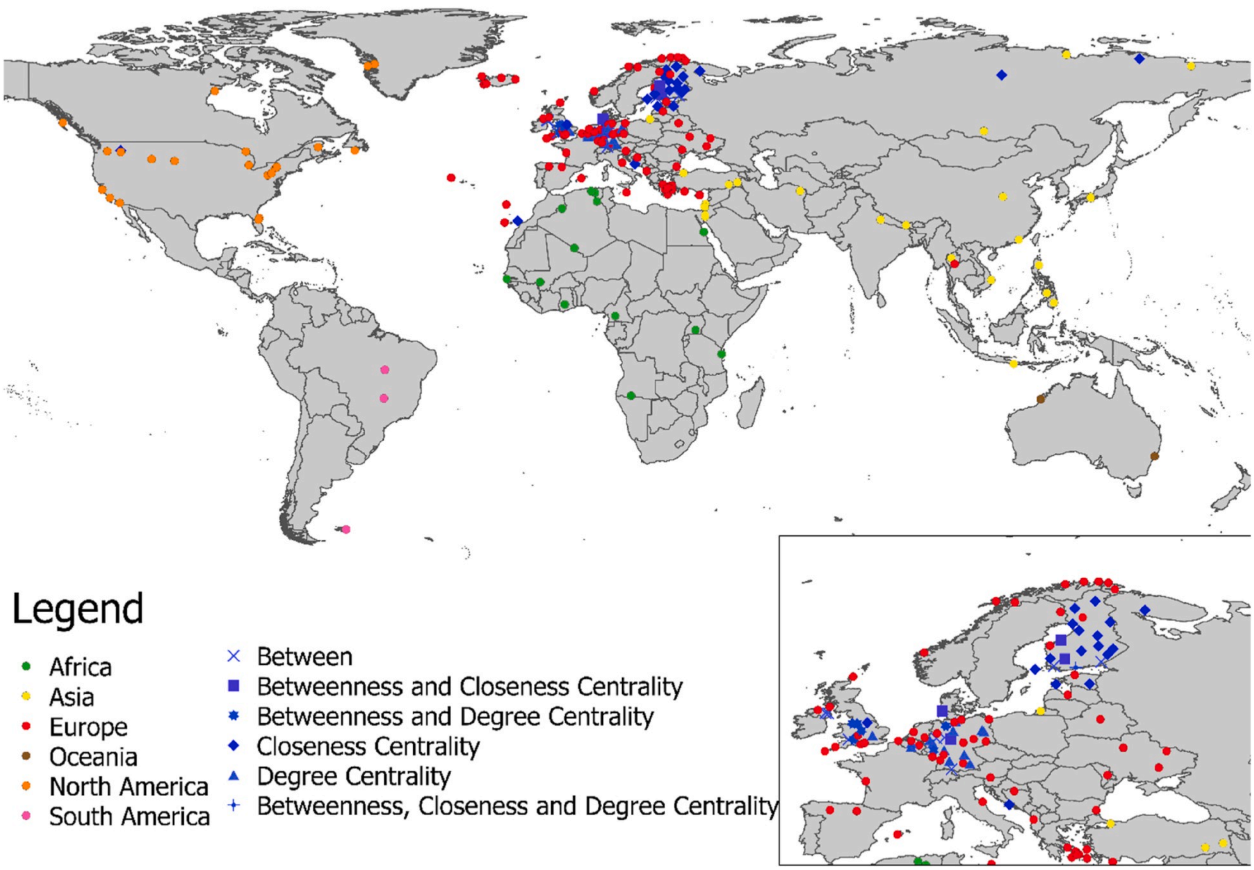
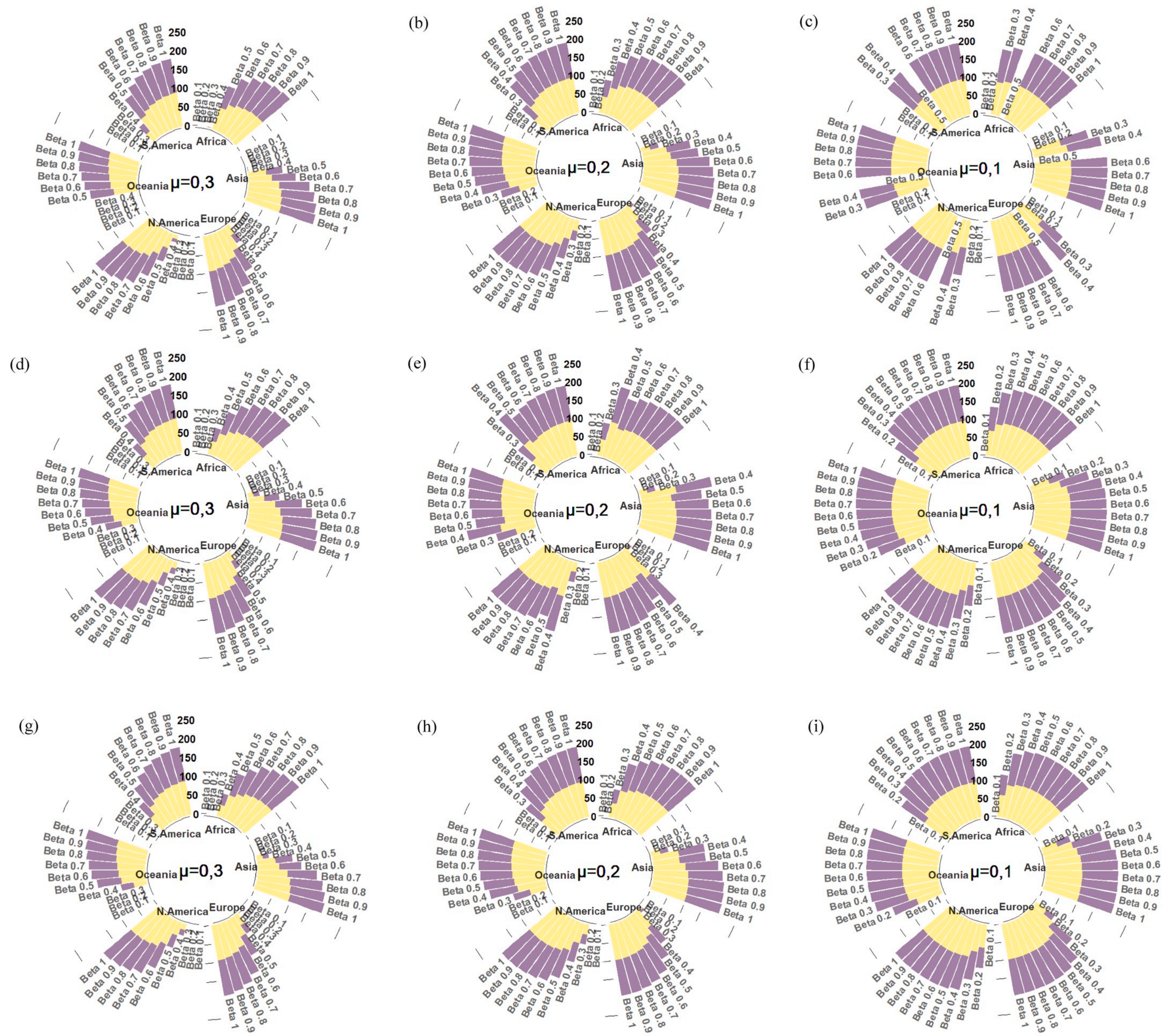


Fig. 6. Map showing the airports studied and the critical airports based on the three Centrality metrics.



Note:

- A, B, C, D, E groups represent the continents; Africa; Asia; Europe; North America; Oceania and South America, respectively.
- Yellow color denotes the number of infections (per 10 000) and Purple color denotes the number of recovered (per 10 000)

Fig. 7. Results of the simulation based on the three Scenarios and on different epidemic parameters (transmission rate and recover rate): a) Scenario 1, μ = 0,1; b) Scenario 1, μ = 0,2; c) Scenario 1, μ = 0,3; d) Scenario 2, μ = 0,1; e) Scenario 2, μ = 0,2; f) Scenario 2, μ = 0,3; g) Scenario 3, μ = 0,1; h) Scenario 3, μ = 0,2; i) Scenario 3, μ = 0,3.

$\mu = 0.1$ (i.e., 10 days for recovery) and for most of the transmission rates the infected and recovered population reaches high numbers. For a recovery rate equal to $\mu = 0.1$, a disease that starts from South America is expected to affect most of the European region. As for the other transmission rates $\beta = 0.2$ and $\beta = 0.3$ North America seem to record the highest number of infections.

The above analysis was able to answer questions related to which continents are most expected to affect the European region in the case of a disease spreading and with what values of parameters (transmission rate and recovered rate). As resulted from the above analysis, the European region is mostly affected by a disease spreading when the disease starts from Africa for every recovered rate. However, the disease is mostly transmitted inside the European region when the transmission rate equals $\beta = 1$, meaning that when an infected individual comes in contact with a healthy individual the healthy individual will surely contact the disease with a possibility of 100%. Table 4 presents an overview of the total number of infected and recovered individuals during a year as predicted by the GLEAMviz simulator inside the European continents concerning the different scenarios developed. The total number of infected depicted in this table denote all the following categories: people that have visited Europe as infected; and residents inside the European region that got infected from others. As concerns the total number of recovered the following categories are included: people that have visited the European region as infected and were recovered during their stay in Europe; and residents of Europe that were infected and recovered. The number of recoveries does not include the number of people that were infected during their stay in Europe and travelled outside the European continent and got recovered. Additionally, it can

Table 4
Total number of infected and recovered individuals based on the three scenarios developed.

Recovery Rates (μ)	Scenario 1 (Africa)		Scenario 2 (Asia)		Scenario 3 (South America)	
	Infected	Recovered	Infected	Recovered	Infected	Recovered
0.1	999.854	999.882	999.476	999.482	999.728	999.744
0.2	991.614	991.615	991.278	991.270	991.001	991.001
0.3	952.870	952.863	952.199	952.185	951.024	951.023
Transmission Rate (β):	1		1		1	

be seen form this table that in some cases, especially when the recovery rate (μ) is equal to 0.1 (i.e., the days an infected person needs for his/her recovery is 10 days), the total number of recovered people is larger than the total number of infected. This can be interpreted as that infected people that were recovered outside the European continent, travelled after their recovery to Europe and therefore are registered as recovered. Also, in the cases where the number of recovered individuals is smaller than the infected individuals is either based on the hypothesis that recovered individuals after their recovery travelled outside the European continent or on the hypothesis that some infected individuals did not recovered but succumb to their illness.

An illustration of the three scenarios developed can be seen in Fig. 8 which describes the spread of disease inside the European region when it originates from the continent of Africa. Special focus was given to the city of Frankfurt, where its airports are identified as critical concerning the Degree and Betweenness Centrality metrics. As can be seen on day 6

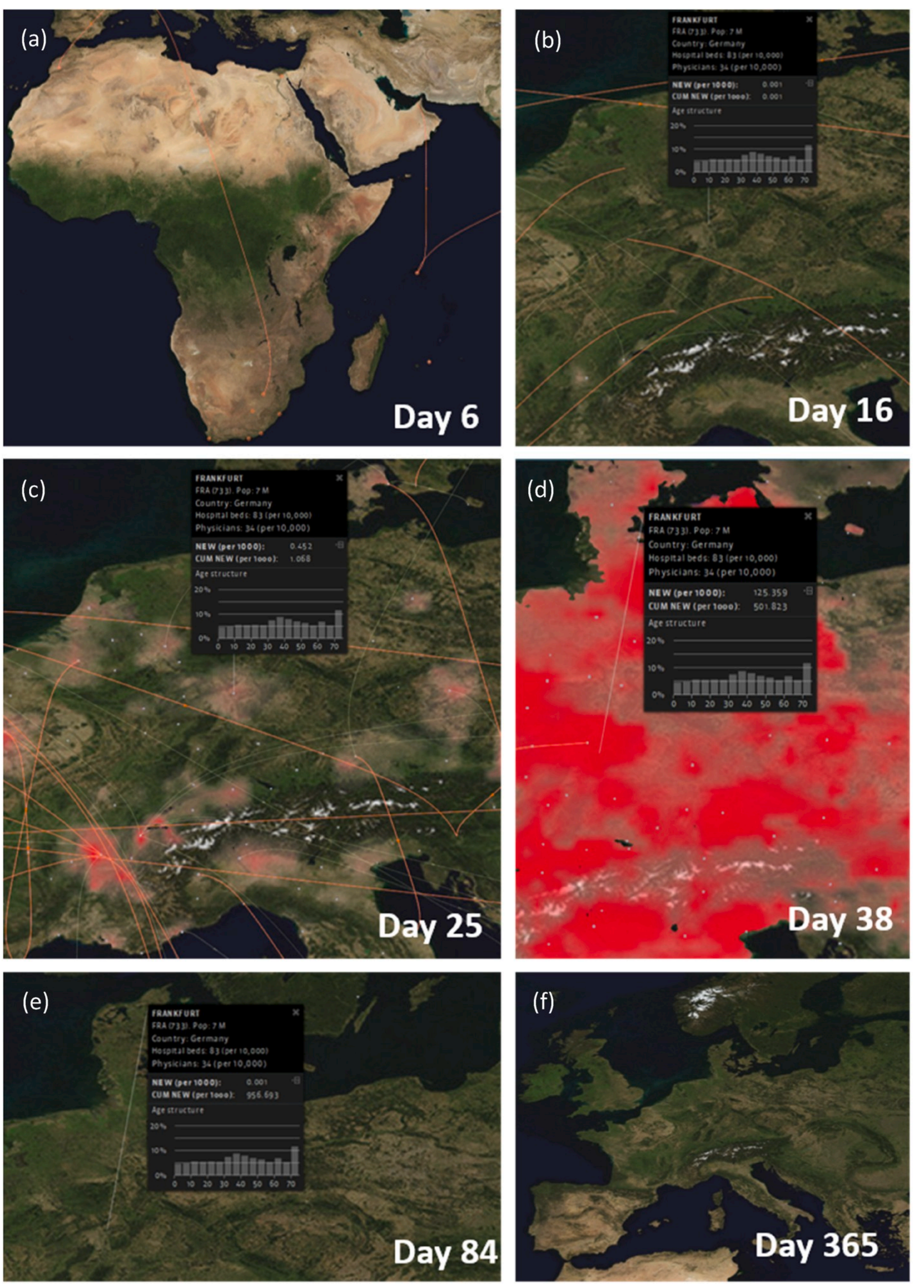


Fig. 8. Disease dynamics within the European region and for the case of Frankfurt analyzing the different stages of the virus: a) Day 6 the disease originates from popular African airports; b) Day 16 first infection on Frankfurt; c) Day 25, 331 infections were recorded in the city of Frankfurt; d) Day 38 Frankfurt recorded the higher number of infections; e) Day 84 the number of diseases was reduced and eliminated for Frankfurt; f) Day 365 infected population in Europe and the entire world were recovered from the disease.

of the simulation (disease outbreak), the first infected passengers were traveling from the airports of Mahe Island, Johannesburg, and Marrakech and for the last two airports, Lyon's airport was the destination. From this trip, 1 infection was recorded in Lyon. On day 16 the first infection was recorded in the city of Frankfurt from a flight that was originated from Mahe Island on day 14. On day 25, 331 infections were recorded in the city of Frankfurt and as it appeared the disease was spread not only through air mobility but also through the roadway. In day 38 Frankfurt recorded a higher number of infections (91.888 people). In day 43 Europe faced an outbreak of the disease where the highest number of diseases was recorded while in Frankfurt the number of diseases was reduced drastically (34,134 infections per 1000 individuals). After that day the number of diseases was reduced and eliminated in day 84 for Frankfurt. In day 365 the infected population in Europe and the entire world were recovered from the disease.

Extending the above analysis, it was considered important to design and test gating strategies that could prevent a disease outbreak in Europe. Therefore, the next steps involve the testing of two challenging scenarios for an aggressive virus with transmission rate $\beta = 0.1$ and recovery rate equal $\mu = 0.1$. In the first scenario the hypothesis of no-control policies in Europe was tested when a disease outbreak started from Africa (worst-case scenario). This scenario was followed by series of cases, were measures are taken. In particular, the measures that were set first were in the identified critical airports and then in the countries where the critical airports are located. Then, an additional scenario was developed based on the hypothesis of a disease outbreak originated from Asia and for alternative control policies, focusing on the set of measures only in a specific country, Italy, one of the most affected European countries by COVID-19.

4.1. A disease outbreak starting from Africa

This section describes the phases of a disease outbreak scenario originating from Africa. In the first phase of the disease outbreak, no-control measures were set for the European continent. Then a second case was analyzed by adopting the hypothesis of setting gating measures inside the European region for controlling the disease spreading in the region. In detail, this hypothesis was tested against one of the worst-case scenarios, which was a disease outbreak from the busiest African airports with a recovery rate of $\mu = 0.1$ and transmission rate equals to $\beta = 1$, which appeared from Table 4 to record the highest number of infections in Europe. However, in order to monitor diseased passengers and for setting gating actions to a possible disease outbreak or a pandemic, we made an exception in the simulation by setting a different transmission rate for the European region. In detail, the transmission rate used was $\beta = 0.1$, which appeared to have zero infections for the case of Europe in every case scenario and represent the case of the application of gating measures. In this way, it is able to estimate the

Fig. 9. Treemap depicting the extent of infection for each continent in the cases; a) Scenario 1 without monitoring strategies; b) Scenario 1 with monitoring strategies only in critical airports; c) Scenario 1 with monitoring strategies in the countries with critical airports.

effectiveness of gating measures in airports for preventing disease spreading. The last implementation tested the capability of airports' gating and passengers' monitoring strategies and their effects on the restriction of a possible disease spreading. Therefore, knowing the critical nodes in the airports' network and the origin of the disease that will affect the European region, it is important to test strategic measures (e.g. passengers monitoring, disease gating scenarios, technological measures for identifying and setting into quarantine infected passengers). In particular, two cases were developed, one for setting barriers directly to the most critical airports and the other one by applying gating strategies in the countries that the critical airports are located. A more obvious picture of the significant decrease of infected individuals can be seen from Figs. 9–11. As it can be seen from Fig. 9 in the no-measures hypothesis the most affected countries from the disease outbreak are Germany, United Kingdom, France, Spain, Italy and Poland. As for the control measures applied in the critical airports, it seems that Germany still remains a highly affected European country with Spain, United Kingdom, France, Italy and Poland following. Finally, when the measures were applied in the countries where the critical airports are located it appeared that the numbers of infections are well decreased, however the most affected countries in Europe are again United Kingdom, France, Italy and Spain.

In Fig. 10 the number of infections per day (and 1000 individuals) and the cumulative number of infections over the year are presented. As it can be seen from Fig. 10, when the disease started from Africa and there were no control measures in Europe the highest number of infections in a day that are expecting to record in Europe is approximately 82.000/1000 individuals and the total number of infection in a year are expected to be almost 1 million individuals. As for the case where measures will be set only in the critical airports the highest of infections in one day will decrease. However, the total number of infections will again be high enough to characterize the disease as a pandemic. In the case where Europe will set measures in the countries were the critical airports are located the total number of infections will decline drastically to 50% of the original worst-case scenario.

In Fig. 11, the European cities that were either affected by flight or by commuting or even not invaded at all are presented. As can be seen in the worst-case scenario all the cities of Europe were invaded by both

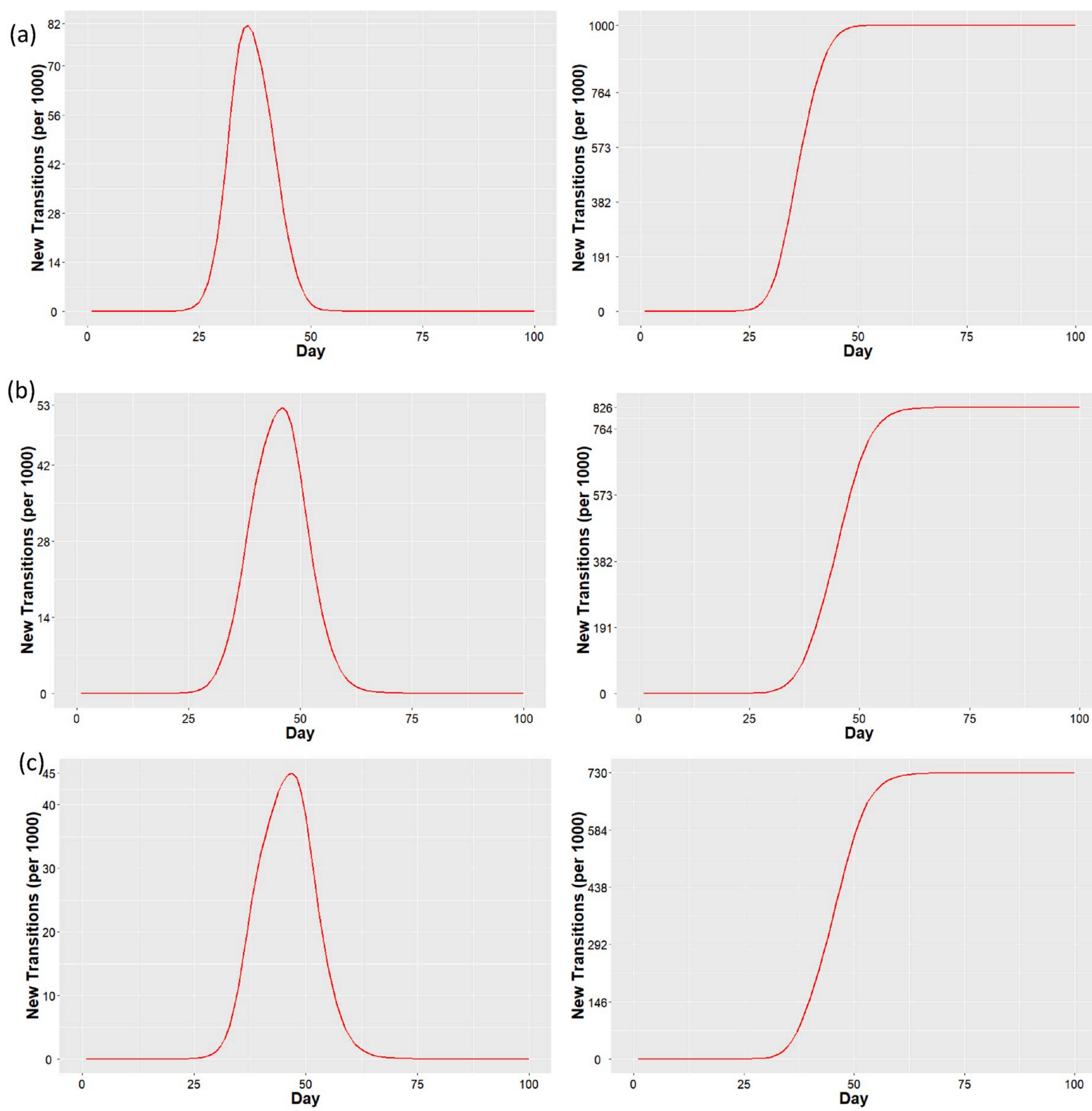
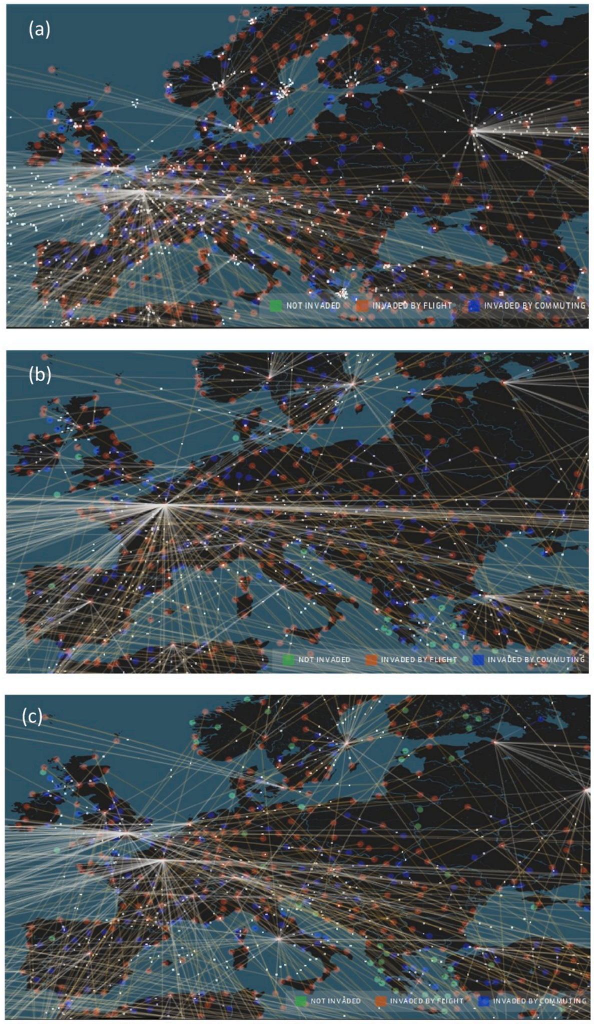


Fig. 10. Diagrams of the distribution of infections and cumulative numbers of infections for a) Scenario 1 without monitoring strategies; b) Scenario 1 with monitoring strategies only in critical airports; c). Scenario 1 with monitoring strategies in the countries with critical airports.



Note: Green Points: not invaded cities; Red Points: cities invaded by flights; Blue Points: cities invaded by commuting.

Fig. 11. Diagrams of the distribution of infections and cumulative numbers of infections for a) Scenario 1 without monitoring strategies; b) Scenario 1 with monitoring strategies only in critical airports; c) Scenario 1 with monitoring strategies in the countries with critical airports.

modes of transport. However, in the case where the measures were set only in critical airports the cities that are recorded with no invasions stands for the Greek cities. As for the case where gating measures are taken in the European countries the cities that were not invaded are mostly the Greek cities or northern cities of Norway and Finland.

Note: Green Points: not invaded cities; Red Points: cities invaded by flights; Blue Points: cities invaded by commuting.

From the above figures it is resulted that the monitoring of infected passengers followed by gating policies are able to change the dynamics of disease spreading within the European region. Additionally, when the policies applied on regions of the transportation network (i.e. countries) and not only on individual airports, then the strategies of gating are much more efficient and as so they are recommended especially in cases of aggressive infectious diseases.

In Fig. 12 the daily distribution of infections in the European countries are presented for the cases when strategies of gating are not applied (Fig. 12a), where strategic measure were set in the critical airports (Fig. 12b) and in the case where gating measures were set in the countries where the critical airports are located (Fig. 12c). For the first case, where no measures were set, Italy appeared to record the highest number of infections per day (approximately 200,000 infected individuals). For the second case of setting gating strategies in critical airports, the 5 countries who suffered the highest numbers of infections are Italy, Austria, Estonia, Ireland and Finland. As for the third case when measures were set in European countries the 5 countries who suffered the highest number of infections are United Kingdom, France, Luxembourg, Netherlands and Austria. The black dotted line represent the European number of infections' and as it can be assumed when Europe sets control in the air transportation access either in countries or only in airports the peak of the highest number of the daily infections drops almost by 50% compared to the no-control strategy.

In the following section, a dedicated analysis is performed focusing in the time of network gating actions, highlighting the criticality of the time factor on when such control measures should be taken.

4.2. Disease outbreak starting from Asia: focusing in a particular country

This section has been devoted on investigating the dynamics of a disease outbreak starting from Asia and affecting Europe in a condition of no-control as well as when control measures are applied. This case-study resembles that of the COVID-19 pandemic and Italy is selected to be tested, a country dramatically affected by this event. The analysis concern numbers of infections, that could be translated to number of deaths using a mortality rate, but these calculations are not included in the scope of this paper. In Fig. 13 the no-control and control cases are presented, where control actions are taken in different time instances. As

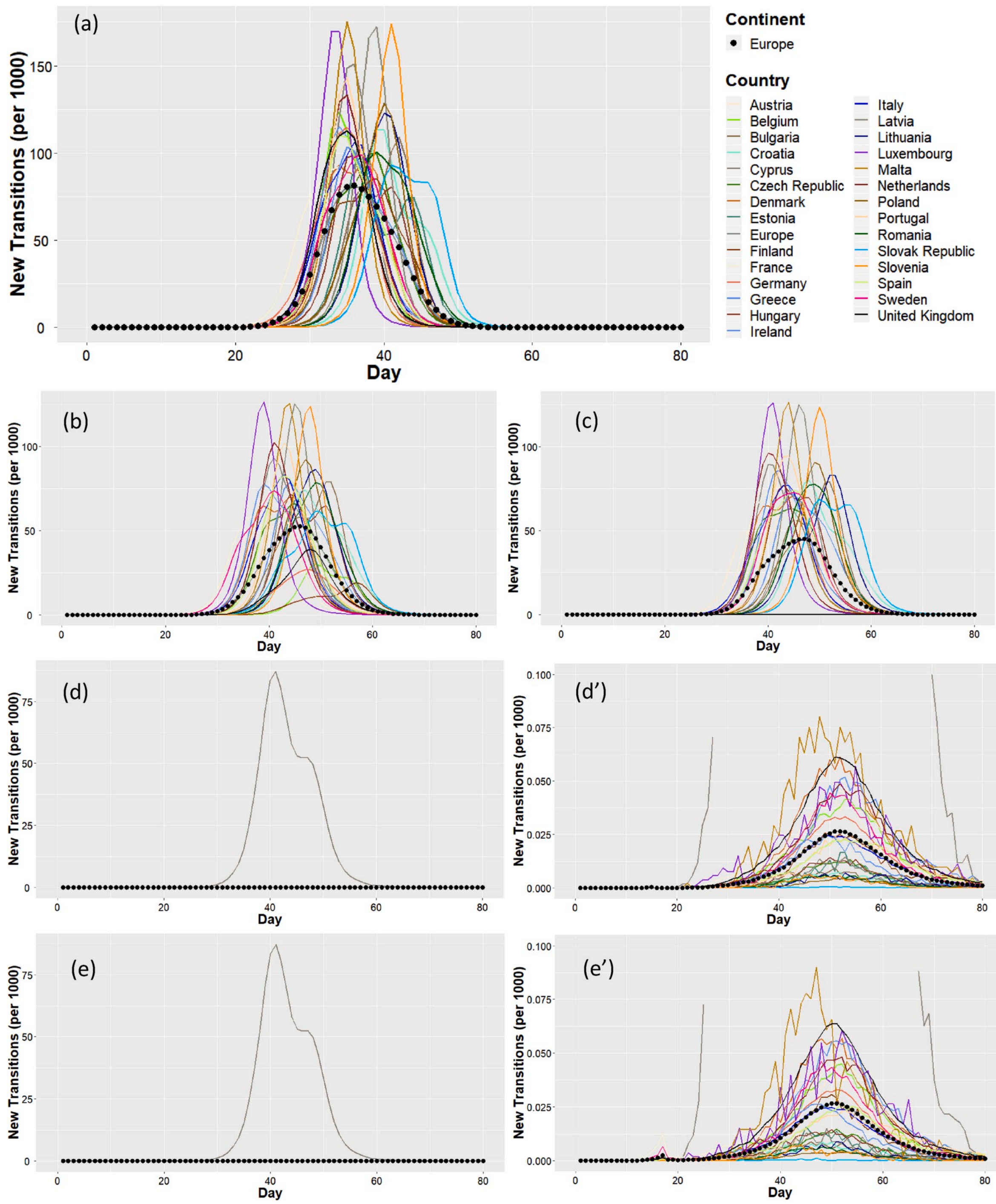


Fig. 12. Distribution of infections in the European countries for: a) the case where there are no gating strategies; b) the case where gating strategies were set for critical airports; c) the case where gating strategies were set for countries; d) gating policies in Europe when it records approximately 30.000 infections and d' focusing on the scale of the countries; e) gating policies in Europe when it records approximately 100.000 infections and e' focusing on the scale of the countries.

can be observed in the no-control case (Fig. 13a), Italy was suffering from infection throughout the country while virus is spread to almost all of its cities in a matter of days. In Fig. 13b,c&d, the case of gating (effectively, closing the service) in the air transportation network in days 31, 39 and 47 respectively are presented. As can be observed, the earlier gating actions are taken the more effective the disease spreading control become. Also, if gating actions are not applied early enough then spreading become out of control and gating actions may not be helpful any more. This element, although expected in general, highlights the importance of the time in closure/control measures applied in large regions like countries, since few days of delay may result in wide spread of viruses in the general population of a region. Though, even in the case that control measures are applied the most populated cities in Italy (particularly Milan, Rome, Bologna, and Venice) were also affected.

In order to further understand the effect of countermeasures on the disease outbreak in Italy epidemic dynamics for the above scenarios are provided in Fig. 14a–d. In detail, in the left-hand side diagrams the evolution of the daily infections in Italy for each scenario is provided accompanied with the right-hand side diagrams where the cumulative infections are presented (all scaled per 1000 individuals). As can be seen

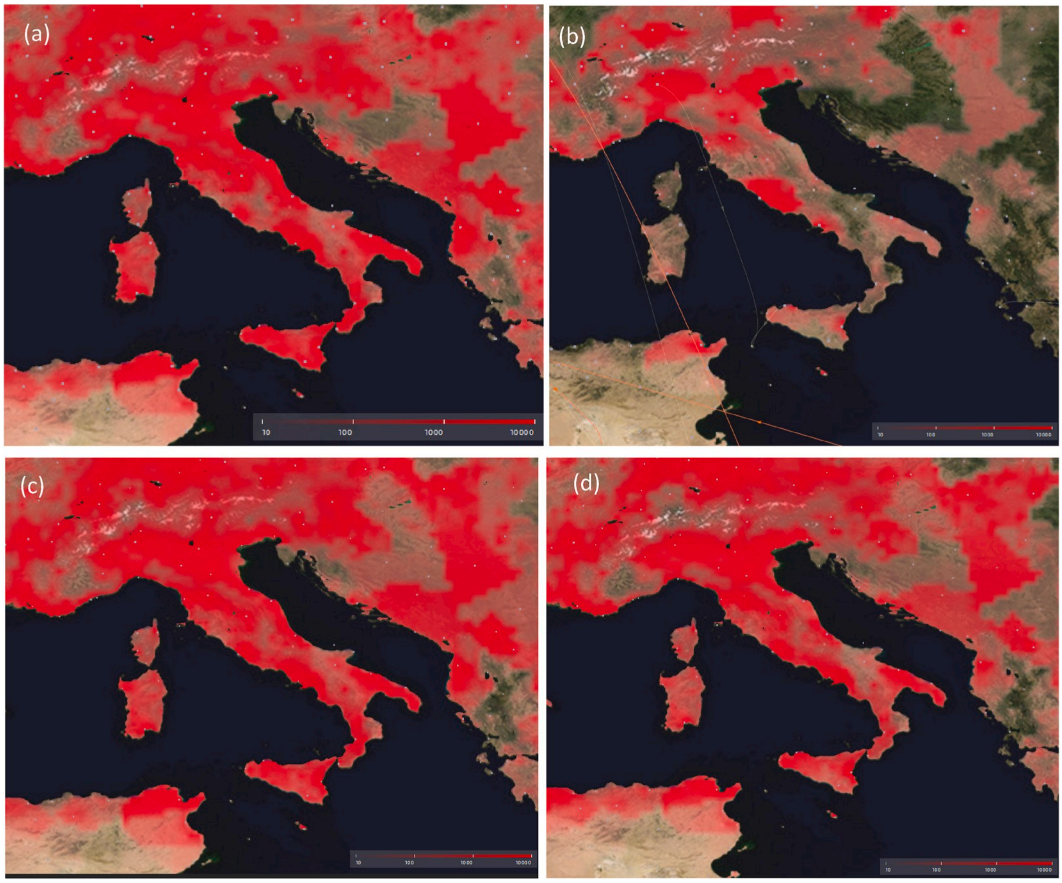


Fig. 13. Map of Italy depicting the conditions were a disease starts to form Asia and there are: a) no control/restrictions applied in Italy; b) when gating measures are taken in Italy in after 31 days of the outbreak; c) when gating measures are taken in Italy in after 39 days of the outbreak; d) when gating measures are taken in Italy in after 47 days of the outbreak.

from Fig. 14a, if no restrictions in the air transportation nodes/airports are applied, a peak in new infections occurs in few days (left-side of Fig. 14a), while the total population may be infected in a matter of less than 25 days (right-side of Fig. 14a). Though, if closure actions are taken in the day 31 (on month after the disease outbreak), then, as presented in Fig. 14b the peak of the daily new infections is limited to the half (50 compared to 110 per 1000 individuals), while only 1/3 of the total population will be infected (305, compared to 1000 per 1000 individuals). The importance of the time factor is further highlighted in Fig. 14c, where airports are closed in day 39 (8 days later than in Fig. 14b). As it can be seen, this delay of 8 days result in the dramatic rise in daily infection rate (from 50 to 110 per 1000 individuals), while the total infections are also rise to 800 per 1000 individuals (compared to 305). Finally, in case that gating actions in airports are applied in day 47 (Fig. 14d), then the measures are obsolete the epidemics resembles that of the no-control case.

Another way that time is measured in cases of epidemics is based on the total number of infected individuals. As so, in Fig. 15, the effects of gating actions in three cases are provided. In detail, in Fig. 15a, gating actions in Italy are applied immediately after the emergence of the epidemic (day 0), in Fig. 15b when the number of infected individuals reached almost 600 individuals (day 17) and in Fig. 15c when the rate of infected individuals reached 5450 per 1000 individuals (day 26).

As can be observed in Fig. 15, when gating actions are taken in such early stages, the virus spread is controlled, limited in large cities where the population density is high. As far as the epidemic dynamics is concerned, in Fig. 16a the case control measures in Italy are applied from the beginning of the epidemic, in Fig. 16b gating actions are applied when Italy records 617 total infections and in Fig. 16c gating actions are applied when the total number of infections in Italy reached 5456 (per 1000) infections.

In these cases, when gating actions are taken early enough these have an immediate and drastical effect, limiting the overall number of infected individuals and widening the period that the epidemic occurs into almost 100 days, compared to the no-control case where large number of the population is infected in few weeks. It should be noted that as indicated in Fig. 16c, in cases where a number of individuals are infected in a country even strict control measures (like gating) are not sufficient to immediately stop the epidemic and rebound effects may occur until the epidemic clears.

Finally, as observed in the above test-cases and as realized from the actual COVID-19 epidemic incident, highly transmitted infective viruses may be spread globally in a high rate and can reach the stage of pandemic in a matter of few weeks. Although the characteristics of the virus used for showcasing the dynamics of spread through the airlines' network can be regarded as extreme and aggressive, it can be used for understanding that the time and the extent of restrictions in the air transportation network is of critical importance. Difficult decisions are sought to be taken, restricting large regions (e.g. countries) at an early stage when infection risk may not be visible to the general public. Though, such actions are necessary for controlling the outbreak of a global or regional severe epidemic.

5. Conclusions

In this paper, a step-by-step procedure is provided for analyzing the dynamics of different severity of disease spreading phenomena. In detail, the structure of the paper was developed in a way for

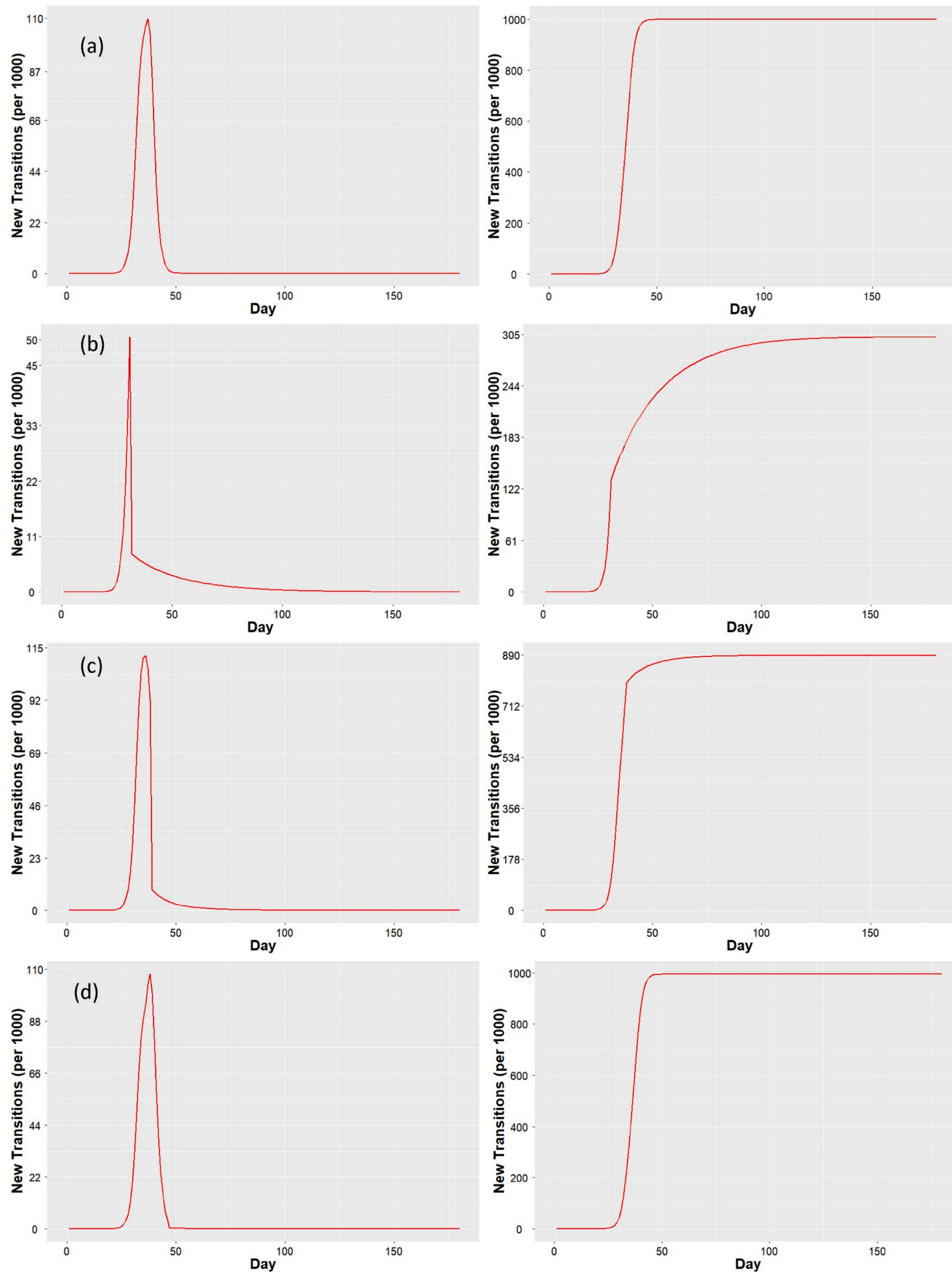


Fig. 14. Epidemic dynamics in the case of Italy depicting the conditions were a disease starts to form Asia and there are: a) no control/restrictions applied in Italy; b) when gating measures are taken in Italy in after 31 days of the outbreak; c) when gating measures are taken in Italy in after 39 days of the outbreak; d) when gating measures are taken in Italy in after 47 days of the outbreak.

investigating the disease spreading phenomena over the globe by examining the complexity of the air transportation network, implementing several stress-tests (scenarios) able to give a clear picture of the phenomenon and setting barriers for possible future disease spreads within the European region. The interest of this analysis was the observation of critical airports and the scenarios that will denote the highest impact inside the European region. The objective of this paper was to highlight possible disease spreading in the European region and to advocate the enhancement of Europe's control measures in order to prevent a disease spreading inside the region.

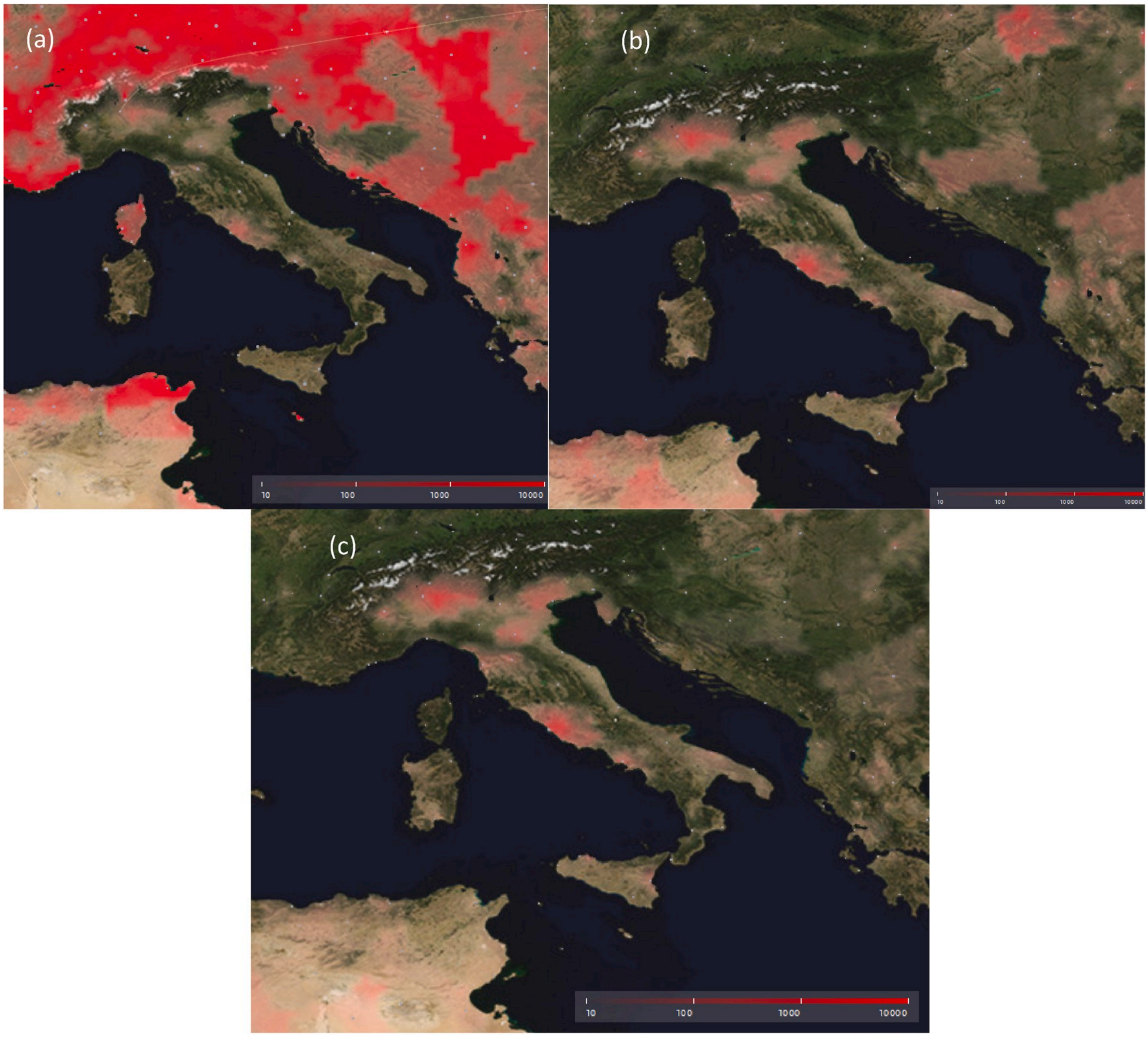


Fig. 15. Map of Italy depicting the conditions were a disease starts to form Asia and there are: a) there are health and safety measures in Italy; b) gating when Italy records 617 total infections; c) when gating strategies are taken when the total number of infections in Italy reached 5456 (per 1000) infections.

The integration of a basic but valid epidemiological model with realistic airline operations and the existing land transportation system, form a detailed dynamic simulation able to reproduce the outbreaks of infectious diseases as these emerge almost in yearly fashion. This controlled simulation framework is able to identify critical nodes in the airline system (i.e. airports with a high possibility to transfer and spread the infectious disease among distant locations), an element of immense importance in policy-making for controlling such phenomena. The results from extensive stress-test focusing in the European continent, suggests that Europe indeed plays a central role in controlling epidemics, but also, it is proven robust in such cases if immediate actions are taken in the first steps of the epidemic phenomenon. In the following research steps, the disease spreading dynamics of the pandemic COVID-19 will be investigated on a global analysis.

CRediT authorship contribution statement

Paraskevas Nikolaou: Software, Investigation, Visualization, Writing - original draft. **Loukas Dimitriou:** Supervision, Conceptualization, Methodology, Writing - original draft.

Appendix

Table 1
Degree Centrality of the Airports

Airport Name	City	Country	Degree Centrality
Frankfurt am Main Airport	Frankfurt	Germany	990
Munich Airport	Munich	Germany	728
Manchester Airport	Manchester	United Kingdom	627
Brussels Airport	Brussels	Belgium	622

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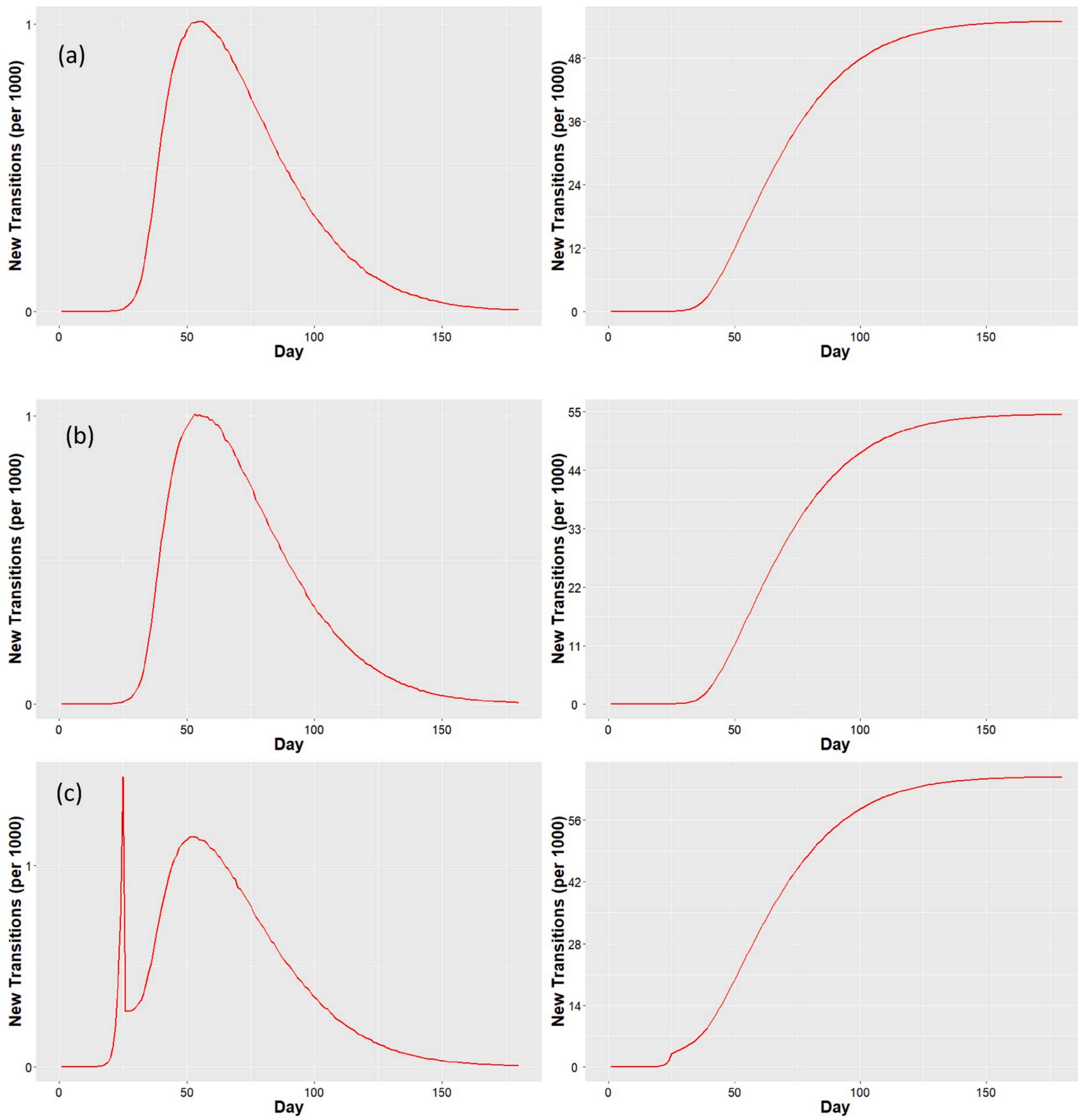

Fig. 16. Epidemic dynamics of Italy depicting the conditions were a disease starts to form Asia and there are: a) gating actions in Italy are applied immediately after the emergence of the epidemic; b) gating when Italy records 617 total infections; c) gating when the total number of infections in Italy reached 5456 (per 1000) infections.

Table 1 (*continued*)

Airport Name	City	Country	Degree Centrality
Düsseldorf Airport	Dusseldorf	Germany	570
Berlin-Tegel Airport	Berlin	Germany	418
Hamburg Airport	Hamburg	Germany	321
Helsinki Vantaa Airport	Helsinki	Finland	320
Stuttgart Airport	Stuttgart	Germany	273
Cologne Bonn Airport	Cologne	Germany	265
Birmingham International Airport	Birmingham	United Kingdom	264
London Luton Airport	London	United Kingdom	214
Bristol Airport	Bristol	United Kingdom	200
Brussels South Charleroi Airport	Charleroi	Belgium	168
Berlin-Schönefeld Airport	Berlin	Germany	165
Hannover Airport	Hannover	Germany	152
Liverpool John Lennon Airport	Liverpool	United Kingdom	116
Bremen Airport	Bremen	Germany	100
Nuremberg Airport	Nuremberg	Germany	95
Frankfurt-Hahn Airport	Hahn	Germany	94

Table 2
Betweenness Centrality of the Airports

Airport Name	City	Country	Betweenness Centrality
Helsinki Vantaa Airport	Helsinki	Finland	7550.035
Westerland Sylt Airport	Westerland	Germany	7515.706
Kassel-Calden Airport	Kassel	Germany	7483.706
Tampere-Pirkkala Airport	Tampere	Finland	7464.706
Friedrichshafen Airport	Friedrichshafen	Germany	7445.039
Turku Airport	Turku	Finland	7443.706
Dortmund Airport	Dortmund	Germany	7420.706
Paderborn Lippstadt Airport	Paderborn	Germany	7395.706
Belfast International Airport	Belfast	United Kingdom	7370.206
George Best Belfast City Airport	Belfast	United Kingdom	7368.706
Birmingham International Airport	Birmingham	United Kingdom	7339.706
Frankfurt-Hahn Airport	Hahn	Germany	7275.706
Manchester Airport	Manchester	United Kingdom	7242.206
Bremen Airport	Bremen	Germany	7203.706
Hannover Airport	Hannover	Germany	7203.706
Cardiff International Airport	Cardiff	United Kingdom	7164.706
Bristol Airport	Bristol	United Kingdom	7123.706
Liverpool John Lennon Airport	Liverpool	United Kingdom	7080.706
Lappeenranta Airport	Lappeenranta	Finland	7035.706
Kokkola-Pietarsaari Airport	Kruunupyy	Finland	5717.919

Table 3
Closeness Centrality of the Airports

Airport Name	City	Country	Closeness Centrality
Jyvaskyla Airport	Jyvaskyla	Finland	0.005263
Kokkola-Pietarsaari Airport	Kruunupyy	Finland	0.005263
Kemi-Tornio Airport	Kemi	Finland	0.005263
Helsinki Vantaa Airport	Helsinki	Finland	0.005263
Lappeenranta Airport	Lappeenranta	Finland	0.005291
Kuusamo Airport	Kuusamo	Finland	0.005291
Kajaani Airport	Kajaani	Finland	0.005291
Sandefjord Airport, Torp	Sandefjord	Norway	0.005291
Kuopio Airport	Kuopio	Finland	0.005291
KittilÃ¤ Airport	Kittila	Finland	0.005291
Mariehamn Airport	Mariehamn	Finland	0.005291
Oulu Airport	Oulu	Finland	0.005291
Pori Airport	Pori	Finland	0.005291
Ivalo Airport	Ivalo	Finland	0.005291
Westerland Sylt Airport	Westerland	Germany	0.005291
Savonlinna Airport	Savonlinna	Finland	0.005291
Tartu Airport	Tartu	Estonia	0.005291
Tampere-Pirkkala Airport	Tampere	Finland	0.005291
Kuressaare Airport	Kuressaare	Estonia	0.005291
Kassel-Calden Airport	Kassel	Germany	0.005291

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