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Analysis of Theoretical Virus Spread Through Global Aviation Infrastructure using Weighted PageRank

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Abstract

As the global air transportation system forms a complex network, this interconnectivity may be seen as the ultimate cause for turning epidemics into global pandemics. A reliable simulation of how a disease might spread through global air traffic flow would have aided airlines in designing and implementing effective and targeted strategies to adjust their emergency responses as operations cease to a halt. Measuring the susceptibility or in other words contribution of individual airports to the pandemic spread and accurately identifying the most influential airports can help guide effective control of epidemic outbreaks.

To aid with this, we have used an extended version of the PageRank algorithm, in order to rank airports according to their contribution to the spread. We hope to accurately identify the potential hotspots i.e., super-spreaders and important channels for epidemic spreads, accounting for factors such as airport connectivity, passenger volume, and the efficacy of preventive measures. In addition, we evaluate the effectiveness of possible intervention strategies such as airport screenings in containing epidemic outbreaks.

Keywords

PageRank, Weighted graph, Directed graph, Interaction

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1 Introduction

1.1 Problem and Motivation

Globalization has revolutionized connectivity, empowering the rapid movement of people and goods across vast geographical distances. The global air transportation system hence forms a complex network. However, this heightened interconnectivity may be seen as the ultimate culprit of global epidemic spread in times of pandemics. Passengers can develop symptoms before, during, and after flights [4], hence possibly infecting other passengers on the same flight as well as the surrounding people in both origin and destination airports.

During the recent global pandemic COVID-19, various strategies were deployed in the aviation industry in an attempt to timely and accurately identify infected passengers at airports to curb epidemic spread, ranging from symptom detection through thermoscanners and PCR-tests to further reaching ones like the ”circuit breaker” introduced in China in 2020, where an airline’s operations were suspended for a definite period of time if five or more passengers were tested positive upon arrival [7]. However, the implementation of such interventions not only takes significant amount of time and cost [1], but also causes great inconvenience to travelers all over the world.

A reliable simulation of pandemic spread through the global air traffic flow would have thus aided airlines in designing and implementing effective and targeted strategies to adjust their operations as emergency response [6]. Measuring the susceptibility and hence contribution of individual airports to the epidemic spread and accurately identifying the most influential airports are thus crucial, albeit challenging, for effective control of epidemic outbreaks on a global scale.

1.2 Goals and Objectives

Our research objective is to investigate the vulnerability of the global air traffic network to epidemic spreads and understand the factors that influence such spreads. After analyzing the structural properties of the network, a simulation using historical airline data, we will examine the robustness of the network using an extended PageRank algorithm. By ranking airports according to their contribution to the spread, we hope to accurately identify the potential hotspots i.e., super-spreaders and important channels for epidemic spreads, accounting for factors such as airport connectivity, passenger volume, and the efficacy of preventive measures. In addition, we attempt to evaluate the effectiveness of possible intervention strategies such as airport screenings in containing epidemic outbreaks simulating a virus spreading through the network.

2 Related Works

2.1 PageRank

PageRank, originally introduced to rank web pages in the World Wide Web [2], was proposed to model epidemic spread in a social network, where individuals with higher rank in PageRank-like infection vector may have bigger importance in the spread of epidemics [3]. There is the need for an extension that incorporates information about weights and virus spreading.

2.2 Random Walk

The initial idea of performing a random walk (RW) on the original airports graph would have been meaningless to model epidemic spread. Indeed, the state space of the corresponding Markov Chain (MC) (graph's nodes) is the set of airports. And no information would be contained in the transition matrix about a way to model the infection.

Additionally, flipping the point of view would not be advisable. The modeling of the spread (as proportion of infected people worldwide) would require having a continuous state space ($[0, 1]$), which is not as trivially handled as a discrete space (using for example the Markov Chain Monte Carlo Metropolis-Hastings algorithm).

There is the need for relaxing the hypothesis: assuming a total number of people worldwide, the RW would be performed on the number of infected people within them. This way, the Markov chain possesses a discrete state space, and it would become feasible to simulate the spread of the epidemic through simulations. Nonetheless, we will not rely on RW during our experiments.

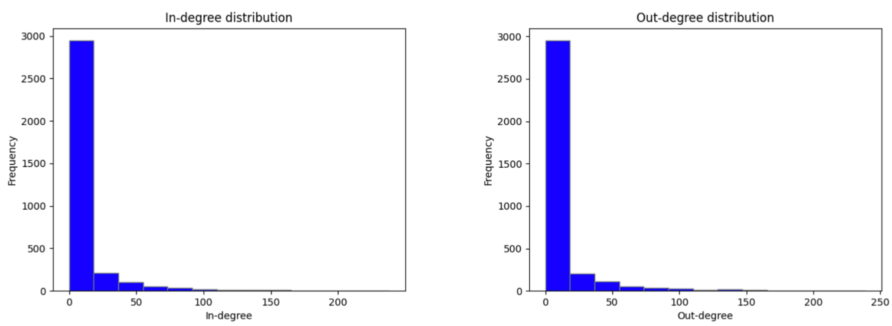
3 Methodology

3.1 Dataset

The dataset is retrieved from the OpenFlights Airports Database [5], containing 67663 routes among 3321 airports operated by 548 airlines spanning around the globe. The data represents a snapshot of the global aviation network accurate until June 2014. For each route, we only consider the origin and destination airports and ignore its operating airline.

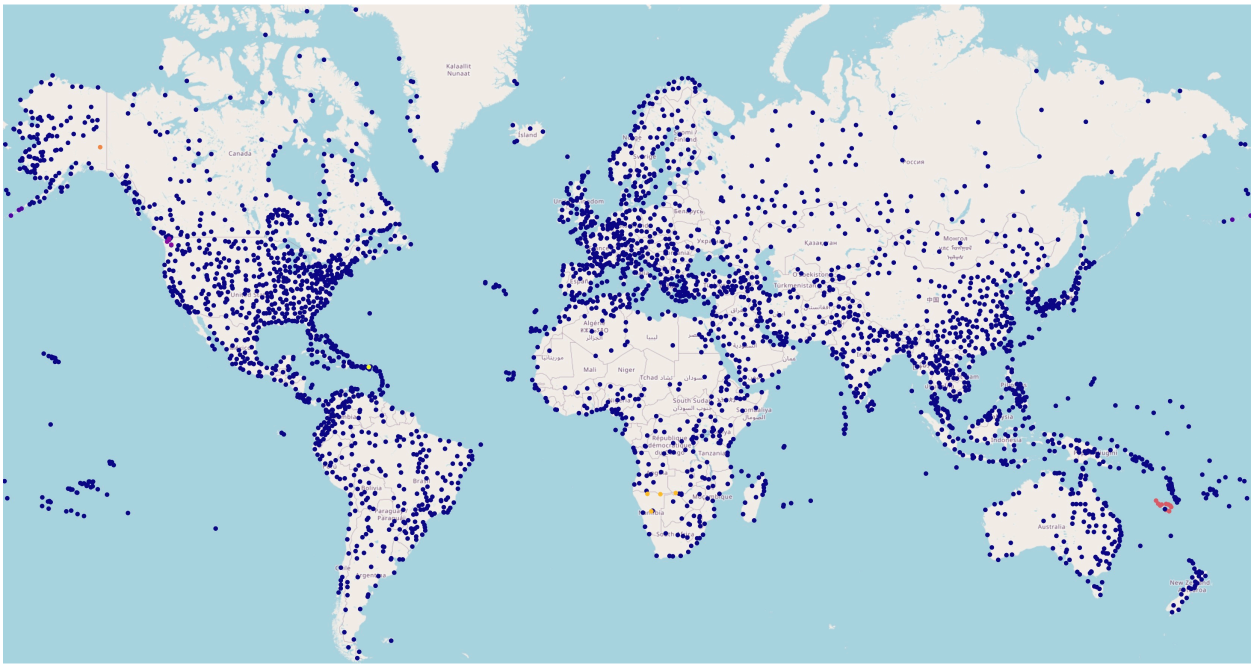
3.2 Graph Representation

- Each node is an airport.
- Each edge is a route between two airports.
- Graph is directed and weighted: weight of each edge being the total number of flights in that specific route.
- The graph is sparse: only 10% of entries of the adjacency matrix A are not null.
- In-degree and out-degree follow a power-law distribution:



(a) (b)

Figur 3.1: In and out degree distribution



Figur 3.2: Connected Components of the routes data. Airports of the same color belong to the same component.

3.3 Airports Ranking

3.3.1 Assumptions

Strong assumptions have to be made in order to make the ranking feasible.

At each time step, all flights depart and arrive simultaneously. In each route, there is only one flight containing 100 passengers per time step, meaning that the total number of people in each airport is constant. Infections and recoveries happen only at the airports, and infected people are distributed proportional to edges' weights at the next time step to destination airports.

For our initial conditions we start with 2% of people in a specific airports infected, while nobody else worldwide.

3.4 Weighted PageRank

In order to factor in the traffic flow intensity in each route (edges' weights), the epidemic spread through interaction at airports, and the possible recovery, we adopted the extended Weighted PR (WPR) proposed by Zhang et al. [8], where we considered the directed and weighted graph $G(V, E)$: iteratively:

$$\phi(i) = \gamma \sum_{j \in V} (\theta \frac{w_{ji}}{s_j^{(out)}} + (1 - \theta) \frac{a_{ji}}{d_j^{(out)}}) \phi(j) + \frac{(1 - \gamma)\beta_i}{\sum_{j \in V} \beta_j} \tag{1}$$

- $\phi(i)$: rank given to node i: by construction, how sensitive airport i is to the epidemic spread;
- a_{ji}: element (j, i) of the adjacency matrix: presence of the route from airport j to airport i;
- w_{ji}: weight of the edge from node j to node i: number of unique flights from airport j to airport i;
- $d_j^{(out)}$: out-degree of node j: number of routes departing from airport j;
- $s_j^{(out)}$: out-strength of node j: total number of flights departing from airport j;
- γ, γ ∈[0,1): teleportation parameter of original PR that prevents getting stuck in dead ends/cyclic patterns: fixed at 0.95;
- θ, θ ∈[0,1]: parameter balancing the weight-degree trade-off: fixed at 0.9. It is indeed reasonable that weight is more critical to the epidemic spread than degree as it more accurately reflects the number of people on the move.

The resulting rank will take into account routes and air traffic, combining them with a term, which models the infection during airport interaction.

The term β_i accounts for some node-specific quantifiable information of i:

$$\beta_i = \alpha S_i^{(in)} + (1 - \alpha) X_i \tag{2}$$

- α, α ∈[0,1], parameter for the convex combination: fixed to 0.45. Reasonably, both number of incoming flights and infection term play a critical role in the spreading;
- $S_i^{(in)}$ is the in-strength of node i;
- X_i is a positive random variable, $X_i \perp S_i^{(in)}$.

X_i accounts for infection spreading. $X_i \sim Bin(n, p)$, where n is the number of people at time step k in the airport i that are not infected, while p accounts for the probability that a single person is getting infected in this time step. For every airport, a sample is performed at each time step.
p is directly proportional to the proportion of already infected people in the airport i: reasonably, a high proportion of already infected people would increase exposure of other passengers to the virus, therefore making it more likely for them infected themselves. Parameter c models the quickness of the virus in spreading among people.

$$p = \frac{c \cdot \#infected}{\#total} \tag{3}$$

By X_i construction, $S_i^{(in)}$ does not influence binomial's parameters.

Ranking has been performed in two variants, not considering and considering a recovery phenomenon.

The number of infected people that recovered is modeled through a Poisson random variable, its parameter being the number of infected people in the airport times the recovery rate (fixed to 0.2). At each iteration, for each airport, a sample (clamped to the number of infected people) is retrieved. Recovery and infection happen simultaneously: the number of newly infected is sampled before updating the total number of sick people. Using a Poisson random variable to model the number of recovered is another strong assumption, as it would be reasonable to consider it depending on the time passed after the infection. However, since it would have made the algorithm too complex, we adopted a model that makes it time independent. Despite this, Poisson random variable is a likely model for the phenomenon: we are assuming that on average, a fraction of infected people, corresponding to the recovery rate, recovers, a phenomenon such that Poisson random variables are well suited for.

3.5 Evaluation through Simulation

3.5.1 Motivation

In order to evaluate the effectiveness of our WPR in ranking and identifying most influential airports, the epidemic spread is simulated in multiple settings in realworld scenarios. We compared the speed and extent of spreads with and without interventions i.e., screening and quarantining passengers who are tested positive, at the top 10 highest ranked airports (threshold chosen arbitrarily), as well as potentially shutting down these airports.

Furthermore, in each setting we compared the effectiveness of interventions based on the ranking obtained through WPR versus rankings obtained through other simpler techniques:

- PageRank: Utilizing PageRank algorithm to rank all the airports, selecting the top 10 among them.
- Degree Centrality: Top 10 most interconnected airports in the world are selected.
- Random Choice: Choosing 10 airports randomly across the world.

It is important to highlight that for these aforementioned rankings, no term modeling the infection (and possibly recovery) is present and taken into account during the algorithm. Indeed, only network topology is used.

For this reason we hypothesize that WPR would give us the most accurate ranking results for intervention prioritization.

3.5.2 Assumptions

In order to simulate the epidemic spread as best as we could with limited resources, we first made some assumptions to narrow down the problem. As mentioned before, we assume that the epidemic breaks out at predetermined locations with 2% of total passengers already infected. We discretize time, assuming each flight takes off and lands once within a time step. At time step 0, the initial number of total passengers at each airport is proportional to the degree of the airport node, as we assume that the more interconnected an airport is, the greater the number of passengers travelling through the airport will be. We also assume that the infection happens only at the airports.

At the top 10 most influential airports, we conduct virtual PCR test screenings to all passengers, with a true positive rate of 0.8. All passengers who are tested positive will be quarantined. The percentage of passengers tested positive is consistently monitored at these airports, which will be shut down shall its proportion exceed 5%.

It is worth noting that passengers cannot travel to airports that have already been shut down. We assume every passenger at each airport to have the same probability to be infected, which is proportional to the number of people who have already been infected at the airport, excluding those who are quarantined. Specifically, for each airport,

$$p = \frac{\alpha \cdot \beta \cdot \#infected}{\#total} \tag{4}$$

- α: representing the infectivity of a certain virus;
- β: multiplying coefficient, fixed at 10. This causes the simulations to converge faster, making it feasible to run on the hardware available to us.

At each time step:

1. Conduct PCR test screenings at important airports, quarantine passengers that are tested positive, and shut down airports if necessary.
2. Assign each passenger's next destination airport based on the weights of the current airport node.
3. Simulate the epidemic spread at each airport.

In order to evaluate the effectiveness of WPR in taking into account the recovery process, we also introduced recovery into our simulation by assuming infected passengers to recover after 5 time steps.

3.5.3 Key Parameters

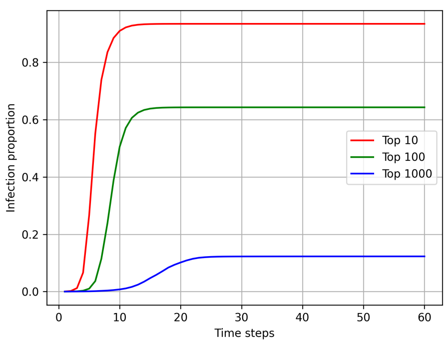
Based on the previous discussions, for both WPR rankings and for all the simulations it is necessary to set the initial conditions and the quickness in spreading (α) of the virus (c in (3) and α in (4)).
We define three types of viruses, $\alpha = 0.1$, $\alpha = 0.25$, and $\alpha = 0.5$.
Infected people, for each one of the three viruses, at the beginning of the WPR ranking and the simulations are respectively in:

- only Arlanda Airport: ARN;
- the ten most interconnected airports in the world: FRA, CDG, AMS, IST, ATL, PEK, ORD, MUC, DME, DXB;
- airports of capital cities of the countries from which Ebola originated (describing the characteristic of being in a less connected region of the world): CKY (Guinea), FNA (Sierra Leone), ROB (Liberia).

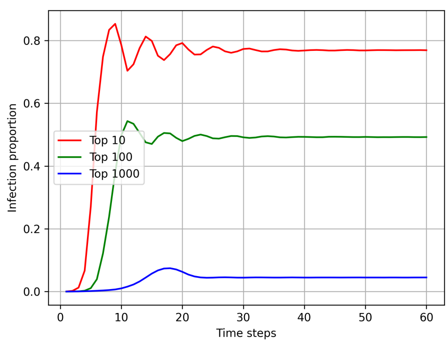
Moreover, for each scenario, we will conduct two types of studies: one without recovery and one with recovery. Therefore, there are a total of 18 different configurations. We believe this will cover a sufficient number of cases, and the results derived from this will have a certain reference value.

3.5.4 Preventing measure efficiency

To demonstrate the effectiveness and validity of our simulation, firstly, we conducted several experiments. We set $\alpha = 0.5$ and assumed the disease outbreak starts at Arlanda (ARN). Following the aforementioned strategy, we do the simulation and perform measures including PCR testing and shutting down airports at the top 10, top 100, and top 1000 airports (based on the PageRank) respectively. We then observed the outcomes under these different conditions.



Figur 3.3: α=0.1, without recovery



Figur 3.4: α=0.1, with recovery

In the left graph, when intervention measures are implemented at the top 10 airports, the infection proportion rises sharply and stabilizes at a high level. When we extend measures to the top 100 airports, the infection proportion significantly drops. When the measures are expanded to the top 1000 airports, the infection proportion continues to go down.

On the right graph, we take into account the recovery of positive passengers. The result provides us almost the same insight. The only difference is that there are some fluctuations of the proportion before reaching stability.

So we can conclude that shutting down airports, conducting PCR tests on passengers, and isolating positive cases can indeed slow down the spreading of the virus. Therefore, we demonstrated that doing simulation in this manner is scientifically rational.

4 Results and Discussions

An analysis of the results revealed that our Weighted PageRank (WPR) algorithm outperforms all other ranking strategies when applied to our simulation, with the unweighted PageRank algorithm following closely behind.

4.1 Airport Rankings

Rankings based only on network topology are almost the same for all the three algorithms used. The more an airport is connected to other airports, the more it will spread the virus worldwide.

Rankings indeed change using our WPR as air traffic and infection spreading come in to play. It is also reasonable that with this ranking, very well-connected airports are highly sensitive to epidemic diffusion. Outcomes remain largely consistent regardless of the initial conditions. This consistency can be intuitively understood, as in the absence of a recovery rate, the infection would spread quickly and uniformly across the network. When the recovery phenomenon is introduced, the system initially exhibits oscillatory behavior but eventually stabilizes into an equilibrium state. We observed that varying α does not produce significant changes in the resulting ranks of the airports. This suggests that the algorithm's sensitivity to this parameter might be lower than initially expected.

Atlanta Airport (ATL) consistently ranks the highest. ATL is a fundamental hub for connecting all the South-west American airports with the rest of the USA. Additionally, together with Los Angeles and Miami, Atlanta is one of the principal hubs to move to South-America. It is reasonable to us that a USA airport ranks first, as in the USA air traffic is employed significantly in day-to-day life. Indeed, for almost all ranking tables produced, half of the top-10 highest WPR ranked airports are American.

A qualitative analysis of our WPR algorithm appears to be working better, since in the other rankings, top ranked airports contains less USA airports, with also a smaller importance. We report only the top-10 highest ranked airport for each algorithm and each configuration of WPR for the sake of simplicity, which can be found in the appendix.

4.2 Findings from Simulation

To comprehensively test the effectiveness of our WPR in identifying the most influential airports, we let the virus originate from different locations.

4.2.1 Virus Originating from Stockholm Arlanda Airport

We first let the virus originate from Stockholm Arlanda Airport (ARN) and obtained 6 rounds of simulation results as shown in Table .1 by altering alpha value and whether to take into account the recovery of infected passengers.

It can be observed that choosing the ten airports randomly has almost the same effect as taking no intervention.

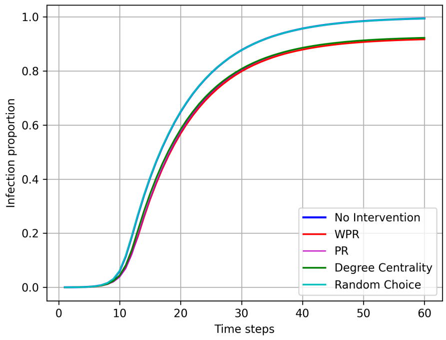
Aligning with our hypothesis, WPR performs the best in identifying the most influential airports as the infection proportion, represented by a red color, consistently stays lowest when performing interventions at most influential airports identified by WPR in all rounds of simulation.

The more infectious the virus, the faster it spreads, the faster the infection proportion stabilizes. This holds true for both curable and incurable viruses. For curable viruses, the infection proportion stabilizes with oscillations. The more infectious the virus, the greater the number of oscillations the infection proportion takes to stabilize. However, the infectivity of an incurable virus has no impact on the infection proportion in the long term, as different curves stabilize to the same level with different alpha values when we do not consider recovery.

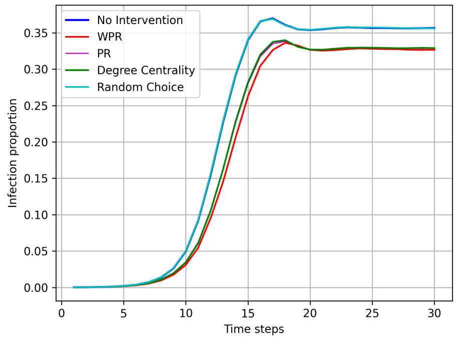
We also noticed that both short-term and long-term infection proportion are lower for curable viruses compared to incurable viruses. The less infectious the virus, the slower it spreads and hence the lower the infection proportion.

4.2.2 Virus Originating from the Top 10 Most Interconnected Airports

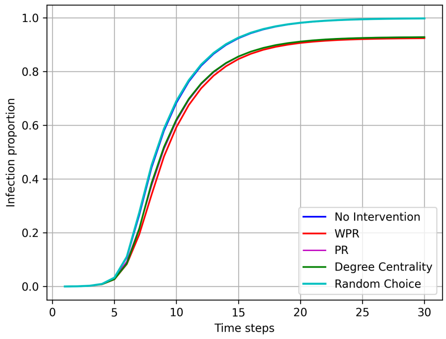
We then let the virus originate from the top ten most interconnected airports. This is an extreme case where PR shall perform the best, as these are the exact ten airports identified through PR and Degree Centrality methods (see Table .3). As these airports are the highest weighted neighboring airports of their neighbors, infected passengers who travel to the neighboring airports are most likely to



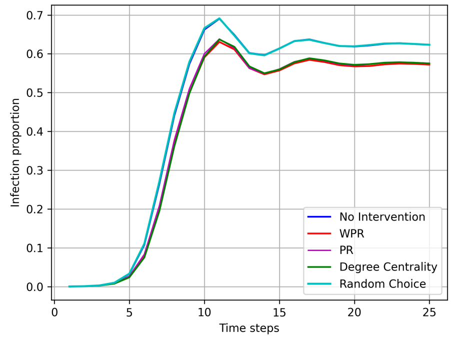
(a) α=0.1, without recovery



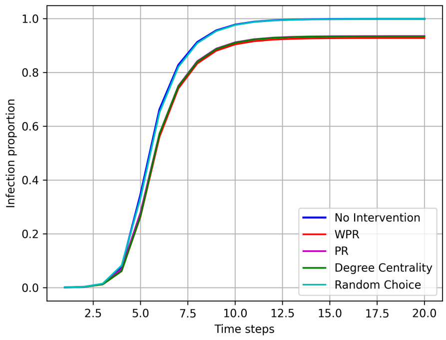
(b) α=0.1, with recovery



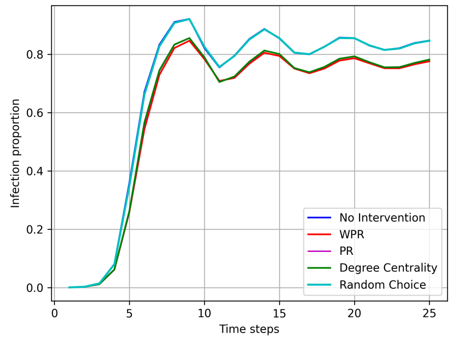
(c) α=0.25, without recovery



(d) α=0.25, with recovery



(e) α=0.5, without recovery

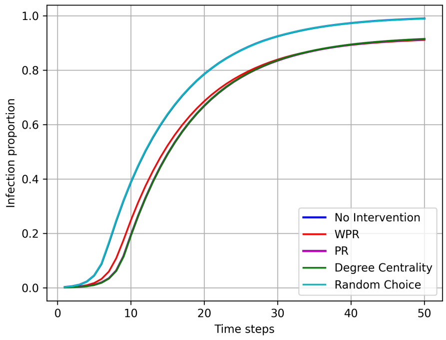


(f) α=0.5, with recovery

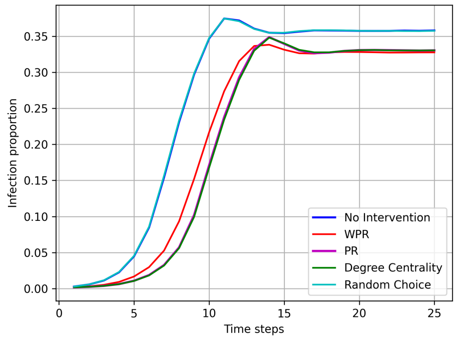
Figur 4.1: Disease originating from ARN

come back to these airports. Hence, by shutting down these airports, the infected passengers have to find other routes and take a longer time to spread the virus to the world. We would also like to see whether a greater number of initially infected passengers will pose a challenge to WPR's performance.

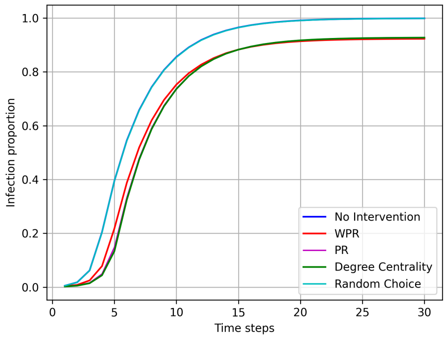
As shown in Table .2, PR indeed performs better than WPR for both curable and incurable viruses in the short term, as seen by the slower spread, which corroborates our hypothesis. In the long term, however, WPR still excels as it the curve representing WPR stays at the lowest level in all six scenarios. Furthermore, WPR is effective in controlling the infection proportion for curable viruses, as seen by the lower magnitude of its first peak compared to PR. Furthermore, by comparing the results of each scenario against those from 4.1.1, we can see that the more interconnected the airports, the faster the spread of the viruses, as seen by the shorter time needed to reach the same level of infection proportion. Last but not least, we found that an increase in the number of initially infected passengers had no negative impact on the performance of WPR in identifying the most influential airports.



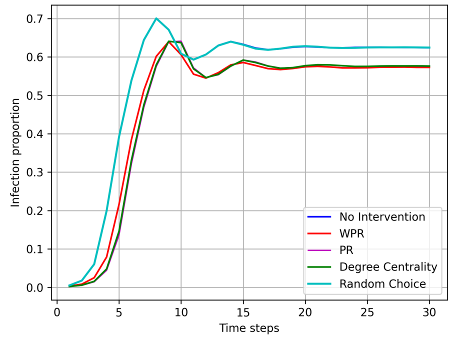
(a) α=0.1, without recovery



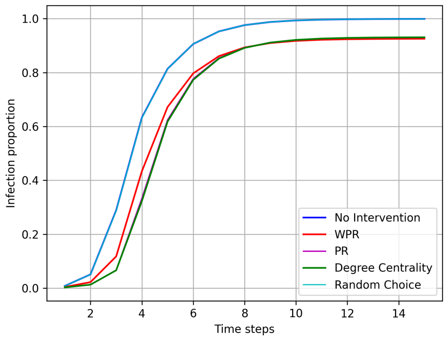
(b) α=0.1, with recovery



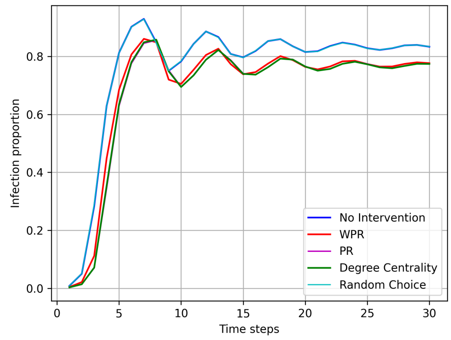
(c) α=0.25, without recovery



(d) α=0.25, with recovery



(e) α=0.5, without recovery



(f) α=0.5, with recovery

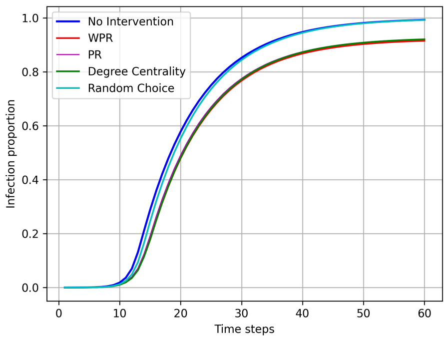
Figur 4.2: Disease originating from top 10 important airports

4.2.3 Virus Originating from Airports in African countries where Ebola started

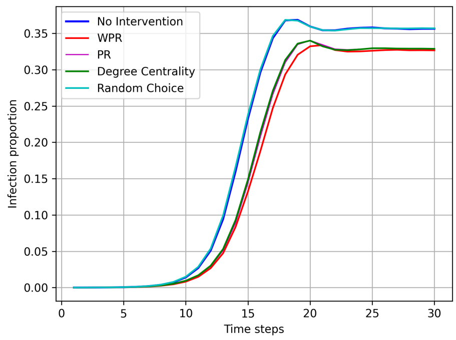
Finally, we considered another extreme case, evaluating whether the results will differ when viruses originate from remote and weakly connected areas in the world. To this end, we selected the international airports in the capital cities of the three countries where Ebola first broke out, namely Guinea, Sierra Leone, and Liberia. They are Ahmed Sékou Touré International Airport (CKY), Freetown International Airport (FNA), and Roberts International Airport (ROB).

Similar to previous findings, we saw superior performance of our WPR in all scenarios, as shown in Table .3.

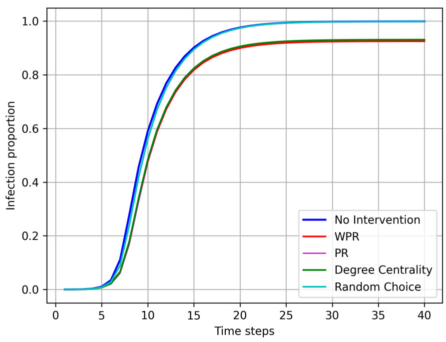
Additionally, we noticed that the viruses take roughly the same time to spread to the world from these airports as ARN in our model.



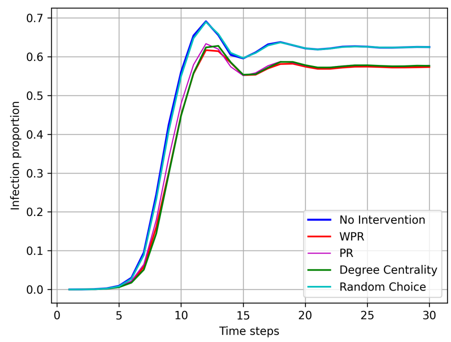
(a) α=0.1, without recovery



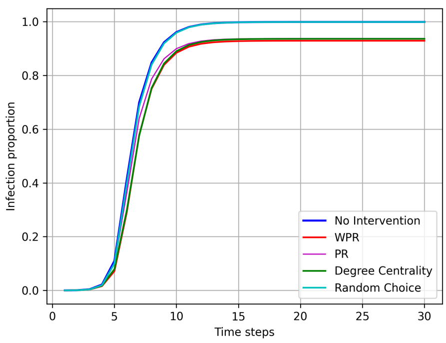
(b) α=0.1, with recovery



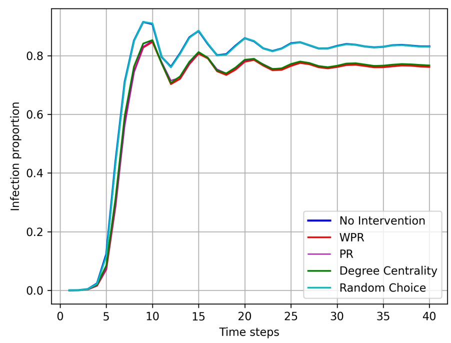
(c) α=0.25, without recovery



(d) α=0.25, with recovery



(e) α=0.5, without recovery



(f) α=0.5, with recovery

Figur 4.3: Disease originating from airports in the three countries where Ebola first broke out

In conclusion, by comparing the simulation results in each of the six scenarios of all three cases, we see that the origin of the viruses has no impact on the infection proportion in the long term. It only affects the speed of the spread of the viruses in the short term.

5 Conclusions

5.1 Final thoughts

A WPR offers a method to rank nodes incorporating information about a phenomenon that is external to graph information. It is a very powerful tool in cases such as the one we have examined in depth, where a graph offers information only corresponding to air infrastructure, not about virus spreading. Instead of the classical PR however, it requires great care to correctly describe a model. The dimensions of the graph that we have analyzed are not trivial, but for even larger graphs it could become unfeasible to run in a reasonable amount of time, requiring a very efficient implementation. Indeed, our WPR requires sampling at each iteration for each node, and adding complexity could make this sample expensive.

5.2 Weak points

To make the model feasible, we made numerous unrealistic assumptions:

- **Aviation Operation:** Particularly regarding how air infrastructure operates and how passengers move globally. Similarly, the modeling of infection and recovery processes also involved significant simplifications.
- **Data Aggregation:** The data used in our simulations are aggregated, leading to the loss of certain nuances. For instance, seasonal variations in specific routes were not accounted for, making time independency one of the strictest assumptions in our model.
- **Code Efficiency:** The implementation of our code lacks optimization, which may affect the efficiency and scalability of the simulations.

Nonetheless, our findings offer a foundational understanding of the role of global aviation in epidemic spread, providing a basis for future improvements.

5.3 Future Work

To enhance the applicability of our model and make our results more meaningful, future work could focus on the following areas:

- **Realistic Infection and Recovery Modeling:** Incorporating a Bayesian model to simulate infections and recoveries more realistically could improve the reliability of airport rankings and their evaluations. Another approach might be to utilize the SIR model.
- **Time-Dependent Data Utilization:** Identifying a dataset that allows for non-aggregated data would enable the implementation of a time-dependent Weighted PageRank (WPR). This approach would enhance the accuracy of rankings by accounting for seasonal variations and other temporal factors.

5.4 Teamwork

Everyone contributes equally to the project, putting effort on it. Teamwork worked very well and was perfectly synchronized and timed. We divided in two teams, one (Andrea and Lennard) working on WPR exploitation and implementation, while the other (Heqiao and Qiyuan) focused on simulating virus spreading. Every component of the team apported critical thinking to others' ideas. We discussed together a lot about assumptions, difficulties, and results.

All the code and complete results can be found **here** on GitHub.

Referenser

[1] Bielecki, Michel m. fl. “Air travel and COVID-19 prevention in the pandemic and peri-pandemic period: A narrative review”. I: *Travel Medicine and Infectious Disease* 39 (2021), s. 101915. ISSN: 1477-8939. DOI: https://doi.org/10.1016/j.tmaid.2020.101915. URL: https://www.sciencedirect.com/science/article/pii/S1477893920304117.

[2] Brin, Sergey och Page, Lawrence. “The anatomy of a large-scale hypertextual web search engine”. I: *Computer networks and ISDN systems* 30.1-7 (1998), s. 107–117.

[3] Ghulam, Ali m. fl. “Disease-Pathway Association Prediction Based on Random Walks With Restart and PageRank”. I: *IEEE Access* 8 (2020), s. 72021–72038. DOI: 10.1109/ACCESS.2020.2987071.

[4] Liu, Shelby. “Air Travel in the Age of COVID-19”. I: (2021).

[5] *OpenFlights: Airport and airline data*. 2017. URL: https://www.openflights.org/data (hämtad 2024-05-06).

[6] Xiaoqian Sun, Sebastian Wandelt och Zhangb, Anming. “COVID-19 pandemic and air transportation: Summary of Recent Research, Policy Consideration and Future Research Directions.” I: (2022). DOI: 10.1016/j.trip.2022.100718.

[7] Yu, Meng och Chen, Zhenhua. “The effect of aviation responses to the control of imported COVID-19 cases.” I: (2021). DOI: 10.1016/j.jairtraman.2021.102140.

[8] Zhang, Panpan, Wang, Tiandong och Yan, Jun. “PageRank centrality and algorithms for weighted, directed networks with applications to World Input-Output Tables”. I: (2021). URL: https://arxiv.org/pdf/2104.02764.

Appendices

Rank	Code	Airport	Value
1	FRA	Frankfurt Airport	238
2	CDG	Paris Charles de Gaulle Airport	233
3	AMS	Amsterdam Airport Schiphol	231
4	IST	Istanbul Airport	230
5	ATL	Hartsfield-Jackson Atlanta International Airport	216
6	PEK	Beijing Capital International Airport	206
7	ORD	Chicago O'Hare International Airport	203
8	MUC	Munich Airport	189
9	DME	Moscow Domodedovo Airport	189
10	DFW	Dallas Fort Worth International Airport	185
...			

Tabell .1: In-degree ranking

Rank	Code	Airport	Value
1	FRA	Frankfurt Airport	239
2	CDG	Paris Charles de Gaulle Airport	237
3	AMS	Amsterdam Airport Schiphol	232
4	IST	Istanbul Airport	227
5	ATL	Hartsfield-Jackson Atlanta International Airport	217
6	PEK	Beijing Capital International Airport	206
7	ORD	Chicago O'Hare International Airport	206
8	MUC	Munich Airport	191
9	DME	Moscow Domodedovo Airport	189
10	DXB	Dubai International Airport	188
...			

Tabell .2: Out-degree ranking

Rank	Code	Airport	Value
1	FRA	Frankfurt Airport	2.69
2	CDG	Paris Charles de Gaulle Airport	2.64
3	IST	Istanbul Airport	2.62
4	AMS	Amsterdam Airport Schiphol	2.61
5	ATL	Hartsfield-Jackson Atlanta International Airport	2.55
6	ORD	Chicago O'Hare International Airport	2.39
7	PEK	Beijing Capital International Airport	2.36
8	DFW	Dallas Fort Worth International Airport	2.17
9	DME	Moscow Domodedovo Airport	2.14
10	MUC	Munich Airport	2.13
...			

Tabell .3: PageRank ranking

Rank	Code	Airport	Value
1	ATL	Hartsfield-Jackson Atlanta International Airport	43.20
2	ORD	Chicago O'Hare International Airport	26.64
3	PEK	Beijing Capital International Airport	26.07
4	CDG	Paris Charles de Gaulle Airport	25.39
5	LHR	London Heathrow Airport	25.26
6	FRA	Frankfurt Airport	24.45
7	LAX	Los Angeles International Airport	23.87
8	DFW	Dallas Fort Worth International Airport	22.74
9	AMS	Amsterdam Airport Schiphol	22.43
10	JFK	John F. Kennedy International Airport	22.33
...			

Tabell .4: WPR ranking with $\alpha = 0.1$, initial condition: Arlanda airport. Without recovery.

Rank	Code	Airport	Value
1	ATL	Hartsfield-Jackson Atlanta International Airport	43.26
2	ORD	Chicago O'Hare International Airport	26.66
3	PEK	Beijing Capital International Airport	26.09
4	CDG	Paris Charles de Gaulle Airport	25.38
5	LHR	London Heathrow Airport	25.24
6	FRA	Frankfurt Airport	24.43
7	LAX	Los Angeles International Airport	23.89
8	DFW	Dallas Fort Worth International Airport	22.77
9	AMS	Amsterdam Airport Schiphol	22.41
10	JFK	John F. Kennedy International Airport	22.34
...			

Tabell .5: WPR ranking with $\alpha = 0.1$, initial condition: Arlanda airport. With recovery.

Rank	Code	Airport	Value
1	ATL	Hartsfield-Jackson Atlanta International Airport	44.59
2	ORD	Chicago O'Hare International Airport	28.01
3	PEK	Beijing Capital International Airport	27.33
4	CDG	Paris Charles de Gaulle Airport	27.10
5	FRA	Frankfurt Airport	26.03
6	LHR	London Heathrow Airport	25.30
7	AMS	Amsterdam Airport Schiphol	24.04
8	LAX	Los Angeles International Airport	23.74
9	DFW	Dallas Fort Worth International Airport	22.70
10	JFK	John F. Kennedy International Airport	22.34
...			

Tabell .6: WPR ranking with $\alpha = 0.1$, initial condition: 10 most interconnected airports. Without recovery.

Rank	Code	Airport	Value
1	ATL	Hartsfield-Jackson Atlanta International Airport	43.27
2	ORD	Chicago O'Hare International Airport	26.66
3	PEK	Beijing Capital International Airport	26.10
4	CDG	Paris Charles de Gaulle Airport	25.39
5	LHR	London Heathrow Airport	25.24
6	FRA	Frankfurt Airport	24.42
7	LAX	Los Angeles International Airport	23.89
8	DFW	Dallas Fort Worth International Airport	22.77
9	AMS	Amsterdam Airport Schiphol	22.41
10	JFK	John F. Kennedy International Airport	22.34
...			

Tabell .7: WPR ranking with $\alpha = 0.1$, initial condition: 10 most interconnected airports. With recovery.

Rank	Code	Airport	Value
1	ATL	Hartsfield-Jackson Atlanta International Airport	43.25
2	ORD	Chicago O'Hare International Airport	26.66
3	PEK	Beijing Capital International Airport	26.09
4	CDG	Paris Charles de Gaulle Airport	25.40
5	LHR	London Heathrow Airport	25.25
6	FRA	Frankfurt Airport	24.43
7	LAX	Los Angeles International Airport	23.89
8	DFW	Dallas Fort Worth International Airport	22.77
9	AMS	Amsterdam Airport Schiphol	24.41
10	JFK	John F. Kennedy International Airport	22.34
...			

Tabell .8: WPR ranking with $\alpha = 0.1$, initial condition: Ebola source airports. Without recovery.

Rank	Code	Airport	Value
1	ATL	Hartsfield-Jackson Atlanta International Airport	43.26
2	ORD	Chicago O'Hare International Airport	26.67
3	PEK	Beijing Capital International Airport	26.10
4	CDG	Paris Charles de Gaulle Airport	25.38
5	LHR	London Heathrow Airport	25.24
6	FRA	Frankfurt Airport	24.42
7	LAX	Los Angeles International Airport	23.89
8	DFW	Dallas Fort Worth International Airport	22.77
9	AMS	Amsterdam Airport Schiphol	24.41
10	JFK	John F. Kennedy International Airport	22.34
...			

Tabell .9: WPR ranking with $\alpha = 0.1$, initial condition: Ebola source airports. With recovery.

Rank	Code	Airport	Value
1	ATL	Hartsfield-Jackson Atlanta International Airport	43.21
2	ORD	Chicago O'Hare International Airport	26.64
3	PEK	Beijing Capital International Airport	26.06
4	CDG	Paris Charles de Gaulle Airport	25.42
5	LHR	London Heathrow Airport	25.26
6	FRA	Frankfurt Airport	24.46
7	LAX	Los Angeles International Airport	23.87
8	DFW	Dallas Fort Worth International Airport	22.74
9	AMS	Amsterdam Airport Schiphol	22.45
10	JFK	John F. Kennedy International Airport	22.34
...			

Tabell .10: WPR ranking with $\alpha = 0.25$, initial condition: Arlanda airport. Without recovery.

Rank	Code	Airport	Value
1	ATL	Hartsfield-Jackson Atlanta International Airport	43.21
2	ORD	Chicago O'Hare International Airport	26.65
3	PEK	Beijing Capital International Airport	26.08
4	CDG	Paris Charles de Gaulle Airport	25.39
5	LHR	London Heathrow Airport	25.26
6	FRA	Frankfurt Airport	24.44
7	LAX	Los Angeles International Airport	23.87
8	DFW	Dallas Fort Worth International Airport	22.75
9	AMS	Amsterdam Airport Schiphol	22.43
10	JFK	John F. Kennedy International Airport	22.34
...			

Tabell .11: WPR ranking with $\alpha = 0.25$, initial condition: Arlanda airport. With recovery.

Rank	Code	Airport	Value
1	ATL	Hartsfield-Jackson Atlanta International Airport	43.49
2	ORD	Chicago O'Hare International Airport	26.91
3	PEK	Beijing Capital International Airport	26.06
4	CDG	Paris Charles de Gaulle Airport	25.75
5	LHR	London Heathrow Airport	25.39
6	FRA	Frankfurt Airport	24.83
7	LAX	Los Angeles International Airport	23.85
8	DFW	Dallas Fort Worth International Airport	22.79
9	AMS	Amsterdam Airport Schiphol	22.71
10	JFK	John F. Kennedy International Airport	22.41
...			

Tabell .12: WPR ranking with $\alpha = 0.25$, initial condition: 10 most interconnected airports. Without recovery.

Rank	Code	Airport	Value
1	ATL	Hartsfield-Jackson Atlanta International Airport	44.47
2	ORD	Chicago O'Hare International Airport	27.98
3	PEK	Beijing Capital International Airport	26.97
4	CDG	Paris Charles de Gaulle Airport	26.96
5	FRA	Frankfurt Airport	26.01
6	LHR	London Heathrow Airport	25.34
7	AMS	Amsterdam Airport Schiphol	23.78
8	LAX	Los Angeles International Airport	23.76
9	DFW	Dallas Fort Worth International Airport	22.74
10	JFK	John F. Kennedy International Airport	22.37
...			

Tabell .13: WPR ranking with $\alpha = 0.25$, initial condition: 10 most interconnected airports. With recovery.

Rank	Code	Airport	Value
1	ATL	Hartsfield-Jackson Atlanta International Airport	43.25
2	ORD	Chicago O'Hare International Airport	26.67
3	PEK	Beijing Capital International Airport	26.09
4	CDG	Paris Charles de Gaulle Airport	25.40
5	LHR	London Heathrow Airport	25.25
6	FRA	Frankfurt Airport	24.43
7	LAX	Los Angeles International Airport	23.89
8	DFW	Dallas Fort Worth International Airport	22.77
9	AMS	Amsterdam Airport Schiphol	24.41
10	JFK	John F. Kennedy International Airport	22.34
...			

Tabell .14: WPR ranking with $\alpha = 0.25$, initial condition: Ebola source airports. Without recovery.

Rank	Code	Airport	Value
1	ATL	Hartsfield-Jackson Atlanta International Airport	43.25
2	ORD	Chicago O'Hare International Airport	26.66
3	PEK	Beijing Capital International Airport	26.09
4	CDG	Paris Charles de Gaulle Airport	25.40
5	LHR	London Heathrow Airport	25.25
6	FRA	Frankfurt Airport	24.43
7	LAX	Los Angeles International Airport	23.89
8	DFW	Dallas Fort Worth International Airport	22.77
9	AMS	Amsterdam Airport Schiphol	24.41
10	JFK	John F. Kennedy International Airport	22.34
...			

Tabell .15: WPR ranking with $\alpha = 0.25$, initial condition: Ebola source airports. With recovery.

Rank	Code	Airport	Value
1	ATL	Hartsfield-Jackson Atlanta International Airport	43.25
2	ORD	Chicago O'Hare International Airport	26.66
3	PEK	Beijing Capital International Airport	26.09
4	CDG	Paris Charles de Gaulle Airport	25.39
5	LHR	London Heathrow Airport	25.25
6	FRA	Frankfurt Airport	24.44
7	LAX	Los Angeles International Airport	23.89
8	DFW	Dallas Fort Worth International Airport	22.77
9	AMS	Amsterdam Airport Schiphol	22.42
10	JFK	John F. Kennedy International Airport	22.35
...			

Tabell .16: WPR ranking with $\alpha = 0.5$, initial condition: Arlanda airport. Without recovery.

Rank	Code	Airport	Value
1	ATL	Hartsfield-Jackson Atlanta International Airport	42.89
2	ORD	Chicago O'Hare International Airport	26.50
3	PEK	Beijing Capital International Airport	25.90
4	CDG	Paris Charles de Gaulle Airport	25.51
5	LHR	London Heathrow Airport	25.38
6	FRA	Frankfurt Airport	24.59
7	LAX	Los Angeles International Airport	23.72
8	AMS	Amsterdam Airport Schiphol	22.61
9	DFW	Dallas Fort Worth International Airport	22.58
10	JFK	John F. Kennedy International Airport	22.29
...			

Tabell .17: WPR ranking with $\alpha = 0.5$, initial condition: Arlanda airport. With recovery.

Rank	Code	Airport	Value
1	ATL	Hartsfield-Jackson Atlanta International Airport	43.30
2	ORD	Chicago O'Hare International Airport	26.69
3	PEK	Beijing Capital International Airport	26.03
4	CDG	Paris Charles de Gaulle Airport	25.45
5	LHR	London Heathrow Airport	25.29
6	FRA	Frankfurt Airport	24.49
7	LAX	Los Angeles International Airport	23.89
8	DFW	Dallas Fort Worth International Airport	22.79
9	AMS	Amsterdam Airport Schiphol	22.47
10	JFK	John F. Kennedy International Airport	22.37
...			

Tabell .18: WPR ranking with $\alpha = 0.5$, initial condition: 10 most interconnected airports. Without recovery.

Rank	Code	Airport	Value
1	ATL	Hartsfield-Jackson Atlanta International Airport	48.59
2	ORD	Chicago O'Hare International Airport	32.03
3	CDG	Paris Charles de Gaulle Airport	31.62
4	FRA	Frankfurt Airport	30.78
5	PEK	Beijing Capital International Airport	30.38
6	AMS	Amsterdam Airport Schiphol	28.65
7	LHR	London Heathrow Airport	25.29
8	IST	Istanbul Airport	25.46
9	MUC	Munich Airport	23.31
10	LAX	Los Angeles International Airport	23.25
...			

Tabell .19: WPR ranking with $\alpha = 0.5$, initial condition: 10 most interconnected airports. With recovery.

Rank	Code	Airport	Value
1	ATL	Hartsfield-Jackson Atlanta International Airport	43.26
2	ORD	Chicago O'Hare International Airport	26.67
3	PEK	Beijing Capital International Airport	26.09
4	CDG	Paris Charles de Gaulle Airport	25.39
5	LHR	London Heathrow Airport	25.24
6	FRA	Frankfurt Airport	24.43
7	LAX	Los Angeles International Airport	23.89
8	DFW	Dallas Fort Worth International Airport	22.77
9	AMS	Amsterdam Airport Schiphol	24.41
10	JFK	John F. Kennedy International Airport	22.34
...			

Tabell .20: WPR ranking with $\alpha = 0.5$, initial condition: Ebola source airports. Without recovery.

Rank	Code	Airport	Value
1	ATL	Hartsfield-Jackson Atlanta International Airport	43.17
2	ORD	Chicago O’Hare International Airport	26.62
3	PEK	Beijing Capital International Airport	26.04
4	CDG	Paris Charles de Gaulle Airport	25.51
5	LHR	London Heathrow Airport	25.28
6	FRA	Frankfurt Airport	24.43
7	LAX	Los Angeles International Airport	23.85
8	DFW	Dallas Fort Worth International Airport	22.73
9	AMS	Amsterdam Airport Schiphol	24.41
10	JFK	John F. Kennedy International Airport	22.34
...			

Tabell .21: WPR ranking with $\alpha = 0.5$, initial condition: Ebola source airports. With recovery.