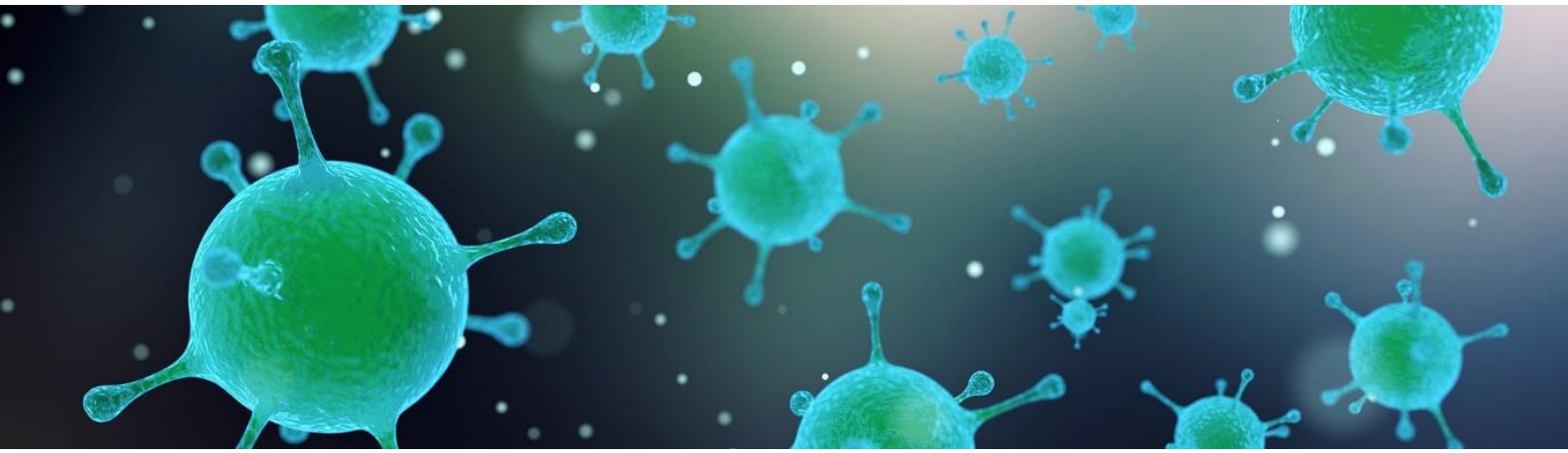
Preventing airborne infectious spreading

The role of airport level operations during epidemics



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Preventing Airborne Infectious Spreading

The role of airport level operations during epidemics

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Preface

This master thesis marks the end of my time at Delft University of Technology. I would like to thank the members of my graduation committee, Bartel van de Walle, Tina Comes and Martijn Warnier, for their guidance. Their help was indispensable for preparing and executing this project.

Furthermore, I would like to thank the experts in the humanitarian field that have taken the time to answer my questions. They gave me great insight in the functioning of screening measures, both at Brussels Airport and in West Africa. Thanks to Kenny Meesters I have been able to get in touch with them.

Last but not least, I would like to thank my family, friends and roommates for the support and much needed distraction during my thesis research and my study in general.

Executive summary

Infectious diseases are responsible for about one quarter of all deaths worldwide and it is likely that major epidemics will emerge in the near future. Through the airline system, diseases can spread around the world rapidly and are more and more likely to do so. At the same time, air connectivity is essential for countries with inadequate land-based infrastructure, in particular during an epidemic when incoming humanitarian assistance is essential. This illustrates the trade-off of passenger airline operations during an epidemic: the likelihood of further spreading of the disease versus the role in combatting that same disease. Policies that prevent infectious diseases from spreading are in place, but knowledge of their effectiveness and impact on the passenger logistics is limited.

The worldwide spread of infectious diseases is shaped by the structure of the airline network. The nodes in this network, the airports, are important in the prevention of infectious spreading. Research regarding screening procedures at airports has shown varying effectiveness, and there are logistical implications for the airports that can harm the network. This research focuses on the connection between the different levels: the airport operations, the distribution of passengers over the airline network and the resulting effects on the spread of the disease. The research question that is the topic of this research is:

How can airports and airlines prevent the spread of an infectious disease through the passenger airline network while maintaining efficient operations?

This study aims to assist airports and airlines in taking effective measures preventing infectious spread through the regional air network, by focussing on the 2014-2015 Ebola outbreak in West Africa. This research connects policies and effects on the airport level with outcomes on the network, using Discrete Event Simulation to create airport models and test the functioning of screening measures under different scenarios.

Infectious disease screening measures include fever screening stations, questionnaires checking for risk factors and rapid tests that check for the actual presence of a disease. Each screening measure has a sensitivity and specificity in *detecting the disease characteristic it screens for*. In this context, sensitivity refers to the correct identification of a case (a true positive), specificity concerns the correct identification of the healthy (a true negative). This means that a fever screening station detects a certain fraction of the individuals exhibiting fever symptoms. However, fever is a common symptom of many diseases, resulting in a possibility of many false positives. A high duration of the incubation time or a low prevalence of fever among the infected can reduce the effectivity of fever screening majorly. Other screening measures, focusing on the actual presence of a virus in the body of a passenger, can be more effective in identifying the carriers of a certain disease. Flight cancellations are a special kind of policy, since they do not screen for any Ebola characteristic, but instead deny every passenger to fly. Hereby this policy has optimal sensitivity but no specificity: all Ebola cases are prevented travelling, just as everyone else.

Screening measures can reduce the spread of infectious diseases, but are unlikely to prevent the spreading entirely. All screening measures show a trade-off between sensitivity and specificity of the disease, resulting in either a high number of infected arrivals, or of false positives. The efficiency of a set of screening measures at an airport can be estimated by determining the amount of false positives for each prevented infected arrival. The policies resulting in the least infected arrivals, also result in

the most false positives per prevented case. In practice, it is difficult to calculate this number because of the uncertainties during infectious spreading.

To successfully deploy screening measures, a focus on the specificity is expected to be more important than the sensitivity of the measure. The specificity determines if a policy is a viable option, with the impact it has on the number of false positives and on the airport logistics. If the specificity is low and secondary screening is required to prevent an excessive number of false positives, the number of prevented infected arrivals will be reduced as well. The rarer the disease, the more important a high specificity is.

Fever screening measures should be deployed taking into account the incubation time of the disease, the prevalence of fever among symptomatic individuals and the overall prevalence of fever in the country. Furthermore, the availability of (staff) resources restricts the deployment of screening measures. When few resources are available, less accurate policies with smaller resource requirements may be deployed, preventing excessive queueing times at the airport and passengers missing their flight. However, this can lead to more infected arrivals.

Screening measures not focussing on common disease characteristics like fever, but rather the actual presence of the virus can reduce the number of false positives. For this measure to be successful, it needs to be effective also for non-symptomatic individuals, early in the course of the disease. Resulting from the time required before the test provides an outcome, waiting times at the airport increase. Furthermore, this screening method is relatively intrusive if it requires a body swab or blood test to perform the screening.

Disease screening at the airport of origin is the most efficient and effective method of screening. Additional screening at hub airports can reduce the spread of the disease slightly. Air cancellations reduce the number of infected arrivals approximately proportional to the number of flights, but do not prevent the disease from spreading and have negative impacts on the affected countries. Likely explanation of the relatively limited spread of infectious diseases over the airline system is that ill people simply do not attempt to fly, whether that is because of their illness, because these diseases often affect the lower income population, or because the deployment of screening measures prevent passengers from attempting to travel.

Contents

Simio simulation model and analyses: https://github.com/sleussink/thesis

1. Problem introduction

Recent outbreaks show the major global impacts of infectious diseases. Examples of epidemics with disruptive global impacts include SARS (Severe Acute Respiratory Syndrome) and Ebola virus disease. 8.000 people were infected by SARS in 2003, resulting in almost 800 deaths, mostly in China (World Health Organization, 2003). In 2014, Ebola spread throughout and outside of West Africa, causing over 10.000 deaths, followed by outbreaks in later years (World Health Organization, 2018b). Infectious diseases are responsible for about one quarter of all deaths worldwide (Fenollar & Mediannikov, 2018). It is likely that new epidemics on the scale of SARS or Ebola will emerge, according to Sylvie Briand, director of infectious hazards management at the World Health Organization (WHO) (Keegan, 2018). Although the total death toll has decreased as a result of medical advancements and increased awareness, the number of outbreaks of infectious diseases has increased steadily since the 1980s (Basir, Ray, & Venturino, 2018). Trends that support the rise of infectious diseases include increased resistance to antibiotics and an increased population density – largely in rapidly growing cities in low and medium income countries (Li, Richmond, & Roehner, 2018; Schneider, Mihaljev, Havlin, & Herrmann, 2011).

International human mobility has increased dramatically over the last decades, which means diseases can spread to the other side of the world within 24 hours, and are more and more likely to do so (Lawyer, 2016). About four billion passengers boarded scheduled flights in 2017, of which two thirds took an international flight (Statista, 2019b). Passenger numbers are expected to increase with about eight per cent per year for the coming 20 years (Statista, 2019a). As a result the airline system can play a major and increasing role in the spreading of a disease (Findlater & Bogoch, 2018).

At the same time, an airport is a main hub for humanitarian relief operations and a coordination centre for humanitarians (Kovács & Spens, 2007; Zhang, Tian, Fung, & Dang, 2018). This holds true especially in areas where needed expertise, medical staff and supplies are lacking, as is the case in for instance West Africa with the spread of Ebola (Shoman, Karafillakis, & Rawaf, 2017). For countries with poor land-based infrastructure, the airline system is a crucial – or even the only – means of transportation. This means, during an epidemic in particular, maintaining air connectivity is of high priority for developing countries.

The above illustrates the trade-off for passenger airline operations during the spread of an infectious disease: the likelihood of further spreading the disease, versus the important role in combatting the same disease.

Induced by the fear for a disease, passengers cancel trips and airlines shut down operations. The Asia-Pacific region experienced a fifty per cent drop in passenger numbers during the 2003 SARS epidemic, and only twenty per cent of flights from some airports were operated during the 2014-2015 Ebola epidemic (International Air Transport Association, 2003; OAG, 2015). Although the WHO and the IATA advise airlines to maintain flight operations during infectious spreading, the majority of airlines cancelled flights during the Ebola epidemic and countries became hard to reach for humanitarian aid workers and other travellers (International Air Transport Association, 2014; Turner, 2018).

This research focuses on strategies by airports and airlines to maintain the connectedness of regions affected by epidemics, while preventing the spread of the disease over the network. This is done with a focus on the feasibility of deploying these measures at the operational airport level.

Societal relevance

The emergence of an infectious disease is highly disruptive, causing death, social unrest and economic downturn. The number of epidemics is growing and a pandemic of Ebola, Influenza or another disease will most likely happen again. Past epidemics have harmed the affected countries terribly. This is worsened by large-scale flight disruptions, isolating regions. The societal relevance of this research lies in the aim to make the airline system and society better prepared for new outbreaks of infectious diseases.

Scientific relevance

Research has been done on the role that the airline system plays in the spread of infectious diseases on a global level, focusing on airports as the nodes in the network. Other research concerns the effectiveness of disease screening at individual airports. This research focuses on the connection between the two: the relation between measures on the airport level and the epidemic spread on the network. The main contribution to the scientific relevance of this work lies in this multiscale approach and the policy recommendations for airports and airlines that can be derived from this research.

Study program relevance

This research is suitable as a graduation project for the master program Engineering and Policy Analysis as the spreading of infectious diseases in developing countries can be seen as an international grand challenge (Kamen, 2016). The problem can be connected to the UN sustainable development goals of *Good Health and Well-Being* and *Economic Growth* (United Nations, n.d.). The analytical approach of this research focuses on the modelling of airline logistics and infectious disease spread, and hereby allows for the usage of typical EPA (modelling) methods. By informing policy makers and airport governing bodies on policies to take, the work has a practical application.

Structure of report

Chapter 2 contains the background information and literature review regarding the research topic. In Chapter 3 the research approach and method is described. Chapter 4 elaborates on the model indicators, which will be used to measure the model's performance. The policies that will form the model input are the topic of Chapter 5. When this is defined, the airport model as described in Chapter 6 can be specified. The airport models are aggregated to the system level, which is the topic of Chapter 7. The subsequent step within the research process is the software implementation. This is not part of the main report, but the Simio model can instead be found on GitHub via the link provided[1]. The verification and validation of the model is described in Chapter 8. Chapter 9 contains the experimental plan that is used to explore the behaviour of the model, of which the results are shown in Chapter 10. This leads to the discussion as described in Chapter 11, followed by the conclusion of Chapter 12. The report structure is visualised in Figure 1-1.

[1] https://github.com/sleussink/thesis

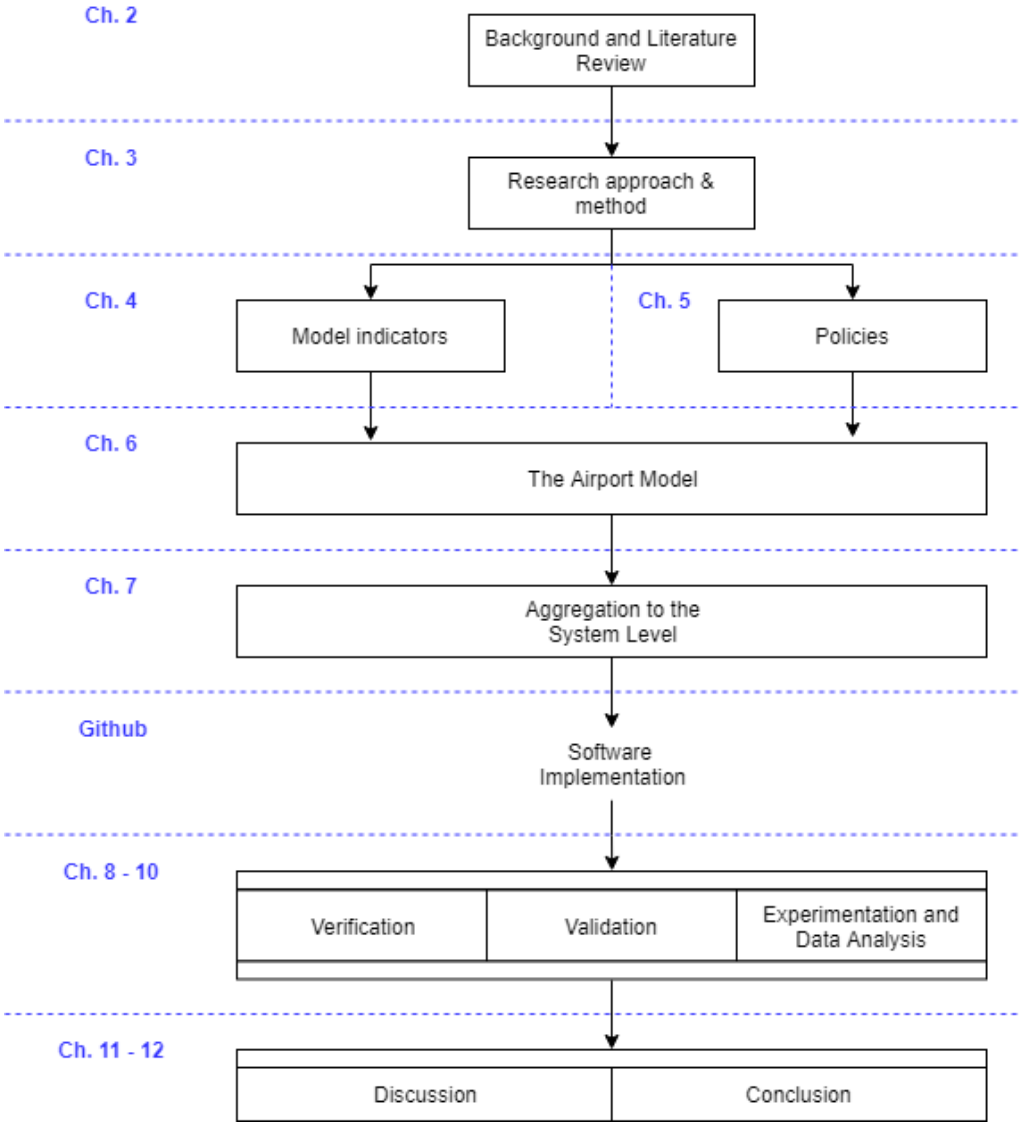


Figure 1-1 Structure of report

2. Background and Literature Review

This section summarizes and combines relevant literature, which forms the basis for the research. Section 2.1 focusses on infectious spreading. Airport models are described in section 2.2. This is followed by section 2.3, which focuses on airports during epidemics. The aforementioned is summarized in section 2.4 and leads to the formulation of the knowledge gap in section 2.5.

2.1. Infectious spreading over networks

The way a disease spreads depends on the contagiousness of the disease and on the characteristics of the contact network, e.g. the number of people each individual gets in touch with. The basic epidemic model is called the SIR model: network nodes are either *Susceptible, Infectious* or *Removed* (diseased) (Colizza & Vespignani, 2007). This model can be extended to include recovered individuals or different states of the disease, where for instance contagion probabilities differ (Easley & Kleinberg, 2010). Research in the field of epidemic spread will only increase in relevance because the level of human mobility will continue to rise and hereby lead to a strong increase in both the frequency that diseases reach the status of an epidemic, and the geographical reach of these epidemics (Findlater & Bogoch, 2018). Research has been done on the role that airline networks play in the spread of infectious diseases, and the role of the nodes in these networks: the airports. By analysing the structure of the worldwide airline network, detailed outbreak scenarios of infectious diseases can be forecasted (Colizza, Barrat, Barthelemy, & Vespignani, 2006). Based on the airport's level of connection with other nodes in the network as well as the size of the airport, the expected force of infection within airports can be calculated. This describes the risk of infectious disease spreading through the network (Lawyer, 2016).

Other research focuses on the development of an immunization approach, targeting the links of the network, the flown routes, to reduce the spreading of a disease (Schneider et al., 2011). The disruption of flights from the affected area can prevent or delay the diffusion of the disease. However, flight cancellations result in difficulties for humanitarian aid workers to reach the area and therefore, isolates the region. This reinforces the destruction of the countries' economies (International Air Transport Association, 2014). It restricts people's movements, or forces them to find alternative means of transportation, e.g. by charter plane or over land. In particular movement by bus or own transportation is, in general, less regulated and may increase the chance of undocumented diffusion of the disease (Wilson, 1995). Furthermore, pandemics have more consequences than solely health effects. The Ebola outbreak had devastating socio-economic impacts on the affected countries: 2.2 billion USD in GDP was estimated to be lost in Guinea, Liberia and Sierra Leone, whereas the global costs of SARS is valued at around forty billion USD (Centre for Disease Control and Prevention, 2014; Lee & McKibbin, 2004). Even countries where a disease has not been present can encounter major economic downturn because of reduced export and induced fear for visiting the countries (Novelli, Gussing Burgess, Jones, & Ritchie, 2018; Turner, 2018).

2.2. Airport models

The logistics of airports, the nodes of airline networks, are the main focus for modellers focussing on the reliability of airport operations and the efficiency of passenger handling. (Alodhaibi, Burdett, & Yarlagadda, 2017; Rodríguez-Sanz et al., 2018). Agent Based Modelling and Discrete Event Simulation are methods that are used for this. Discrete Event Simulation allows for the modelling of processes involving concrete logistical processes and waiting times, and is therefore highly suitable for the

specification of processes involving queues and flows of people in physical environments, such as airports (Alodhaibi et al., 2017; Zeigler, Muzy, & Kofman, 2019). Agent Based Modelling takes the smallest factor in the system, the agent, as the starting point, and can be used for logistical models as well (Badham et al., 2018).

Airport models are built to simulate airport logistics, since smooth airport operations are of high importance for a well-functioning airline network, and airport delays a main cause of traveller's discomfort (Granberg & Munoz, 2013; Rodríguez-Sanz et al., 2018). One research describes key performance indicators (KPI's) in six focus areas: Airport Operations, Airport Economy, Airport Environmental Issues, Airport Safety and Security, and Airport Customer Service (Granberg & Munoz, 2013). These areas are defined by concrete, measurable KPI's, for instance *Check-in waiting and processing times* and *Staff costs per passenger*. Other research focusses on a list of factors: Check-in, Security, Convenience, Ambiance, Basic facilities and Mobility, where waiting time is also an important characteristic (Bezerra & Gomes, 2016).

When a disaster strikes, airports function as hubs for humanitarian logistics and as initial disaster relief coordination centres. In case of evacuation the airport is prone to significant outgoing movements as well, hereby making them crucial nodes in the humanitarian network (Smith, 2008). Research focusing on the resilience of airports mainly concentrates on natural sudden-onset disasters: airports having to cope with the consequences of i.e. hurricanes, floods or earthquakes (Van Wassenhove, 2006). Such events often result in a decrease of the capacity of the airport due to damaging of facilities and an increase in air traffic for disaster relief (Kovács & Spens, 2007; Whitning, 2010). Airport models have been constructed focusing on how to improve airport services to make the airport more resilient after sudden onset disasters (Feil, 2018).

2.3. Airports during epidemics

The focus area of this research is the role of airports during a disaster in particular: epidemics. The global spread of this slow-onset disaster is rooted in the way individual airports handle the flow of passengers, as research on the H1N1 pandemic proves (Van Wassenhove, 2006; Warren, Bell, & Budd, 2010). Concretely this concerns the prevention of infected passengers departing from an airport, or arriving in the country of departure, using various screening techniques (World Health Organization, 2014). These techniques include screening travellers for disease symptoms, like fever, or focusing on disease risk factors, like contact with infected individuals. Screening can be conducted at the airport of departure in the affected region, at the arrival airport, or at a transfer airport (Gold et al., 2019).

Research has been done regarding the performance of airport screening. Most research exclusively focuses on the number of passenger arrivals, the prevalence of fever and the sensitivity and specificity of fever screening measures, to make predictions on correct case detection. In this context, sensitivity refers to the correct identification of the infected (also: true positive rate), specificity concerns the correct identification of the healthy (true negative rate) (Brenner & Gefeller, 1997). Entry screening for SARS at Canadian airports is considered ineffective, with a positive predicted value (precision) of zero, with major financial investments required (St John et al., 2005). On the contrary, fever screening to detect Dengue at Taiwanese airports has been regarded effective, as it successfully identified 40 infected Dengue cases (Shu et al., 2005). Important to highlight here is that the paper by Shu et al. focuses on the absolute number of true positives, not on the sensitivity of the measure (true positive *rate*). Furthermore, the paper does not make claims regarding the missed cases (false negatives), since

making an estimation of that number is said to be 'difficult'. Other research focuses on influenza screening, identifying a sensitivity of screening of only 5.8 per cent (Hale, Hoskins, & Baker, 2012).

Research that goes a step further includes multiple screenings, logistical processes and/or other screening measures in the model. These papers are described in more detail in the remainder of this section.

Researchers focusing on screening for SARS at airports state that the "poor scientific evidence" on the efficacy should not be ignored. However, they do highlight the positive reassuring effect of screening measures on the general public, as authorities can demonstrate their vigour and alertness (Bitar, Goubar, & Desenclos, 2009). This research compared the sensitivity and specificity of fever screening by non-contact infrared thermometers, which is a common tool for airport fever screening as it circumvents the need for physical contact, and hereby lowers the chance of disease transmission.

The estimated effectiveness of fever screening for Ebola at airports is the focus of other research. Exit screening is proven to be the most effective policy, possibly supplemented with entry screening depending on the duration of the flight (Read, Diggle, Chirombo, Solomon, & Baylis, 2015). However, exit screening is expected to only detect 35,6% of infected passengers. During the Ebola epidemic, effectiveness of the measures has proved to be low. Of the 77 outbound travellers that have been detained following exit screening procedures in West Africa from August till September 2014, none turned out to be infected with Ebola, while a large part of the detained individuals were diagnosed with malaria (Gostic, Kucharski, & Lloyd-Smith, 2015). Even in the most optimistic scenario, arrival screening will miss the majority of cases. At the same time, four travellers not detected by exit or entry screening have been diagnosed with Ebola in the US and Europe.

A simulation on the efficacy of influenza screening uses discrete event simulation to model the arrival of passengers at San Francisco Airport (Brigantic et al., 2009). This research sees potential in both exit and entry screening, although the need for identification of asymptomatic passengers is highlighted. These passengers carry the disease, but do not yet show symptoms, like fever. Screening for disease risk factors can be a solution to this, but is not included in this research. Screening measures require significant resources and can result in delays, although these effects are only incorporated for entry screening in San Francisco, not for exit screening in the affected region.

Recently researchers constructed a discrete event simulation model of screening procedures in African, European and American airports for the detection of Ebola (Gold et al., 2019). Scenarios include no screening, exit screening, entry screening and transfer screening. Exit screening was capable of detecting 83.4 per cent of travellers who were sick with Ebola. Additional entry and transfer screenings offered little benefit. The model used in this research was highly aggregated, consisting of three network nodes: Africa, Europe and USA. Hereby this research did not focus on the actual network, the different airports or the logistics at those airports. Furthermore, the difficulty of identifying asymptotic, but ill travellers is disregarded.

2.4. Summary

The worldwide spread of infectious diseases is shaped by the structure of the airline network. The nodes in this network, the airports, are important in the prevention of infectious spreading. Research regarding screening procedures at airports has shown varying effectiveness, and there are logistical

implications for the airports that can harm the network. Three kinds of models relevant to this research can be identified:

1. Disease spreading over the airline network
2. Airport screening measures
3. Airport performance indicators

Part of the literature highlighted above mentions concrete criteria on which the performance of the system is measured. This literature and their criteria are listed in Table 2-1. This illustrates the focus of airline network models on the higher-level disease spreading, whereas airport screening measures mostly focus on sensitivity and specificity – or true and false positives or negatives, which describe the same principle. Some research focusses on airport factors during infectious spreading, as passenger time in system and financial investment. These airport characteristics are further elaborated on in research regarding airports in non-disaster situations.

Table 2-1 Criteria used in research infectious spreading

Source	Focus	Criteria
(Colizza et al., 2006)	Disease spreading over the airline network	Airports receiving infected passengers
(Lawyer, 2016)	Influenza spreading over the airline network	Time until disease becomes pandemic
(Schneider et al., 2011)	Disease spreading over the airline network	Average infection probability
(St John et al., 2005)	SARS airport screening measures	True positives; Financial investment
(Shu et al., 2005)	Dengue airport screening measures	True positives
(Hale et al., 2012)	Influenza airport screening measures	Sensitivity
(Read et al., 2015)	Ebola airport screening measures	Detected infected passengers
(Gostic et al., 2015)	Influenza, SARS, MERS & Ebola airport screening measures	Detected infected passengers
(Gold et al., 2019)	Ebola airport screening measures	Correct detection; Missed detection; False alarm rate
(Bitar et al., 2009)	SARS airport screening measures	Sensitivity; Specificity
(Brigantic et al., 2009)	Influenza airport screening measures	False negatives; False positives; True positives; Passenger time in system
(Granberg & Munoz, 2013)	Airport performance indicators	Multiple, including: Total traffic in terms of aircraft movements; Staff costs per passenger; Check-in waiting and processing times; Security control waiting and processing times; Amount and duration of delays
(Bezerra & Gomes, 2016)	Airport performance indicators	Multiple, including: Waiting time; Process efficiency;

2.5. Research gap

Existing models that attempt to estimate the effectivity of airport screening measures for Ebola and other diseases, lack in adequate modelling of the disease characteristics over time. An example is the impact of the incubation period, which significantly lowers the effectivity of fever detection, but is not taken into account in previous research. Furthermore, research so far does not focus on the functioning of airports within the airline system during the spreading of a pandemic. Literature shows examples of airport logistical models, or high-level network models. However, the connection between these levels is crucial. Measures on the airport level can cause logistical challenges for the airport, but allow for continued operations on the network level. This hereby maintains international connectedness for the affected countries and prevents the disease from spreading as well as further economic decline within the area. By modelling scenarios where adequate airport measures prevent the large-scale cancellation of flights, policy makers are better prepared for future outbreaks. This research focuses on the connection between the different levels: the airport operations, the distribution of passengers over the airline network and the resulting effects on the spread of the disease. This is visualized in Figure 2-1.

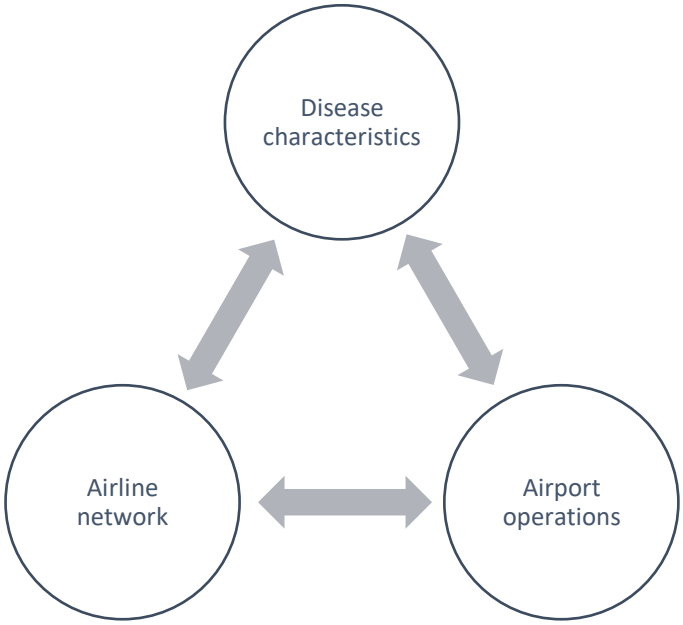


Figure 2-1 Research levels of interest

3. Research approach & method

Section 3.1 elaborates on the research method that will be used in order to answer the research question. In section 3.2, the sub questions are introduced. This is followed by section 3.3, which covers the methodological framework that guides the research process.

The knowledge gap as identified earlier leads to the formulation of the main research question. This question is the basis on which the sub questions are built, forming the starting point of the report structure. The main research question is the following:

How can airports and airlines prevent the spread of an infectious disease through the passenger airline network while maintaining efficient operations?

3.1. Research method

The research question will be answered by making a **simulation model for a case study**.

The **modelling approach** allows for the implementation of a wide range of relations to describe the system's behaviour over time and the implementation of policies under different scenarios. The internal logistics of airports in the region will be modelled, focusing on policies preventing pandemic spread. The distribution of the healthy and infected passengers between the airports will form the network connecting the airports. This approach can provide accurate quantitative outcomes over different policy options and therefore can be used to explore different scenarios.

Point of attention for a modelling method is the accuracy of the model outcomes is only as high as the quality of data that is put into the system. When data collection is done inadequately or data is simply not available, the model will generate less accurate results. However, considering the novelty of modelling the connection between these layers in the system, the model could still prove useful on a more conceptual level when accurate data of the affected countries is not available.

Defining the general objectives of the model beforehand assists the modeller in making decisions regarding the scope and scale of the model. General objectives are the requirements of the model as a tool (Furian, O'Sullivan, Walker, Vössner, & Neubacher, 2015). Requirements for this model include:

- limited run-time, allowing for multiple replications over different scenarios
- clear visualization for communication purposes
- preferably: possible re-usability for other outbreaks

The **case study approach** gives practical relevance to the research and makes specific data gathering possible. Point of attention is the possible difficulty of data gathering, as the airports in countries affected by infectious diseases generally have less data available than airports in more developed countries. A disadvantage of a case study can be the limited generalizability of the conclusions to other cases (e.g. other diseases or regions) (Yin, 2003).

Requirements for a topic of the case study assisting in answering the research question are:

- an infectious disease, spreading through a region connected by a passenger airline network
- a disease with a sufficiently long incubation period, resulting in potentially undetected spreading over the network
- a non-hyper-contagious disease, making detection policies at airports potentially effective

The 2014-2015 West African Ebola outbreak is chosen as the case study for this research. The epidemic resulted in a large number of casualties, but also in economic downturn and social unrest. Although the WHO and the IATA advised airlines to maintain flight operations, the majority of airlines cancelled flights and countries became hard to reach for humanitarian aid workers and trade (International Air Transport Association, 2014; Turner, 2018). With over 10,000 deaths, this outbreak resulted in more victims than all of the previous outbreaks combined (Gross, 2018). The likelihood of recurrence is illustrated by the current outbreak of Ebola in Congo which is the second biggest in history, with over 2000 known cases as of June 2019 (World Health Organization, 2019b). In July 2019, the WHO declared this outbreak a "Public Health Emergency of International Concern" (World Health Organization, 2019a).

Timeframe

The 2014-2015 Ebola outbreak was declared a Public Health Emergency of International Concern by the WHO from the 8th of August 2014 until the 29th of March 2016 (Centers for Disease Control and Prevention, 2016). This research will cover the period of time that saw the most rapid increase in (suspected) Ebola cases during this period, which is September 2014 – February 2015 (Center for Disease Control and Prevention, 2016). This means the research will cover varying levels of spread of the disease, including the most critical period of the epidemic. It also covers a timeframe long enough to make well founded claims about the behaviour of the model. To assist in one of the aims of this research, better preparedness for future outbreaks of infectious diseases, scenarios covering possible future outbreaks of Ebola will be explored as well. This includes for instance an outbreak in the scale of the 2014-2015 epidemic, with the current flight operations.

Geographical reach

A regional network of the main airports in Guinea, Sierra Leone and Liberia will be constructed. These are the countries that have been hit hardest during the Ebola outbreak of 2014-2015 and suffered from isolation because of large-scale abruptions of flight operations (International Air Transport Association, 2014; World Health Organization, 2018a). Furthermore, two larger hub airports in the region will be included in the model. These airports are used for transferring passengers from the affected area and allow for modelling the effects of screening procedures on bigger airports. However, globally they are still of modest size, in order to aid the modelling process. The research will focus on passenger flight operations connecting these airports and connecting this region with airports around the world, directly and via the hubs. An overview of the region and the airports of interest can be found in Table 3-1.

Table 3-1 Airports of interest in West Africa

Airport	Code	City	Country	Weekly passengers 2019[2]
Roberts Int'l Airport	ROB	Monrovia	Liberia	6,000
Freetown Lungi Int'l Airport	FNA	Freetown	Sierra Leone	7,000
Conakry Int'l Airport	CKY	Conakry	Guinea	12,000
Blaise Diagne Int'l Airport	DSS	Dakar	Senegal	40,000
Kotoka Int'l Airport	ACC	Accra	Ghana	46,000

[2] Estimation based on 2019 FlightAware arrival & departure data using average African airlines' load factors (FlightAware, 2019; International Air Transport Association, 2018)

3.2. Sub questions

This section elaborates on the sub questions that are formulated in order to answer the main research question, including the methods that are used to answer the different sub questions.

1. *How to evaluate the effects of airport and airline policies aimed at the prevention of infectious spreading?*

Before the modelling phase can commence, it is necessary to understand which outputs are expected of the model. These outputs together determine the successfulness of different policies and are called the Key Performance Indicators. Although the main policy objective of the research is to prevent the spreading of Ebola infected individuals through the system, this is not the only indicator; otherwise the cancellation of all flights would be an optimal outcome. As highlighted in the literature review, the isolation of countries during infectious spreading as a result of the cancellation of flights, has a highly disruptive effect on the country (International Air Transport Association, 2014). This means indicators will relate to the reduction of infectious spreading, as well as to continuous flight operations and logistical consequences of policies on the airport level.

This research question will be answered by conducting desk research. Literature focused on infectious spreading, airport throughput indicators and the impact of connectedness of countries during disasters will be consulted.

2. *What are policies that airports and airlines take to prevent the transit of infected individuals, and what is their effectivity?*

The second sub question focusses on the measures that airlines and airports take to track disease spreading by airline passengers. Measures by airlines include the reduction or abruption of flight operations, preventing the spread of the disease but also hindering individuals' mobility (International Air Transport Association, 2014; Read et al., 2015). On the airport level, measures include fever screening, and checking for Ebola risk factors. What is required is insight in the characteristics of these measures. This will result in an overview of which a mock-up is shown in Table 3-2. This is an essential step for the modelling of the airport logistical processes in the later phase of research.

Table 3-2 Mock-up of airport screening measures

Measure	**Sensitivity**	**Specificity**	**Processing time**	**Capacity**	**Staff**
Non-Contact Infrared Thermal Camera	xx-xx %	xx-xx %	xx-xx seconds	xx	x
Non-Contact Infrared Thermometer	xx-xx %	xx-xx %	xx-xx seconds	xx	x
Questionnaires	xx-xx %	xx-xx %	xx-xx seconds	xx	x
Etc					

Consulting humanitarian experts and conducting desk research will help to answer this research question. Since information from the staff responsible for the airport screenings in West Africa might be hard to come by, interviews will be done with experts involved with the entry screening at Brussels Airport. This information will be supplemented by experiences of humanitarians who were active in the Ebola struck region during the epidemic to adequately reflect the conditions at the airports in the

region. A challenge regarding this sub-question is the fact that accurate information on the effectiveness of screening can be lacking, and exact effects of these measures on the airport logistics can be unknown. This can be covered by conducting experiments covering the range of uncertainty.

3. *How can passenger flow logistics at airports with regards to infectious spreading be formalized and modelled using Discrete Event Simulation?*

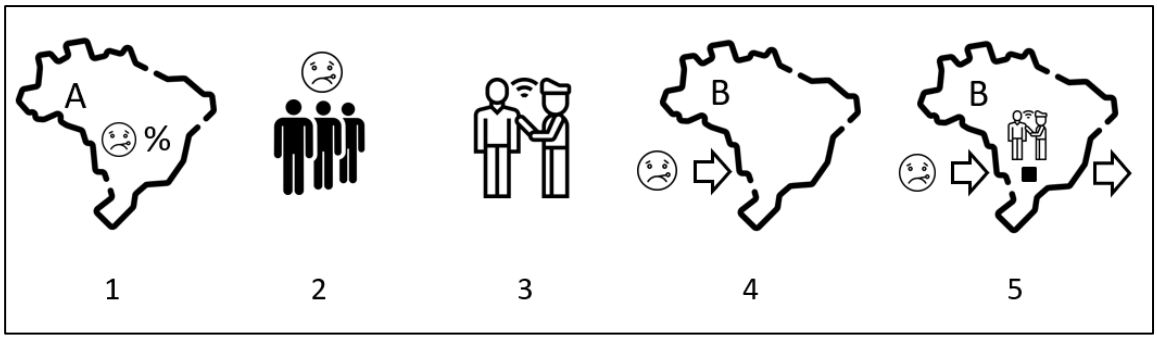
This question concerns the procedures on the airport level. Both the regular airport operations (e.g. security, customs) and the Ebola screening measures are included in the models of the five airports as specified before. Healthy and infected passengers will transfer through the airport models. The measures as defined in research question 2 will be implemented as policies to be turned on and off in the model, to test these policy measures in the experiments later. One generic airport model will be made, with different capacities for passenger handling and screening to account for the differences in airports' sizes. This is done because the layouts of specific airports are not known. Furthermore, the use of a generalized model airport eases the modelling process.

The airport models will be made using Discrete Event Modelling. This is a common method for the simulation of logistical processes, and logistical airport models in particular (Alodhaibi et al., 2017; Zeigler et al., 2019). An alternative suitable modelling method is Agent Based Modelling, often used to model the transmission of diseases (Badham et al., 2018). However, because of the long incubation period and relatively low contagiousness of Ebola, the assumption is made that there is no disease transmission during stay at the airport and the flight (Gostic et al., 2015). This assumption is supported by health authorities (Centre for Disease Control and Prevention, 2015). From a modelling perspective this means every individual in the model has a health status, which will not change throughout the model run. This allows for a modelling method to dominantly focus on logistical processes, rather than a focus on the individual agent. Therefore Discrete Event Simulation is chosen as method. Modelling will be done in Simio, which is designated Discrete Event Modelling software (Schriber & Brunner, 2001).

4. *How do airports interact with the system during infectious spreading?*

The focuses of the fourth question are the passengers arriving at the airport and their movements over the airline network. Based on the prevalence of Ebola within the different countries, passengers will have a health status assigned when they enter the airport. Basis of the network are the flight operations to and from the airports in Guinea, Sierra Leone and Liberia, supplemented with the hubs in Senegal and Ghana. The network model's function is to distribute the passengers over the airports within the model. The airports outside of countries of interest are not the main focus of the network, but will be nodes in the network that provide and receive passengers. Information regarding the current flight operations on the network will be retrieved from FlightAware, which contains up to date information regarding airlines' arrival and departure times (FlightAware, 2019). To model the 2014 situation with large scale flight cancellations, historical data from Openflights will be used, supplemented with news articles giving insight in airlines' cancellations (Openflights.org, 2014).

A generalized, simplified visualization of the successive steps in the model run is shown in Figure 3-1.



1. A fraction of the population in country A is infected with Ebola. The Ebola case count as reported by the WHO will be used to determine the prevalence of Ebola in the population (Center for Disease Control and Prevention, 2016).
2. Based on this fraction, a certain number of infected individuals will attempt to board a flight. Information regarding flight patterns is derived from FlightAware and OpenFlights (FlightAware, 2019; Openflights.org, 2014).
3. Measures on the airport will or will not detect an Ebola infected individual attempting to travel – covered in detail in sub question 3.
4. If passed screening procedures, the infected individual will arrive in country B. This is an outcome that could function as a KPI, which will be defined in sub question 1.
5. Another possibility is a passenger transferring at a hub airport in country B, where screening can take place as well, followed by a possible infected arrival in country C.

Figure 3-1 Basic steps in the model run

5. *How do policies for airports and airlines perform during an Ebola epidemic under different scenarios?*

Finally, the fifth research question aims to derive concrete conclusions for airports and airlines in epidemics. Multiple policies on the airport and airline level will be assessed, with their impact on both the airport logistics and the infectious spread. This will include the 'base case' where no measures are taken. The policies will be tested under various scenarios, and with difference disease screening characteristics. Validation of the outcomes will be done by comparing the results with experts' experiences. This sub question will result in concrete recommendations for the airports and airlines, contributing to answering the main research question.

3.3. Methodological framework

Now the research method is defined and the research questions are formulated, the methodological framework can be constructed. The framework which forms the basis of this research, consists of two frameworks, which are combined and adapted to optimally suit this research. These frameworks are:

1. Methodological framework for agent-based modelling (Nikolic & Ghorbani, 2011)
2. Hierarchical Control Conceptual Modelling framework (Furian et al., 2015)

Starting point of the methodological framework used in this research is a framework for developing agent-based models of socio-technical systems by Nikolic and Ghorbani. The general steps as described in this framework are common to software engineering methodologies, and can therefore be used as a basis for models of socio-technical systems, also for other modelling methods (Nikolic & Ghorbani, 2011). The five steps of the framework are shown in Figure 3-2.

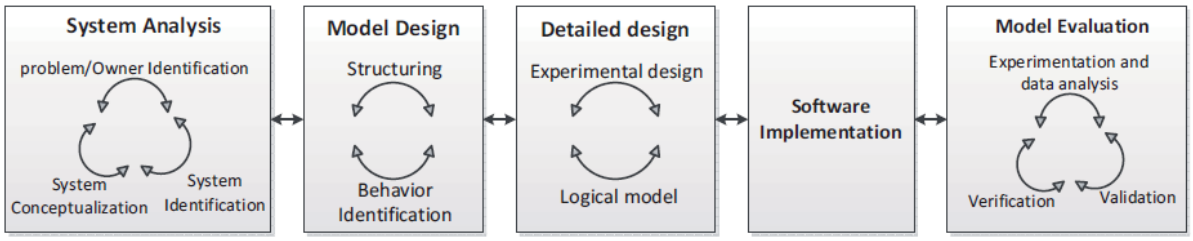


Figure 3-2 Methodological framework for agent-based modelling (Nikolic & Ghorbani, 2011)

First step of this framework is the system analysis. In this phase the problem, as well as the owner of the problem, is identified. Furthermore the system composition and boundaries are defined, to determine what is and what is not part of the area of interest. Specifying the conceptualisation of the system in a communicable way rounds off this phase. Second step is the model design phase, which further defines what will be modelled. Within this framework, specific focus is put on the agents and their behaviour, and a definition of the model environment. This is followed by the detailed design, in which the detailed model logic is specified, and a particular focus is put on the outputs: what is it we want to measure by conducting the experiments? Thereafter, the detailed design as specified before is implemented in software. When this is done, the model is being evaluated in three ways:

1. Verification: Does the model do what I want it to do?
2. Validation: Does the model mirror reality in an accurate way?
3. Experimentation and data analysis: Conduct experiments and interpret the outcomes.

Nikolic and Ghorbani discuss these steps in more detail, but the sub-steps for the first phases of the framework are applied specifically to the agent based modelling method, and therefore are less suitable for this research. Other frameworks exist for the conceptualization phase of a discrete event simulation model. The Hierarchical Control Conceptual Modelling (HCCM) framework is developed to describe the conceptualization of a discrete event model in detail (Furian et al., 2015). This framework is shown in Figure 3-3.

The initial phases of the framework of Figure 3-3 partially overlap with the first steps of Nikolic and Ghorbani's framework. Phase one concerns the understanding of the problem situation: what is the problem of interest? Phase two consists of the formulation of the modelling and general objectives. General objectives are defined as requirements on the simulation model as a tool, e.g. run-time,

development period and re-usability. Modelling objectives are related to the aims of the organisation: what are the desired outcomes of the system as simulated by the model? Phase three consists of the definition of input factors and output responses. Output responses are the indicators that are used to assess if the modelling objectives have been met. Input factors concerns the data that can change over different experiments, as well as policy levers that are used in experiments.

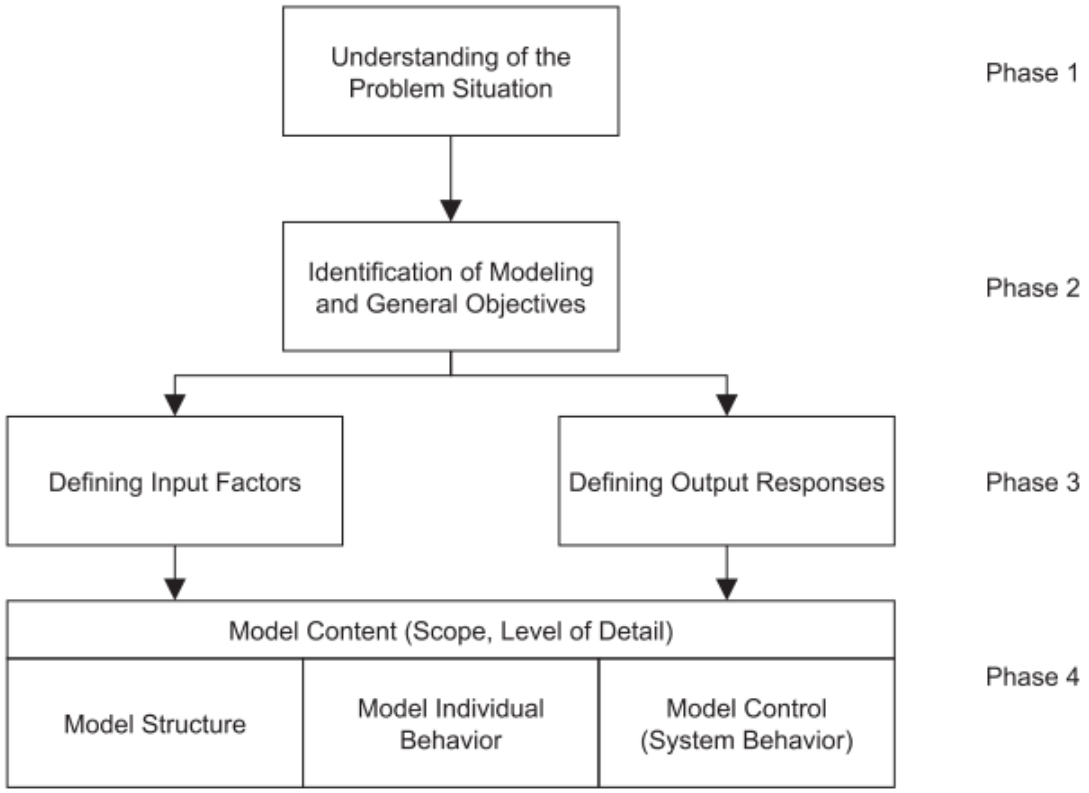


Figure 3-3 Structure of Hierarchical Control Conceptual Modelling framework (Furian et al., 2015)

Final phase of the framework by Furian et al. is the model content phase. In this phase the scope and level of detail of the model is defined. Firstly, the model structure is defined, which covers the entity structures included in the model. The core structural elements are covered in this phase, visualized by for instance a UML class diagram. Secondly the behavioural part of the model is covered. This concerns the flow of entities through the system and their interactions. Thirdly, the model control is described. This part covers the control units of the system of interest: how are decisions within the model made? This last step finalizes the conceptualization phase of the discrete event modelling cycle.

The framework to be used in this research is a combination of the aforementioned frameworks. The first three phases of the framework by Nikolic and Ghorbani are substituted for the discrete event specific steps of Furian et al.'s framework. This framework is used to describe the conceptualization of the airport models. This is followed by the aggregation of the airport models to the system level, where flight schedules and passenger flows are described. The next phases are the *Software Implementation* and *Model Evaluation* part of the framework by Nikolc and Ghorbani. Finally, a section *Discussion* and *Conclusion* is added to complete the framework. This results in the framework of which a graphical representation is shown in Figure 3-4. The report structure as shown in Chapter 1 is derived from this framework.

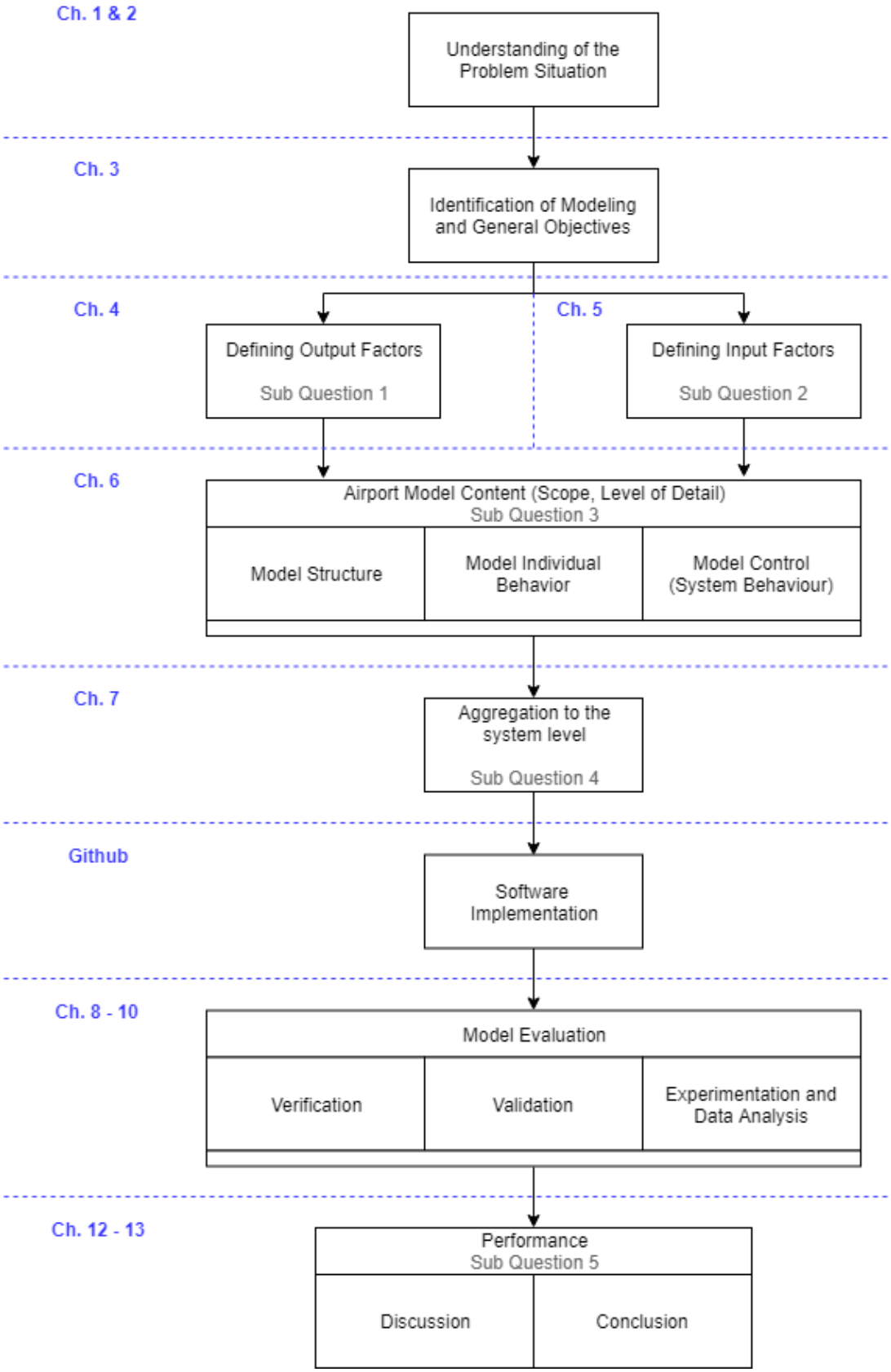


Figure 3-4 Methodological framework based on Nikolic & Ghorbani (2011) and Furian et al. (2015)

4. Model indicators

This chapter answers the first sub question: **How to evaluate the effects of airport and airline policies aimed at the prevention of infectious spreading?** Model indicators are the output factors as mentioned in the framework of Figure 3-4. Section 4.1 explains how the main research question touches upon three main areas of interest. Indicators will be formulated that specify the areas of interest and will be used as outcomes of the model in section 4.2. This is summarized in a table in section 4.3.

4.1. Focus areas

The main research question illustrates the trade-off between the prevention of an infectious disease spreading and the airport and airline operations:

How can airports and airlines prevent the spread of an infectious disease through the passenger airline network while maintaining efficient operations?

Within this research question, three relevant fields of interest can be defined:

Disease spreading	-	prevent the spread of an infectious disease
Connectedness	-	while *maintaining* efficient operations
Airport operations	-	while maintaining *efficient* operations

Disease spreading refers to (preventing) the spread of Ebola, key in the airport and airline measures. Connectedness refers to the importance of non-isolation of the affected area. Airport operations refer to the need for smooth airport logistics, also during the deployment of screening measures. The indicators that determine the performance of policy options will be related to these focus areas.

4.2. Indicators related to the focus areas

Based on airport sources related to infectious spreading and airport logistics, indicators are determined to assess the performance of the model. These indicators are derived from literature as described in Table 2-1. Each indicator relates to one focus area as defined above. These indicators are highlighted in this section, with their characteristics summarized in Table 4-1 to 4-6.

Indicator 1: Infected arrivals

The aim of all disease screening measures is to prevent or minimize the number of infected passengers that depart from the affected area and arrive at another airport undetected. They are identified as a threat to the country of arrival as they can cause further spreading of the disease.

Table 4-1 Indicator infected arrivals

Infected arrivals	**The number of infected (undetected) passenger arrivals**
Unit of measurement	Total cases
Aim to	Minimize the value of this indicator
Covers aspects from Table 2-1:	Airports receiving infected passengers; Time until disease becomes pandemic; Average infection probability; True positives; Sensitivity; Detected infected passengers; Missed detection; False negatives
Relates to focus area:	Disease spreading

Indicator 2: False positives

A false positive result means a healthy traveller is wrongly suspected of carrying Ebola. This outcome prevents a passenger to travel to their destination. Furthermore, a false positive result in disease screening can lead to a healthy individual being detained with actual Ebola cases, which carries a chance of Ebola transmission (Nouvellet et al., 2015).

Table 4-2 Indicator false positives

False positives	**The number of non-Ebola, detained passengers**
Unit of measurement	Total cases
Aim to	Minimize the value of this indicator
Covers aspects from Table 2-1:	False alarm rate; Specificity; False positives
Relates to focus area:	Connectedness

Indicator 3: Flights operated

This indicator relates to the network function of airports and the importance of non-isolation of the affected areas. This is crucial for a country's economy and pandemic control by humanitarian aid workers (Shoman et al., 2017).

Table 4-3 Indicator flights operated

Flights operated	**The share of flights being operated**
Unit of measurement	Percentage of flights
Aim to	Maximize the value of this indicator
Covers aspects from Table 2-1:	Total traffic in terms of aircraft movements
Relates to focus area:	Connectedness

Indicator 4: People reach destination in time

Similar to the previous indicator; humanitarians and other passengers need to be able to reach their destination on time (Shoman et al., 2017). Factors like flight cancellations or excessive queueing time at the airport can prevent passengers from reaching their destination (Granberg & Munoz, 2013).

Table 4-4 Indicator people reach destination in time

People reach destination in time	**The share of people wanting to travel that reach their destination on time**
Unit of measurement	Percentage of passengers
Aim to	Maximize the value of this indicator
Covers aspects from Table 2-1:	Amount and duration of delays
Relates to focus area:	Connectedness

Indicator 5: Time in queues

Airport screening measures can lead to long queueing times at airports, causing passengers' exasperation and the possibility of missing their flights (Brigantic et al., 2009; Granberg & Munoz, 2013).

Table 4-5 Indicator time in queues

Time in queues	**The average time spent in queues on airports**
Unit of measurement	Average minutes per passenger
Aim to	Minimize the value of this indicator
Covers aspects from Table 2-1:	Passenger time in system; Check-in waiting and processing times; Security control waiting and processing times; Waiting time
Relates to focus area:	Airport operations

Indicator 6: Airport resources

Airport screening measures can require significant airport resources, consisting mainly of staff deployed and screening facilities set up (Brigantic et al., 2009). Airport economic indicators include staff costs per passenger, due to a lack of data calculated as number of staff deployed (Granberg & Munoz, 2013).

Table 4-6 Indicator airport resources

Airport resources	**The required resources (personnel) at airports**
Unit of measurement	Screening staff deployed
Aim to	Minimize the value of this indicator
Covers aspects from Table 2-1:	Staff costs per passenger; Process efficiency; Financial investment
Relates to focus area:	Airport operations

4.3. Overview of indicators

An overview of the indicators as described in Section 4.2 is shown in Table 4-7. It shows which indicator relates to which focus area, the unit of this indicator, and the desire to minimize or maximize this indicator.

Table 4-7 Key performance indicators and their focus areas

	Disease spreading	**Connectedness**	**Airport operations**
Infected arrivals (Total cases, MIN)	X		
False positives (Total cases, MIN)		X	
Flights operated (Percentage of flights, MAX)		X	
People reach destination on time (Percentage of passengers, MAX)		X	
Time in queues (Average minutes per passenger, MIN)			X
Airport resources (Screening staff deployed, MIN)			X

5. Policies

This chapter answers sub question 2: **What are policies that airports and airlines take to prevent the transit of infected individuals, and what is their effectivity?** Policies are the input factors as mentioned in the framework of Figure 3-4. Section 5.1 describes the measures for airport exit screening as advised by the WHO. This is followed by section 5.2 on the potential of inbound screening. Section 5.3 introduces an innovative screening measure: the Ebola Rapid Diagnostic Test. In section 5.4, measures on the network level, the airline system, are described. The data from literature is combined in section 5.5 resulting in the overview of policies that answers the sub question.

5.1. Exit screening

Exit screening aims to identify individuals with possible disease symptoms before departure, restricting their travel. This section explains the following measures, as advised by the WHO (World Health Organization, 2014):

- Measurement of body temperature
- Visual observation
- Questionnaire
- Medical examinations

Measurement of body temperature is advised by the WHO during an epidemic, since fever is the main symptom of an Ebola infection with around 85% of the patients present with fever during the course of the disease (European Centre for Disease Prevention and Control, 2014; WHO Ebola Response Team, 2014). The following devices exist for fever screening, exhibiting a trade-off between capacity and accuracy:

1. A Non-Contact Infrared Thermal Camera (NCITC) screens passengers as they pass the range of the camera. Screening capacity is high but accuracy is low, with a fever detection rate which can be as low as only seventy per cent (European Centre for Disease Prevention and Control, 2014).
2. A Non-Contact Infrared Thermometer (NCIT) is a portable device that scans a traveller's forehead from a close distance. Capacity is lower but accuracy is higher than a thermal camera, with a sensitivity range of 80-99 per cent (Centre for Disease Control, 2014; Gold et al., 2019).
3. In-ear Infrared Thermometer measurement is a physical contact device. After each measurement, the in-ear probe needs to be replaced to prevent cross-contamination (Gold et al., 2019). Because of the need for physical contact, whilst not performing better than other screening options, this method has not been deployed for airport fever screening during the Ebola outbreak (Belgian head nurse Ebola, 2019). Therefore this measure is not included in experiments of this research.

Regardless which measurement method is chosen, fever measurement will result in a low sensitivity and specificity. Fever is a highly common symptom of diseases, and the main disease detected during Ebola screening in 2014 was malaria, which is significantly more prevalent than Ebola with over 200 million suspected cases in the African continent (Gostic et al., 2015; World Health Organization, 2019c). Contrarily, not all passengers infected with Ebola exhibit fever (yet) when passing fever-screening stations. The relatively long incubation period of 9.4 days increases the chance of undetected infectious passengers (Read et al., 2015). Furthermore, every measurement device has accuracy lower than 100 per cent, resulting in undetected fever symptoms. Because of fear of an interrupted trip,

passengers may conceal their fever by using antipyretic drugs or simply splashing water in their face, which can mislead non-contact measurement devices (European Centre for Disease Prevention and Control, 2014). The specificity can finally be deteriorated by the circumstances at the airports. Health care workers highlight difficulties during fever screening at Brussels Airport, where arriving passengers had to wait in line for screening in a cold jet bridge, lowering their body temperature. The opposite could happen at African airports in warm conditions, resulting in an increased number of false positives (Crisis management officer Belgian Ministry of Health, 2019; Belgian head nurse Ebola, 2019).

Visual observation by trained observers for signs of Ebola infection is another advised measure (World Health Organization, 2014). However, possible symptoms to observe include coughing and sneezing, which are highly unspecific and can easily be concealed (Gostic et al., 2015). No data is found on the performance of observers, and it is not included as a policy in previous research (Gold et al., 2019). Therefore this measure is considered outside the scope of this research.

Questionnaires are used to assess if individuals have been in an area where Ebola is widespread, if the passenger has been in close contact with symptomatic individuals or attended funerals, and to inquire about symptoms (Coördinatieteam Ebola, 2014). Hereby it is possible to identify asymptomatic carriers. However, it is unclear how honest people are regarding the subject. Research assumed that only a maximum of 25 per cent of (potentially) infected individuals fill in a questionnaire truthfully, partly induced by fear of travel restrictions. This number is based on studies on Influenza A/H1N1 screening, on a total of only thirty infected passengers assumed to be aware of their exposure risk (Gostic et al., 2015; Gunaratnam, Tobin, Seale, Marich, & McAnulty, 2014; Hale et al., 2012). This is the only known source of information regarding the honesty of reporting.

Medical examinations are conducted if one of the aforementioned aspects gives reason to suspect chance of an Ebola infection. This screening can take multiple hours and can result in the passenger being escorted to a quarantine station at a hospital (Gold et al., 2019). The medical examination takes place outside of the airport's terminal and will result in a passenger missing their flight. Therefore this measure is considered outside the scope of this research.

5.2. Inbound screening

It is possible to develop symptoms during flight, which could not have been detected during exit screening. That, in combination with the low success rate of exit screening, could be an argument to choose for inbound screening at arrival in airports outside of Africa. Seven undetected cases are expected to have travelled outside of the main affected area by passenger flight: four humanitarians to Europe and North America, and three travellers to other countries in Africa (Centers for Disease Control and Prevention, 2019). Inbound screening can include the measures as discussed in Section 5.1. However, research describes inbound disease screening as costly and disruptive, mostly worth considering when exit screening is unreliable or screening capacity at the airport of departure is inadequate (Airports Council International, 2009; Centers for Disease Control and Prevention, 2014). The chance of becoming febrile during a flight is very small, because of the long (9.4 days) incubation time of Ebola (Read et al., 2015). This means that for the 6,5 hour flight from Monrovia, Liberia to Brussels, Belgium, the chance of developing symptoms, when already being infected, is 2.88 per cent[3] (Brussels Airlines, 2019). The small added detection rate of Ebola by implementation of inbound

[3] 9.4 days times 24 hours = 225.6 hours incubation time. 6.5/225.6 = 0.0288

screening as concluded in research (Gold et al., 2019), can be explained by the identification of previously missed symptomatic individuals, and is thereby assumed to be just as effective as screening twice at the airport of departure (Gostic et al., 2015). Finally, transmitting Ebola during a flight is highly unlikely because of the intimate contact required for disease transmission (Centre for Disease Control and Prevention, 2015). Even if the disease were transferred in-flight, no symptoms would yet be present during inbound screening.

5.3. Ebola Rapid Diagnostic Test

During the 2014 Ebola epidemic, new technology was under development to detect for infections more rapidly (Fleck, 2015). Previously it took days or a week before laboratory tests determined if an individual was infected (Butler, 2018). New Rapid Diagnostic Tests (RDT's) have a high sensitivity and specificity, allow for mobile screening and are highly suitable for screening people in for instance airports (Dhillon, Srikrishna, & Kelly, 2018). Results are available as quickly as within 15 minutes after sampling, which would allow for implementation of these tests during airport throughput (World Health Organization, 2015).

Point of attention is the intrusive nature of the screening, as opposed to e.g. fever detection. As specified in the WHO International Health Regulations, a state party may require arriving or departing passengers to undertake "a non-invasive medical examination which is the least intrusive examination that would achieve the public health objective" (World Health Organization, 2005). This document qualifies the external collection of saliva samples to be non-invasive. This means that an RDT using saliva samples may be used to screen passengers, but an RDT using blood samples may not. As such, an RDT could be a suitable airport screening measure.

5.4.Measures at network level

The majority of airlines serving the Western African region responded to the worsening of the Ebola epidemic by the suspension of (the majority of) its flights to and from the region (Mark Anderson, 2014). A justification for this lies in the fact that a reduction of travellers out of the region reduces the chance that an infected passenger travels abroad and spreads the disease. Other reasons from the airline perspective are the reduction in passenger demand and staff's fear of operating on flights to and from the region (France24, 2014). Korean Air even cancelled its flights to Nairobi, even though Kenya is located on the other side of Africa and had not encountered any cases of Ebola (Al Jazeera, 2014). The only major airlines that maintained operations to the main affected areas are Brussels Airlines and Royal Air Maroc. As Brussels Airlines' vice president stated, "it is our humanitarian duty to operate there" (Ferrell & Agarwal, 2018).

Although 'closing off' the region might seem like a viable strategy to contain Ebola, research in disease containment strategies shows that the restriction of mobility is ineffective in countering a disease (Lima, De Domenico, Pejovic, & Musolesi, 2015). Traffic reductions would only delay, not mitigate the chance that the Ebola outbreak extends to other countries (Poletto et al., 2014). Furthermore, the isolation of the area results in negative secondary effects, for instance preventing humanitarian aid workers to access the region. Researchers even claim that "if not for Brussels Airlines and Royal Air Maroc's moral mandates and continued service, these bans could have turned Ebola into a worldwide pandemic" (Ferrell & Agarwal, 2018).

5.5. Aggregation and narrowing down of ranges

As described in this chapter so far, the disease screening measures detect different characteristics of the disease. An overview is shown in Table 5-1. This overview does not include in-ear measurements, visual observations and medical examinations, for reasons mentioned in Section 5.1.

Table 5-1 Screening measures detection factors

	Fever	**Ebola Risk Factors**	**Ebola Virus**
NCITC	X		
NCIT	X		
Questionnaire		X	
Rapid Diagnostic Test			X

Each policy has a sensitivity and specificity in detecting the Ebola characteristic it screens for. This means the values of sensitivity and specificity should be interpreted in relation to this characteristic. In other words:

- The effectivity of fever screenings (NCITC and NCIT) is measured as percentage of the passengers having fever.
- The effectivity of questionnaires is measured as percentage of the passengers with known exposure to Ebola risk factors. Within this research, it is assumed all the infected are aware of their exposure risk.
- The effectivity of RDT's is measured as percentage of the actual presence of the Ebola Virus.

Research regarding disease screening measures results in a wide range of values of sensitivity and specificity. A list of sources and the resulting values is shown in Appendix F, and can be aggregated to the ranges as shown in

Table 5-2. Flight cancellations can be expressed by a sensitivity and specificity as well: the sensitivity is 100 per cent (all Ebola cases on a flight are stopped), and sensitivity is zero per cent (all other passengers are denied travelling as well).

Table 5-2 Screening characteristics full ranges

Policy	**Sensitivity (%)**	**Specificity (%)**
NCITC	44.1 – 89.7	92 – 99.1
NCIT	29.4 – 99	75 – 99.6
Questionnaire	20 – 25	85 - 100
RDT	84 – 100	92 - 100
Flight cancellation	100	0

The information of the previous tables is narrowed down, resulting in the ranges to be used in the model as shown in Table 5-3. To obtain these ranges of sensitivity and specificity, the outliers that were included in the ranges of

Table 5-2 have been filtered out. Those valued are assumed to be exceptions and not included in further research.

Table 5-3 Screening ranges to be used in model

Policy	**Sensitivity (%)**	**Specificity (%)**
NCITC	70-90	92-99
NCIT	80-90	95-99
Questionnaire	20-25	85-99
RDT	84-100	92-100
Flight cancellation	100	0

6. The airport model

This chapter answers sub question 3: How can passenger flow logistics at airports with regards to infectious spreading be formalized and modelled using Discrete Event Simulation? This chapter describes the functioning and the structure of the airport model. Basis for this chapter is the Model Content phase from the HCCM framework, as shown in Figure 6-1 (Furian et al., 2015). This framework separates the model content in three parts: Model Structure (Section 6.1), Model Individual Behaviour (Section 6.2) and Model Control (Section 6.3). Furthermore, section 6.4 describes the elements that are out of scope of this research, and section 6.5 lists the main assumptions within the airport models, as well as the unknowns that are covered by experiments to be conducted later. The chapter exclusively focusses on the *Airport* model content; the aggregation to the airline network is covered in Chapter 7.

Airport Model Content		
par. 6.1 Model Structure *Which elements are included?*	**par. 6.2** Model Individual Behaviour *How do the entities behave?*	**par. 6.3** Model Control *How are the decision made?*

Figure 6-1 Contents Chapter 6

6.1. Model structure

The model structure represents the elements the model contains. This can be explained in different ways. Firstly a UML diagram is shown, which focuses on the entity structures. This is followed by more graphical visualisation, highlighting the airport layout. The successive areas of attention are regular airport operations and their characteristics, followed by the details regarding the airport screening operations.

UML diagram

Figure 6-2 shows the UML diagram that visualizes this model structure. The modelling framework by Furian et al. extinguishes two types of entity structures: active and passive. Active entities exhibit behaviour and can change their role. An example of an active entity is a passenger or a customs officer. The behaviour of active entities is explained in more detail in section 6.2. Passive entities, like the NCIT screening station, do not show behaviour throughout the model run and are not explained further.

The first row of each object, the grey box, shows the name of the class. The white box below shows whether this entity is active or passive, and the attributes associated with this class. These are generally the states of the entity in the model. Some objects contain an empty white box, meaning they do not own any attributes, apart from those that they inherited from their parent object.

As shown in the UML diagram, groups consist of passengers. There are two types of passengers: departing and arriving passengers. Departing passengers want to reach their destination and therefore have to be at their gate on time. A plane then carries these passengers out of the system. Arriving passengers are modelled in a more simplified way. They do not contain flight information apart from their origin, and their plane is considered out of scope of the model. However, at hub airports arriving passengers can transfer to a departing flight as well. This means in the model that an arriving passengers transforms in a departing passenger.

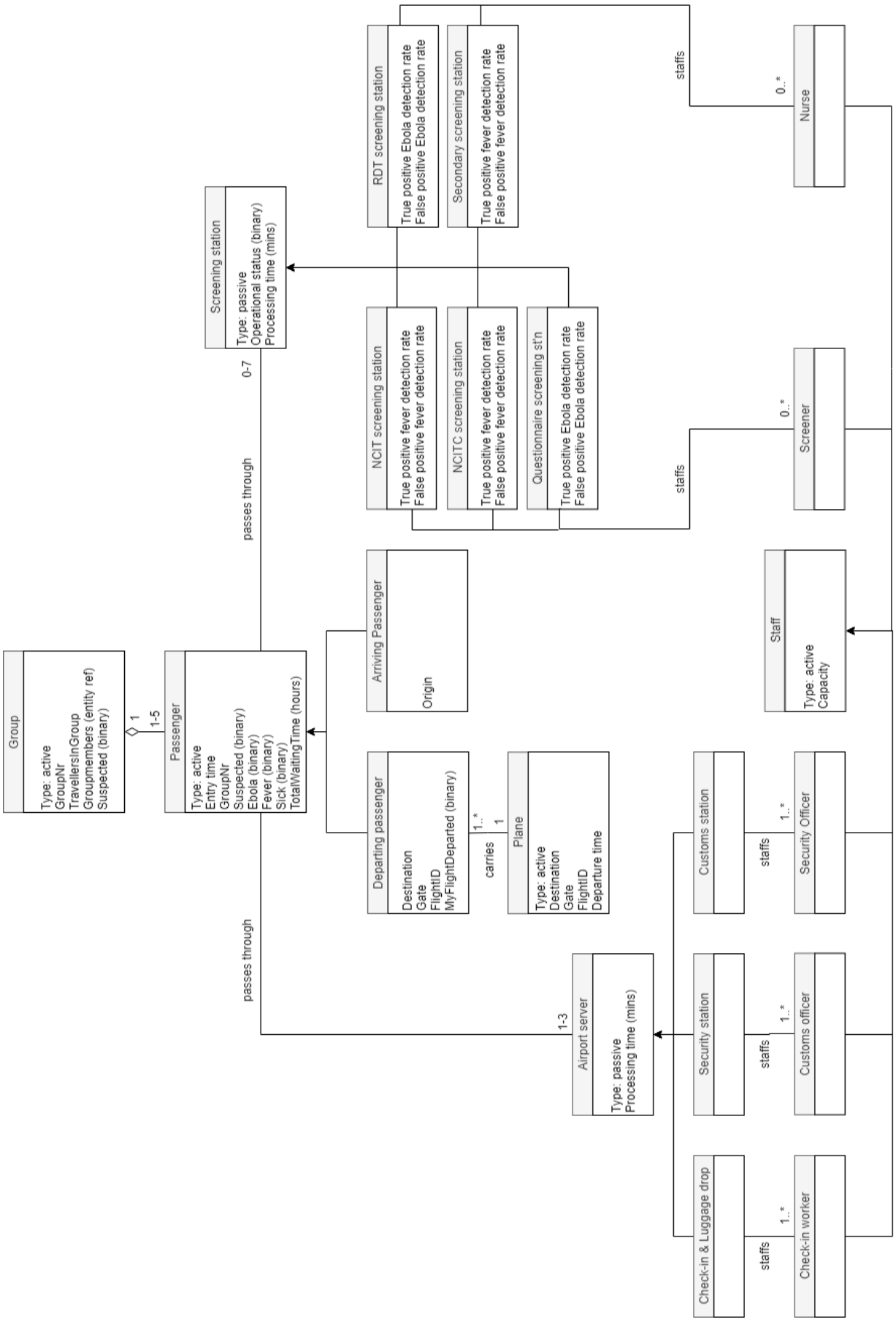


Figure 6-2 Airport UML diagram

The passengers pass through airport servers and screening stations. Airport servers have a certain processing time as defined in Chapter 5, and are staffed by their respective workers. Screening stations also have a processing time, and can furthermore be operational or not. An important factor in the system is the sensitivity and specificity of the screening stations, which is modelled using the true positive and false positive rate of these stations.

Furthermore, as capacity of airports is solely modelled by varying the number of airport staff, the airport servers and screening stations do not have a defined capacity. Instead, the number of workers staffing this station determines the capacity. Since this is the topic of attention in the following section, this UML-diagram does not include the operations the entities execute.

Airport layout

The model structure as defined in the UML diagram can also be presented as done in Figure 6-3, which mirrors the actual airport situation and the Simio model to be developed. This basic airport layout as shown in Figure 6-3 is constructed based on expert interviews and airport logistics models. The figure shows three locations for screening stations in a passenger's route through the airport, which can contain a station for fever screening, collecting questionnaires, or both. This is in line with the situation as described by humanitarians in West Africa during the 2014 Ebola epidemic (Belgian Humanitarian Aid Worker, 2019). This is supplemented with a station where secondary screenings of suspected passengers by a nurse take place, as was common during the epidemic at Brussels Airport. If a passenger is suspected to be infected with Ebola after this screening, the passenger undergoes a medical examination. Hereafter the passenger is either quarantined or released, but misses their flight either way. The process after secondary screening is regarded out of scope of the model, the process up to that point is covered by means of the KPI's *False positives* and *People reach destination in time*. The airport layout as shown in Figure 6-3 forms the basis of the models of all five airports included in this case study.

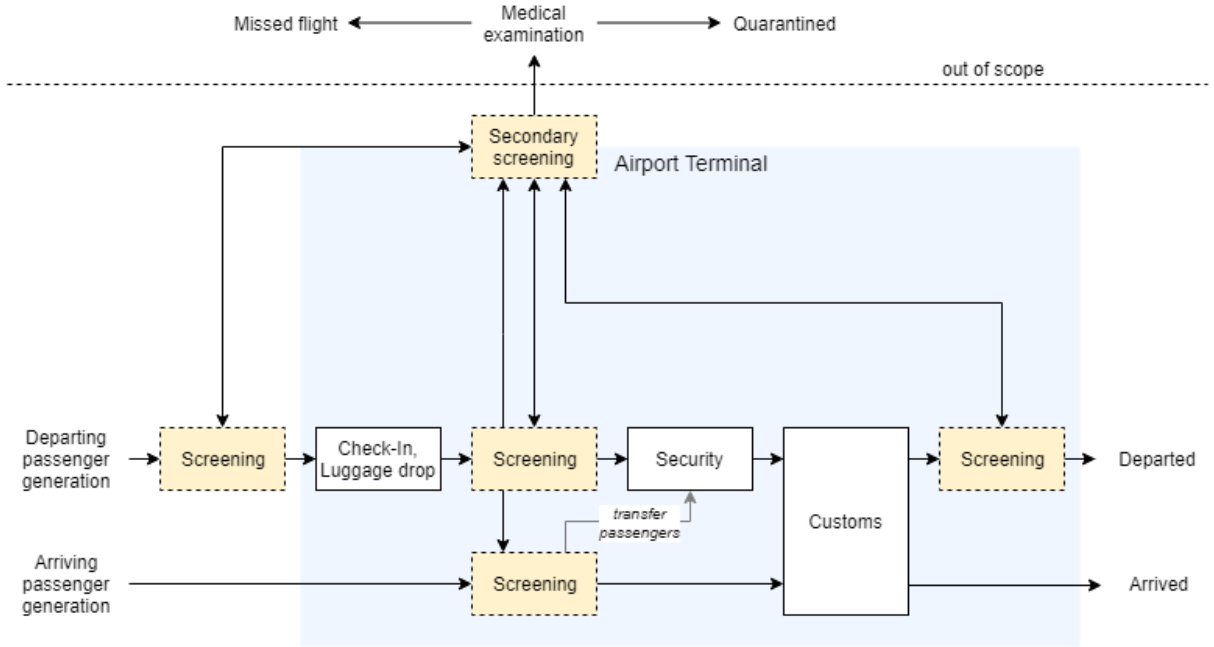


Figure 6-3 Structural view of the airport

To estimate the walking distance on the airports, the terminal size of Blaise Diagne International Airport (the largest airport within the scope of research) is taken as a proxy. This terminal measures approximately 200 by 100 meters, and an estimated maximum travel distance of 200 + 100 = 300 meters is used. This means it will take a passenger no more than 3.5 minutes to walk through the terminal assuming the standard walking speed of 1.4 m/s. Depending on which gate the plane departs from, the walking distance measures 250 – 300 meters. The connection between the arriving and the departing passengers, as shown in figure 6-2, allows for the modelling of transfer passengers.

Regular airport operations

Processes in the regular airport servers include the check-in & luggage drop, security and customs stations. The information regarding processing times of these stations from literature is listed in Table 6-1.

Table 6-1 Airport processing times from literature

Source	Server	Processing time
(Alodhaibi et al., 2017)	Check-in	0.5 min/bag
(Esteban, 2008)	Check-in	1.5 min
(Alodhaibi et al., 2017)	Security	0.5 min
(Mao & Wu, 2017)	Security	0.5 min
(Alodhaibi et al., 2017)	Customs	Random.triangular(0.2,1,2) mins

The processing times from Table 6-1 are narrowed down to the values to be used in the simulation model. These values are shown in Table 6-2. By using the 'random' expressions, variation in the processing times is included in the model.

Table 6-2 Airport processing times to be used in the model

Server	Processing time
Check-in	Random.exponential(1.5) min
Security	Random.exponential(0.5) min
Customs	Random.triangular(0.2,1,2) mins

As mentioned before, accounting for the differences in airport capacities is done by means of varying the number of staff at the airport operations. There are three different types of staff for these airport operations

1. Check-in workers
2. Security officers
3. Customs officers

The Check-in workers serve the *Check-in and Luggage* drop station for departing passengers. Security officers are active in the *Security* server for departing and transferring passengers. Finally, customs officers staff the shared *Customs* station for all passengers.

Lacking actual airport information, the number of employees is the outcome of experiments using the passenger flows, varying the number of employees at each part of the airport process. When (close to) no passengers miss their flights because of excessive queueing, the number of staff is assumed to be

adequate. For reasons of simplification this number does not vary over time. This means the number of staff reflects the required peak capacity. All workers are staffed throughout the entire model run.

Airport screening operations

Screening for Ebola is done in the airport screening stations. These screening stations are located in the fields marked *Screening* in Figure 6-3. Table 6-3 includes the measures as elaborated on in Chapter 5, supplemented with a secondary screening station. Secondary screening refers to a distinguished screening station where a nurse takes a traveller's temperature and conducts a questionnaire. Within the model, this is incorporated as a fever screening station. This is after the traveller has been categorized as 'suspected' in a first fever screening, as was the layout at Brussels Airport in 2014 (Crisis Management Officer Belgian Ministry of Health, 2019; Belgian Head Nurse Ebola, 2019).

Values of sensitivity and specificity as described in Chapter 5 are used in the airport model to screen passengers for Ebola (characteristics). Since the values for the sensitivity and specificity of secondary screening are unknown, the outer ranges of NCIT and RDT screening are used.

The screening processing times are derived from literature and expert interviews and can be found in Table F-4 of Appendix F. The processing time for NCTIC screening consists of the time it takes to walk past this screening station and is assumed to be five seconds. Since multiple passengers are screened simultaneously, the screening time is reduced to one second on average, per screener that staffs this station.

Table 6-3 Screening characteristics to be used in the model

Policy	**Sensitivity (%)**	**Specificity (%)**	**Processing time**	
Questionnaire	20-25	85-99	30 sec exp	
NCITC	70-90	92-99	1 sec exp	
NCIT	80-90	95-99	10 sec exp	
RDT	84-100	92-100	Sample collection:	30 sec exp
			Wait for result:	15 min
			Result sharing:	30 sec exp
Secondary screening	80-100	92-100	10-15 min	

The values regarding sensitivity and specificity are values for individual measurements. When combining policies, effectivity of successive measurements might be lower, as a share of the cases with fever have already been filtered out (Gostic et al., 2015). Quantitative information regarding this effect is not available, hence it is disregarded. This means for example that if three NCITC screening stations are operational in sequence, they will all have the same specificity and sensitivity for the identification of fever cases.

As highlighted in section **Error! Reference source not found.**, fever screening and questionnaires detect different disease characteristics (body temperature vs (reporting on) Ebola risk factors). Some researchers regard these screening stations as independent assessments, meaning that if one of the two raises suspicion for Ebola, the traveller is sent through to secondary screening (Gold et al., 2019). Experts from the field in Brussels Airport noted that travellers are only flagged as suspected Ebola cases if they have a fever *and* the questionnaire gives reason for concern (Australian Humanitarian Aid Worker, 2019). Both scenarios are included in the experiment.

An important measure for the performance of airports during infectious diseases is the required deployment of resources at airports. Resulting from a lack of data of required financial resources, the number of staff deployed for screening measures is used as the unit of measurement. As at Brussels Airport during the 2014 Ebola epidemic, relatively limited trained screeners are used for the initial fever screenings and checking of questionnaires. Secondary screening is carried out by nurses (Crisis Management Officer Belgian Ministry of Health, 2019). Ebola screening by means of conducting an RDT is completed by a nurse as well (Dhillon et al., 2018). This is incorporated in the airport models. The required number of screeners and nurses results from experiments. Other experiments include the type, number and location of Ebola screening stations.

6.2. Individual model behaviour

This section elaborates on the entity's behavioural perspective: what does a day of an entity in the model look like? This is done for the entities categorized as 'active' in the model structure section (Furian et al., 2015). The *Group* entity is disregarded since it does not exhibit individual behaviour beside the passengers' behaviour. Therefore, the relevant active entities as derived from the UML diagram are:

- Passengers
  - Departing passengers
  - Arriving passenger
- Staff
  - Check-in workers
  - Customs officers
  - Security officer
  - Screeners
  - Nurses
- Planes

The entities' behaviour is visualised using activity cycle diagrams. These diagrams visualize the behaviour of the model from a specific entity's perspective (Birta & Arbez, 2007). Each activity conducted by an entity is visualised as a rectangle. A circle shows that an entity awaits the next step. This can be the result of waiting in a queue, travelling to another location in the model, and/or awaiting a requested action. Multiple arrows exiting an object means that different subsequent steps are possible. The entity performs the consecutive actions as shown in the figures until an object without outgoing arrows is found. If no such object is included in the diagram, the entity performs the actions until the end of the model run.

Figure 6-4 shows the activity cycle diagram for departing passengers. On their route through the airport model, the passengers go through the regular airport operations and, if operational, the Ebola screening operations. Passengers travel through the airport in groups. The average travel party size consists of 1.6 persons (National Travel and Tourism Office, 2015). Within the simulation model, the minimum travel party size is 1 and the maximum is 5. To adequately reflect airport processes, travel parties stay together at the airport. This means they wait for group members at screening stations. Furthermore, if one member of the travel party is sent to secondary screening, the entire party accompanies this suspected traveller. If one member of the travel party is sent to medical examination and hereby misses their flight, the entire travel party is marked as suspected of Ebola infection and not permitted to fly.

Activity cycle diagrams for passengers

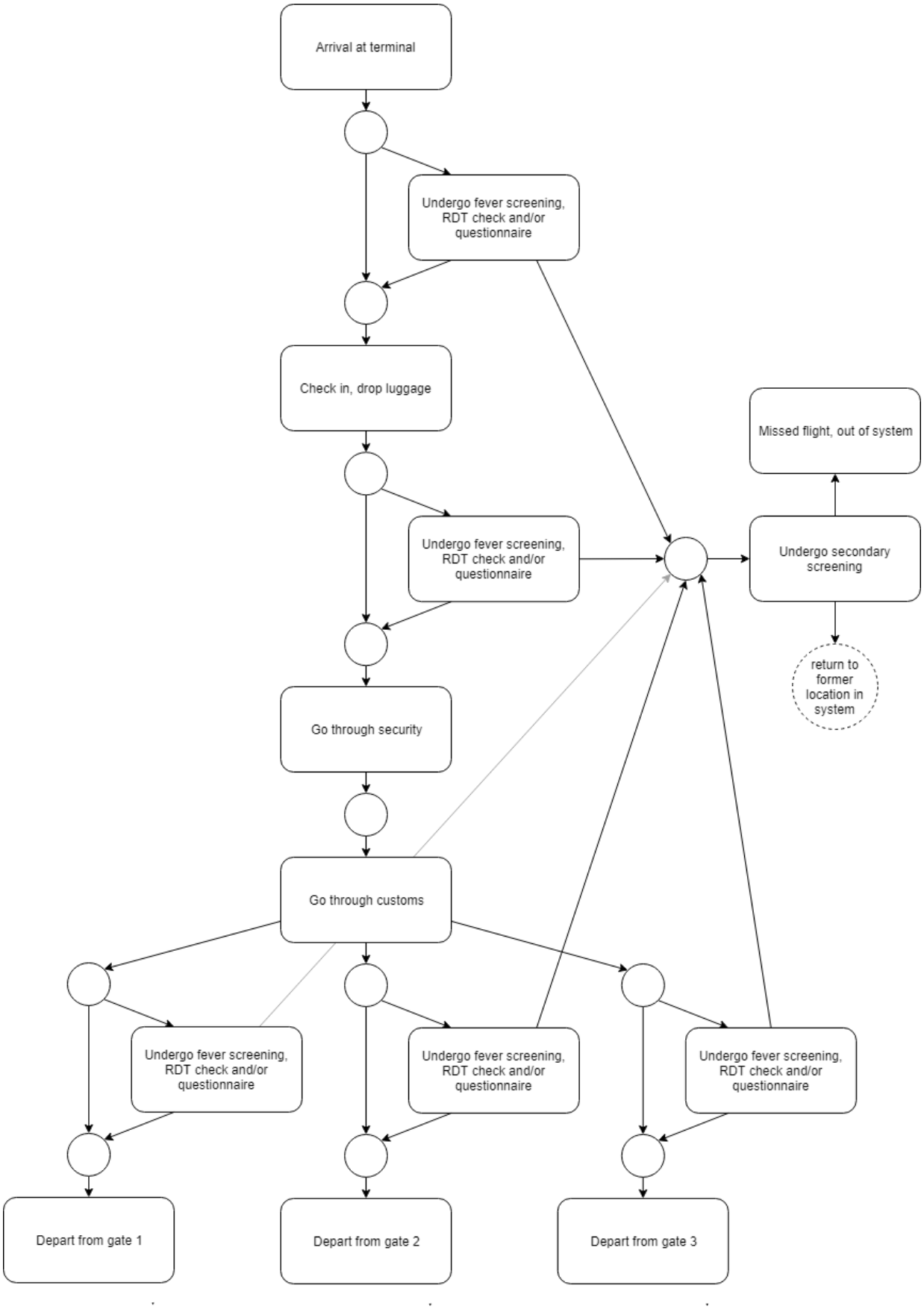


Figure 6-4 Activity cycle diagram for departing passengers

Figure 6-5 shows the activity cycle diagram for arriving passengers. At the dashed 'wait circle' before customs, the passenger either continues to leave the terminal and enter the country, or transfers to another flight. The latter is possible at one of the hub airports.

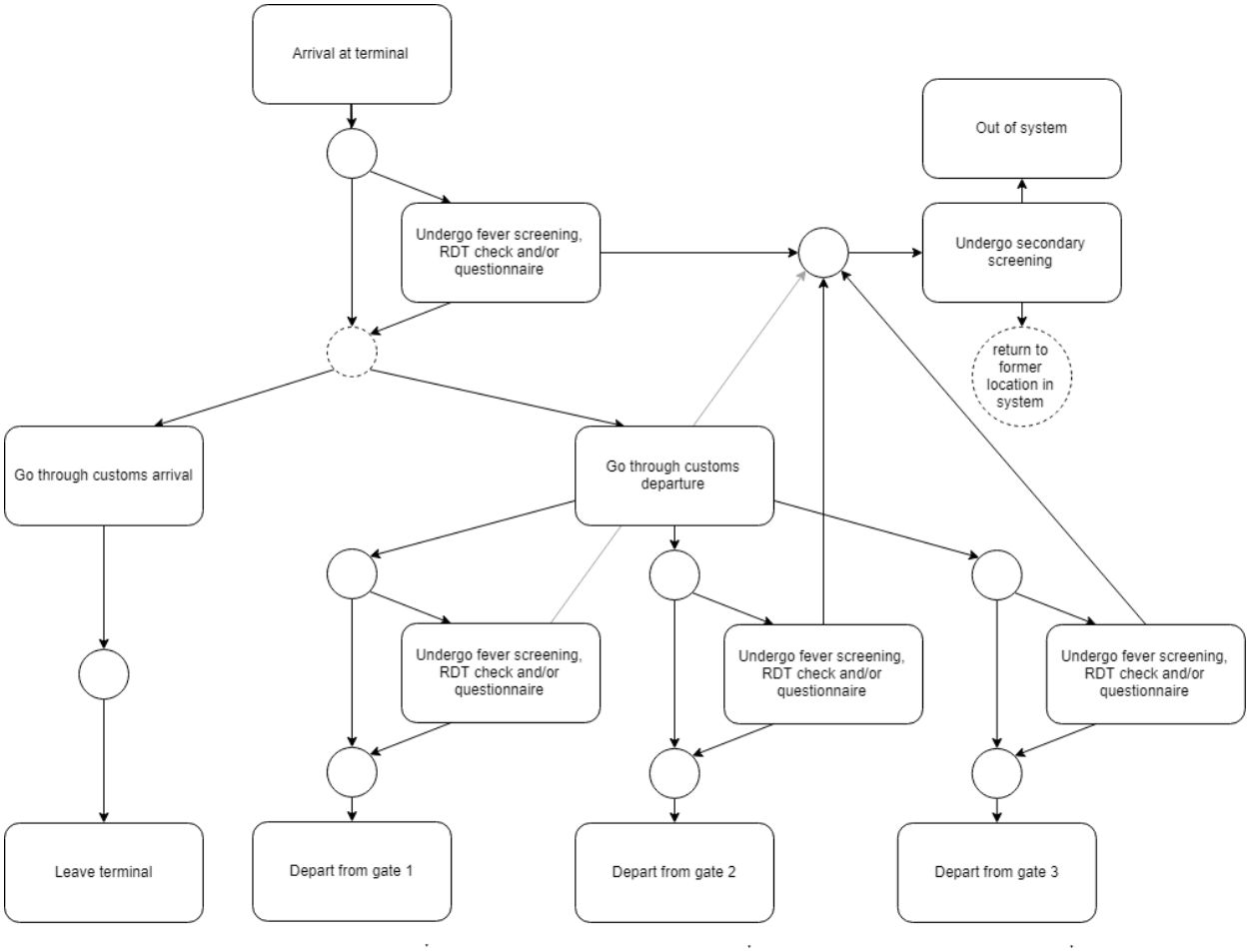


Figure 6-5 Activity cycle diagram for arriving passengers

Activity cycle diagrams for staff

The activities of check-in workers, security officers and screeners are straightforward and visualized in Figure 6-6 diagram A. They wait until their presence is required at their respective working stations. When finished processing a passenger, they are available again. Important simplification is that the physical location of this resource is disregarded: after screeners work at screening location A for a period of time, the employee can seamlessly proceed with their work at location B. The result is that the absolute number of staff will not mirror reality; it will be lower in the model. However, the number of staff will still illustrate the *relative* increase in required resources and hence still provide insight in the operational effects of the measures.

Diagram B of Figure 6-6 shows the activity cycle diagram of customs officers. This differs from the previous employees because they have separate control stations for arriving and departing passengers, between which they move based on the demand. Figure 6-6 diagram C shows the three activities of nurses: collecting and checking swab samples at RDT screening stations, and performing

the secondary screenings. Naturally, these activities only occur when such a screening station is active in the model.

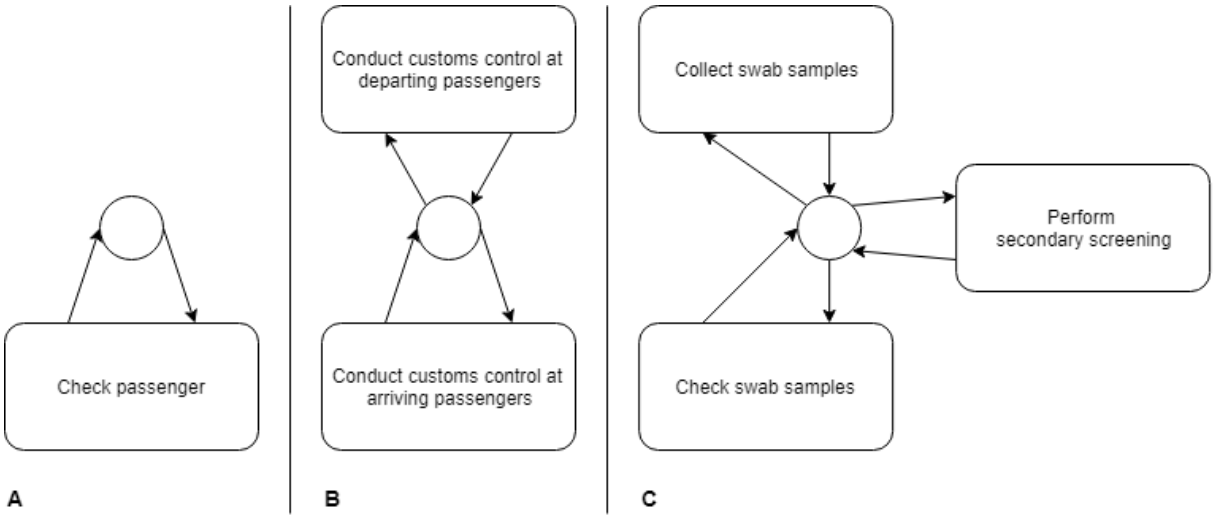


Figure 6-6 Activity cycle diagram for (A) check-in workers, security officers and screeners; (B) customs officers and (C) nurses

Activity cycle diagram for planes

Figure 6-7 shows the activity cycle for a plane. The only action of a plane is to depart at its departure time. Within the simulation model, the plane returns to the gate after delivering its passengers. At that moment, the plane is ready to perform the next flight departing from that gate, hence the circular flow of the plane activity cycle.

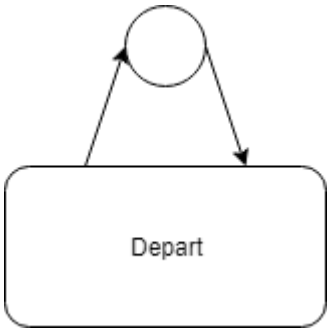


Figure 6-7 Activity cycle diagram for planes

6.3. System behaviour

This section covers the third part of the airport's conceptualization phase: the system behaviour. This part elaborates on how decisions are made within the model and includes the control policies of the system. It can be related to the activity cycle diagrams of Chapter 6.2: it explains the processes where entities can choose between different activities. The most relevant decisions are visualized and explained in this section. The decision rules are visualized using flow diagrams. The process is initiated the moment the action, shown in the circle at the top, occurs. The diamond shape shows a decision rule with two possible outcomes. The rounded rectangles represent a selection rule. The decision rules result in one of the actions as shown at the bottom of the diagram. Some decisions are not included since they are policy levers: for instance whether a screening station is turned on or off.

Check-in and bag drop, security and customs behaviour

Figure 6-8 shows the decision rules that apply during the presence of queues at the regular airport operations stations: check-in, security and customs. The processes at check-in and security are comparable and thus both represented by Figure 6-8 diagram A. When a queue exists at the station, the system checks if a check-in or security staff member is available. If this is the case, the passenger that is first in line is allocated staff capacity and served at the station. If no staff member is available, no action is taken. Since the queue will persist to exist, the system will continue checking for available staff members.

The process for allocating customs officers to waiting passengers shown in Figure 6-8 diagram B starts comparable to the previously described process. Difference is that customs officers serve two stations: one for departing and one for arriving passengers. Throughout the model the assumption is made that departing passengers always have priority over arriving passengers; this is done to reduce the number of passengers that miss their flight. Therefore, customs officers first check if there are passengers waiting at the departure stations of customs, before staffing the arrival customs station.

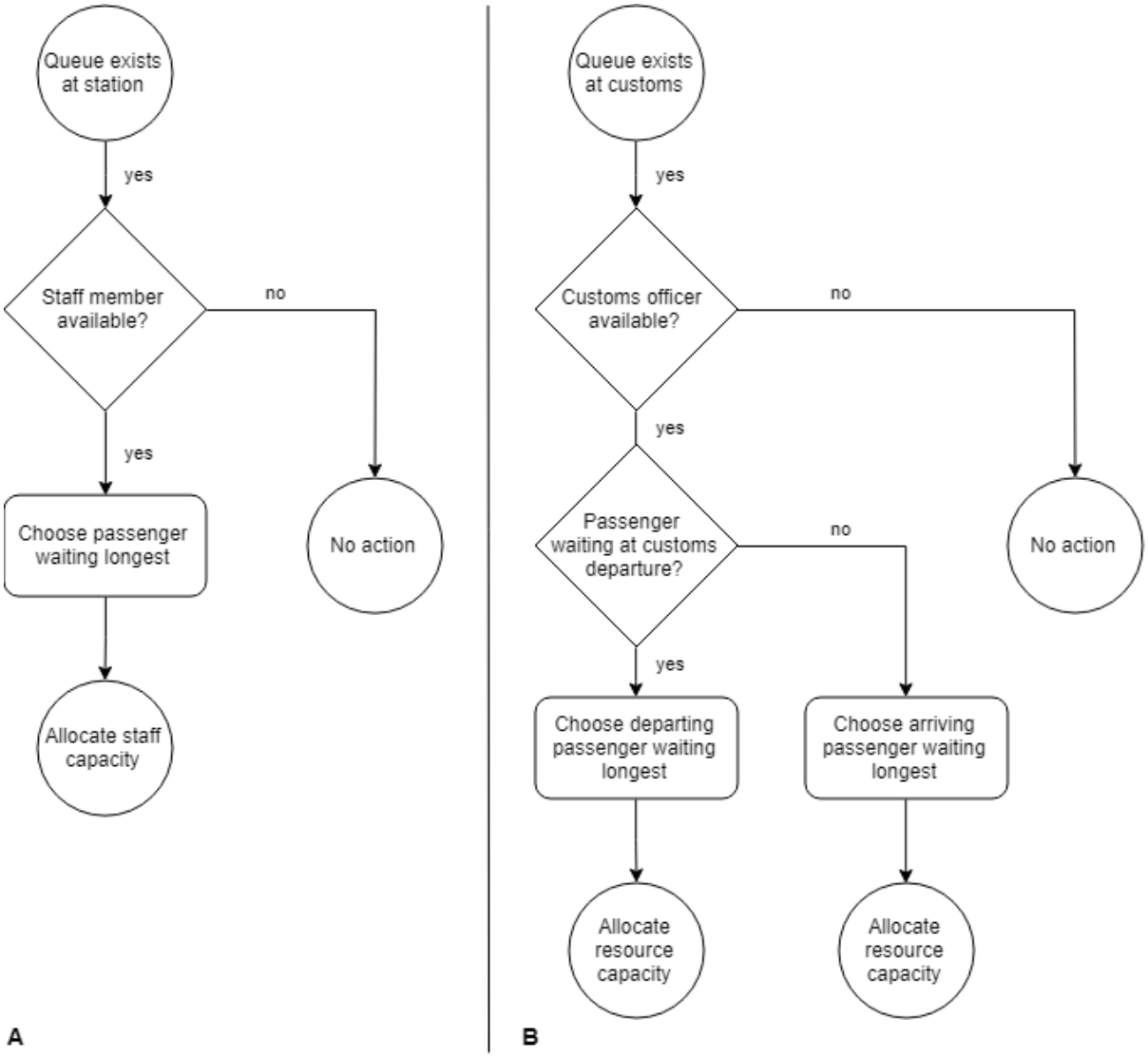


Figure 6-8 Decision flow diagram check-in & security arrival (A) and customs arrival (B)

Screening behaviour

Figure 6-9 shows the allocation of screening capacity to one of the screening stations. The same process applies to both screeners and nurses. This is comparable with the allocation of other staff members as described previously in this section.

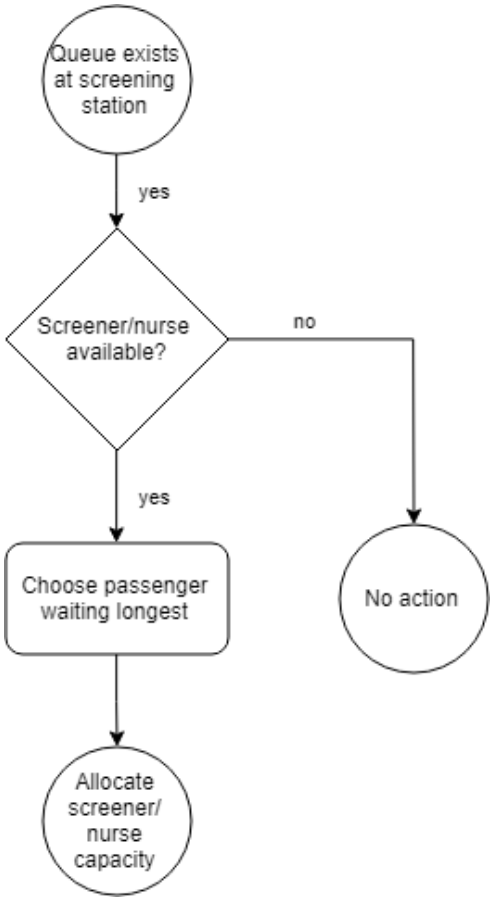


Figure 6-9 Decision flow diagram screening capacity request

Figure 6-10 shows the consecutive processes at these screening stations. Diagram B shows the process at secondary screening (resulting in passengers being detained), while diagram A shows the decision rules at the other screening stations. Passengers are screened on fever or the actual presence of Ebola. The chance of actually being flagged as suspected depends on the true positive and false positive rates (representing sensitivity and specificity) at the screening stations, which are varied over the experiments. Suspected passengers are sent to secondary screening, the remainder of passengers continue the regular process.

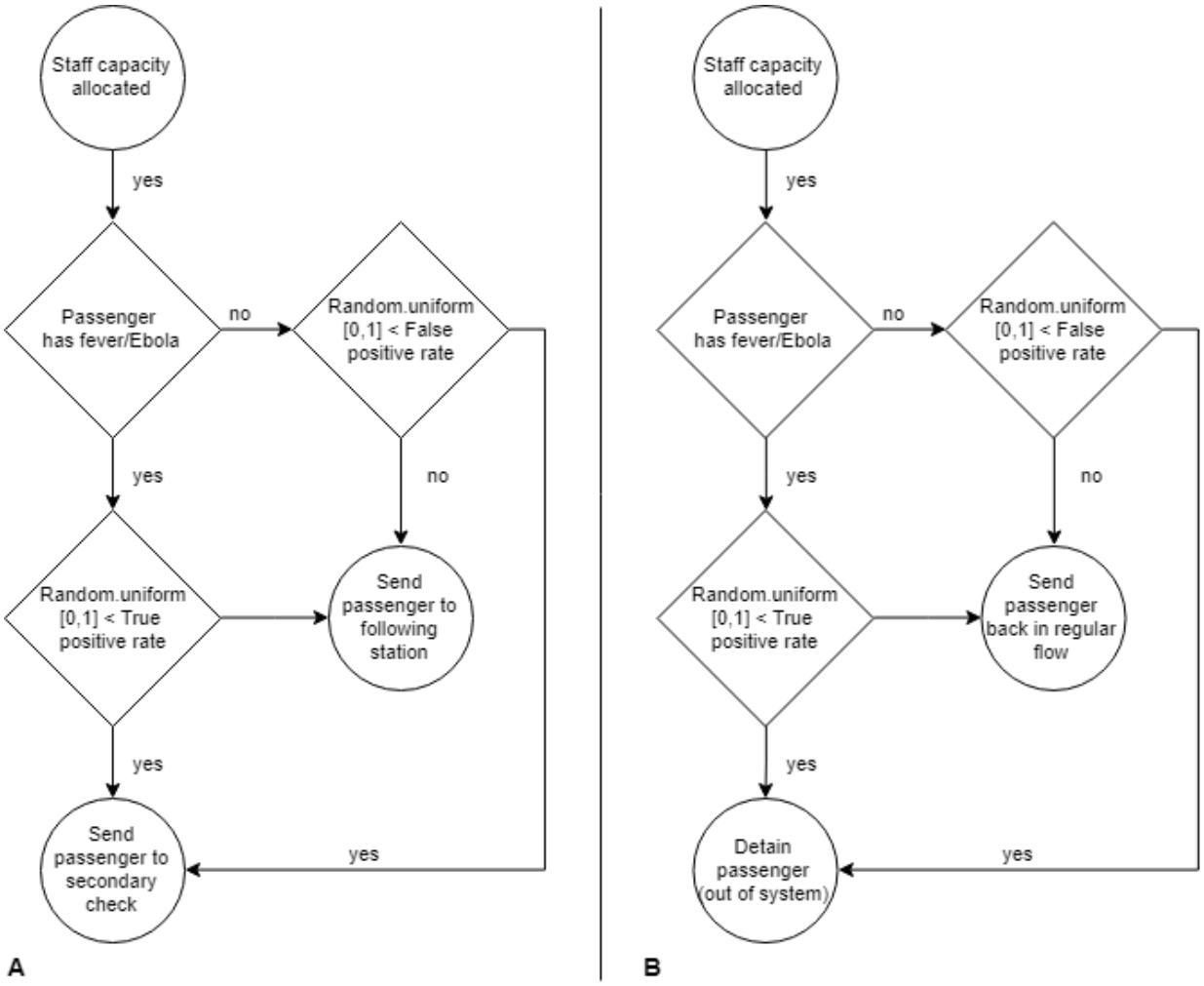


Figure 6-10 Decision Flow diagram screening by screener (A) and nurse (B)

Flight departure and passenger transfer

At various point during their route through the terminal, passengers check if their flight has departed yet. If so, they are removed from the terminal, as shown in Figure 6-11 diagram A. At the hubs, arriving passengers can transfer to a departing flight. Lacking actual numbers, it is assumed that ten per cent of arriving passengers transfer at these hub airports. This process is visualized in Figure 6-11 diagram B.

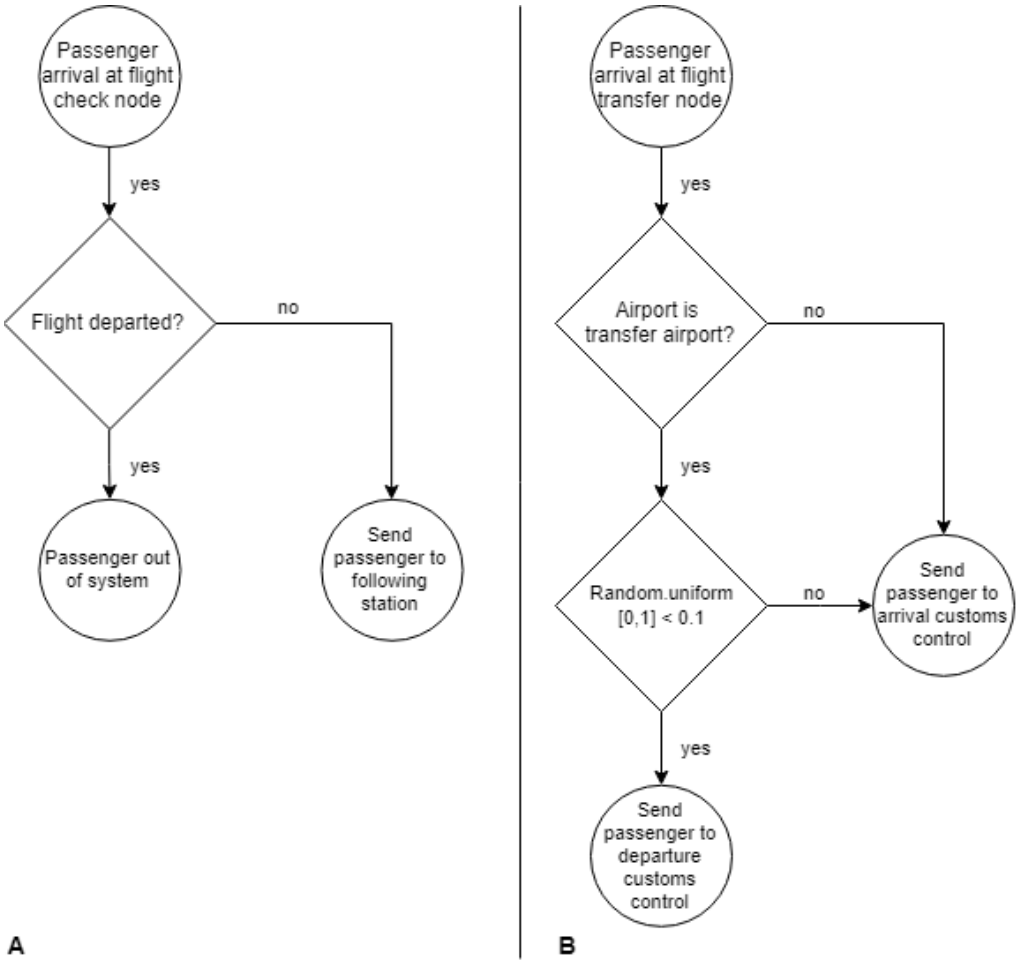


Figure 6-11 Decision flow diagram flight missed (A) and passenger transfer (B)

6.4. Out of scope

The processes as described in this chapter only cover a minor part of the operations at any airport. This section highlights a non-exhaustive list of airport operations that are out of scope of this research. Firstly, everything that happens outside of the walls of the passenger airport terminal is not included in the airport models, except for airport entrance screening. Hereby one can think of cargo handling, aircraft taxiing, catering services etcetera. This also means that the process after a passenger is marked suspected after secondary screening is not included. Important to highlight is that the interactions between airports and the effect on infectious spreading are included in this research. Airport interactions are further covered in Chapter 7.

Security screening concerns the checking of passengers' luggage, but luggage is not explicitly included in the model. No airport operations, except for *check-in and luggage drop*, *security screening* and *customs* are included in this research. When it comes to the passenger flows through the airport, people continue in a straight line through all the screening stations, without passing through stores, toilets or other airport facilities. Passengers afraid to miss their flight because of delays in the airport do not skip queues or receive preferential treatment: all passengers are served based on the time they entered the queue.

Airport disease screening staff is regarded a resource that can be requested, but does not require a move by this resource. Concretely this means that the physical location of screening staff within the

terminal walls is disregarded. After working at screening location A for a period of time, the employee can seamlessly proceed with their work at location B. This will result in a lower staff demand than can be expected in reality. Furthermore, staffing schedules are disregarded: airport staff is considered a stable available resource that can be requested if needed.

6.5. Assumptions and experiments

Throughout this chapter, different aspects of the individual airport level model face a certain level of uncertainty. There are two solutions for this: making assumptions or conducting experiments. This section lists the main assumptions that are made and the experiments that will be conducted later in this research.

Assumptions

- One generic airport model is made, employee numbers represent the airport capacities.
- There are three types of regular airport staff: check-in workers, security officers and customs officers.
- There is a stable number of staff, representing the staff needed at peak capacity.
- The physical dimension of staff is disregarded.
- Secondary screening sensitivity and specificity covers the range of the other screenings' sensitivity and specificity.
- Screening stations' effectivity is independent from other stations.
- Screeners conduct questionnaires and fever screening.
- Nurses conduct RDT screening and secondary screening.
- Passengers travel in groups, with an average travel party size of 1.6.
- The travel group waits for a member in a process.
- If a passenger is sent to secondary screening, the rest of their travel party waits there till screening is finished.
- If one member of a travel party is not permitted to travel, the rest of the group decides not to fly.

Experiments

- Required staff numbers for regular operations
- Passed Ebola cases without screening
- Functioning of Ebola screening measures
- The effect of requiring both fever symptoms and having Ebola risk factors to be suspected of having Ebola, versus either fever symptoms or Ebola risk factors.
- Needed staff numbers for screening operations
- Potential of RDT screening

7. Aggregation to the system level

This chapter answers sub question 3: ***How do airports interact with the system during infectious spreading?*** This chapter elaborates on how the airports within the network interact, and how measures at one airport impact other airports through the network. Figure 7-1 visualises the contents of this chapter. Section 7.1 focuses on the departing passengers' health statuses. Section 7.2 describes the airline network that distributes the passengers to the other network nodes, and hereby possibly spreads the disease. Section 7.3 concerns the role of hub airports within the network. Finally, section 7.4 covers the assumptions on this level, as well as the experiments to be conducted.

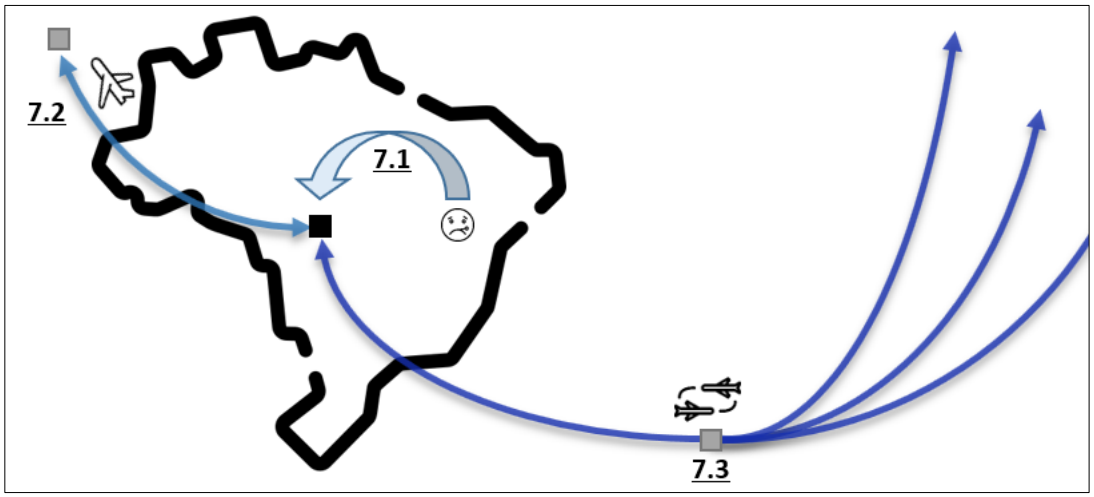


Figure 7-1 Overview chapter contents

7.1. Departing passengers

As in previous research, passengers transferring through the airport have one of five health statuses as shown in Figure 7-2 (Gold et al., 2019). A passenger's status determines the chance of being marked as a suspected Ebola case in one of the screening stations. The arrival of infected passengers and the detainment of non-infected passengers are indicators for the functioning of the system (Chapter 4). Passengers who are sick with diseases other than Ebola are included in the model, as these individuals have a higher chance of detection for Ebola in fever screening: a false positive. This section elaborates on the health statuses as shown in the figure.

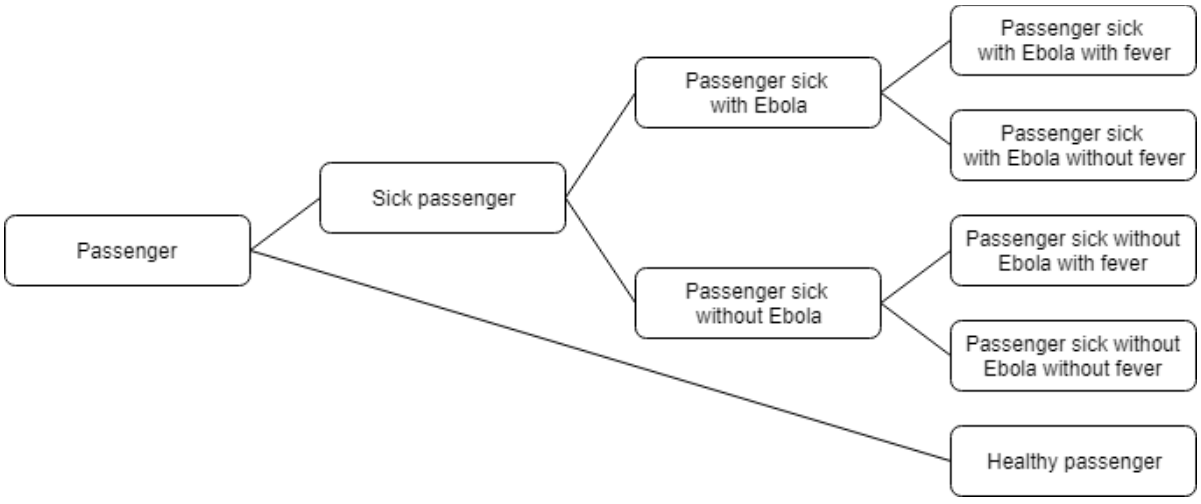


Figure 7-2 Passengers' states

Passenger sick with Ebola

The prevalence of Ebola in the nation of departure determines the chance of an individual passenger being infected with the disease. Development of the total number of Ebola cases and deaths over time per country is shown in Figure 7-3 (Center for Disease Control and Prevention, 2016). Only the timeframe that is covered in this research is shown: September 2014 until February 2015.

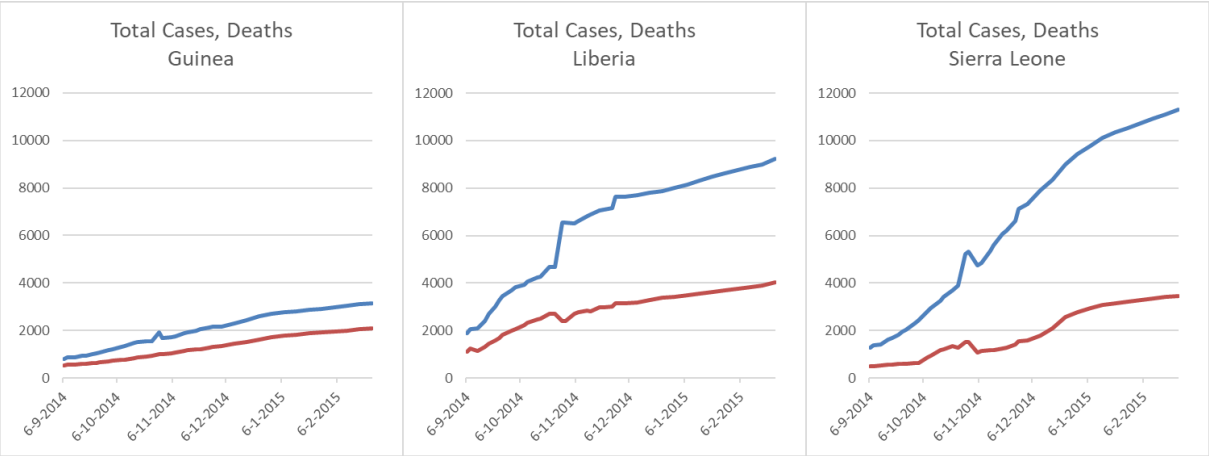


Figure 7-3 Total Ebola cases (in blue) and deaths (in red) over time

From this information, the following can be derived:

1. The (absolute) number of Ebola cases was the highest in Sierra Leone and in Liberia.
2. The rise of (known) Ebola cases was very high in the end of October 2014.
3. There is major uncertainty regarding the number of Ebola cases, as shown by the *decrease* of both the known Ebola cases and deaths in November 2014. In reality this is not possible, since the graph shows the summed number of cases over time. This means that previously cases were wrongfully counted.

Based on this information, an estimation of the chance that a passenger departing from one of these three countries is infected with Ebola is made. The key assumption underlying this statement is that the chance of a random passenger being sick with Ebola equals the ratio of Ebola prevalence in the country. This would result in the formula as shown in Equation 1.

$$\frac{Ebola\ cases - Ebola\ deaths}{Population\ of\ country\ X} = Chance\ of\ passenger\ being\ sick\ with\ Ebola$$

Equation 1 Chance of Ebola (1)

However, this equation assumes that every individual who does not die from Ebola remains sick. In reality this is not true. Data regarding the current Ebola cases over time is not available, but researchers assume a curing time of 2.5 to 3 weeks after becoming symptomatic (Büyüktahtakın, des-Bordes, & Kıbış, 2018). Based on this information, a different estimation of Ebola prevalence can be made. Equation 2 shows this formula. The formula takes the additional Ebola cases from the last three weeks, which is deducted by one third of the Ebola deaths in this period. This fraction is assumed because the remainder of Ebola deaths will result from infections that occurred before this time period. Figure 7-4 shows the resulting number of Ebola cases resulting from applying this formula on the data from Guinea, Sierra Leone and Liberia.

$$\frac{New\ Ebola\ cases\ in\ the\ last\ 3\ weeks - \left(\frac{1}{3}\right) * New\ Ebola\ deaths\ in\ the\ last\ 3\ weeks}{Population\ of\ country\ X}$$

$$= Chance\ of\ passenger\ being\ sick\ with\ Ebola$$

Equation 2 Chance of Ebola (2)

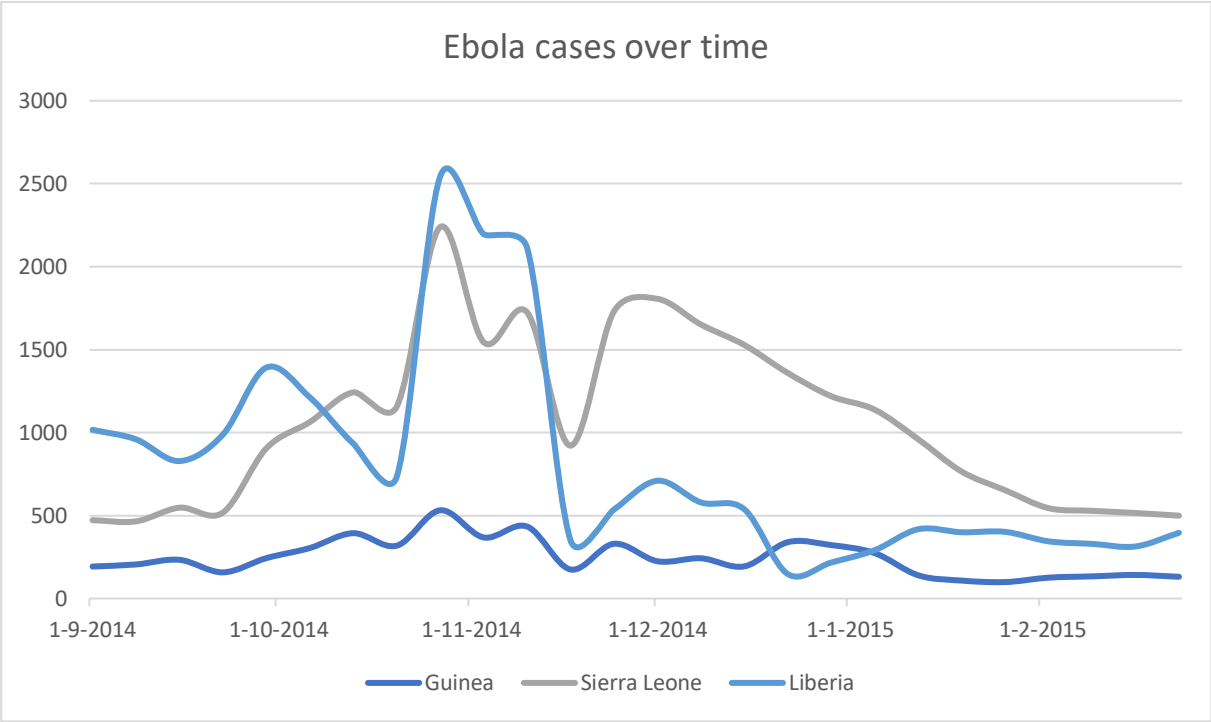


Figure 7-4 Ebola cases over time

This formula takes the change of Ebola cases and deaths as an estimation of current Ebola cases. Hereby this formula is probably a closer estimation of the actual number, but still does not draw the complete picture. Researchers estimate 17 to 70 per cent of Ebola cases go unreported (Scarpino et al., 2015). Furthermore, new Ebola cases will generally only be known (and thus reported) when the individual is symptomatic; meaning the actual current number of Ebola infected individuals is actually higher.

In the experiments, Equation 2 is used to estimate the Ebola prevalence in the three countries, and therefore the chance of a passenger being sick with Ebola from these countries. The resulting percentages of Ebola prevalence is shown in Table G-1 in Appendix G. To account for the underreporting of cases, experiments will include a multiplication factor of 1.17 to 1.7.

Furthermore, the above implies that the fraction of airline passengers infected with Ebola equals the fraction of a country's population to be infected. This is unlikely to be correct. Ebola affects the poorer classes of society disproportionally. Poverty can even be qualified a driver of Ebola transmission (Fallah, Skrip, Gertler, Yamin, & Galvani, 2015). Simultaneously, air travel in Africa is mostly a luxury product, particularly aimed at the rich. Furthermore, an individual feeling sick because of an Ebola infection (or resulting from another disease) will likely not attempt to travel. The aforementioned means that the chance of identifying an Ebola patient at an airport is expected to be smaller than

somewhere else in the country. According to the Crisis Management Officer Belgian Ministry of Health (2019), the passengers with the highest risk factors probably consist of two groups:

1. Humanitarian aid workers, who are close to Ebola patients because of the work they perform.
2. Lower middle-class travellers: the people that are able to buy a plane ticket, but have a chance of coming into contact with Ebola infected people, at e.g. markets and public transport.

To account for the uncertainty, experiment runs include different scenarios for Ebola prevalence. A scenario with a lower Ebola prevalence is included to account for the fact that Ebola patients are less likely to fly.

Passenger sick with Ebola with/without fever

An individual infected with Ebola has a 83-87 per cent chance of developing a fever after the incubation period of 2-14 days, with an average of 9.4 days (European Centre for Disease Prevention and Control, 2014; WHO Ebola Response Team, 2014). The disease characteristics are summarized in Table 7-1. Because of this long incubation period, it is estimated that two thirds of infected passengers will not yet be presenting with symptoms (European Centre for Disease Prevention and Control, 2014). This implies that the actual presence of fever is not 85 per cent, a mere 28.3 per cent. In order to compare the data with previous research regarding Ebola screening at airports, both numbers are included in the experiments. The percentage is multiplied with the prevalence of Ebola to estimate the chance of being a passenger being sick with Ebola with fever. The remainder of the passengers with Ebola is a 'Passenger Sick with Ebola without fever'.

Table 7-1 Ebola disease characteristics

Disease characteristic	Value	Source
Chance of fever over course of Ebola	83%	(European Centre for Disease Prevention and Control, 2014)
Chance of fever over course of Ebola	87%	(WHO Ebola Response Team, 2014)
Ebola incubation period	2 – 14 days	(European Centre for Disease Prevention and Control, 2014)
Ebola incubation period	4 – 14 days	(WHO Ebola Response Team, 2014)
Curing time	2.5 – 3 weeks	(Büyüktahtakın et al., 2018)

Passenger sick without Ebola with/without fever

Other diseases, more prevalent than Ebola, might raise suspicion of being infected with Ebola. In previous research, the assumption was made that 1 per cent of the passengers were infected with another infectious disease, of which 5 per cent had a fever (Gold et al., 2019). This might be an optimistic guess as it is estimated that in Liberia alone, 911.000 cases of Malaria are present (World Health Organization, 2018c). Of a population of 4.7 million this means that one in five Liberians is infected with Malaria. Therefore, experiments are included that account for higher disease ratios in the countries.

Healthy passenger

The remainder of passengers are regarded healthy.

7.2. The airline network

The airline network consists of the flights operated between the airports of interest, and to the airports outside of the area. The passengers transported over this network can be infected with Ebola, which, if undetected at an airport, results in the further spreading of the disease at the country of destination, one of the outcomes as defined in research question one. Other relevant outcomes are the number of passengers that reach their destination in time and the percentage of flights operated, which reflect the functioning of the network.

Three airline timetables are included in this research. The first network is called *Regular 2014 operations.* This concerns the airline operations in 2014, at the start of the Ebola network. This network is suitable for testing policies on how measures at the airport level could have prevented the spread of Ebola over the airline network. However, in reality the majority of airlines cancelled their flights, resulting in marginal airline operations from some of the airports. This scenario is called *Minimal 2014 operations* and is included as well. Although in reality airlines cancelled more and more flights gradually, one timetable is incorporated for the minimal network operations. The current (2019) flight network is incorporated to illustrate the possible consequences of an Ebola outbreak now, and to test measures to prevent a spreading. This scenario is also used to incorporate measures at the hub level. This network is called *2019 operations.* The method for obtaining the timetables can be found in appendix H.

All the five timetables are weekly and repeated over the simulation time. All scheduled flights are assumed to be operational (after deducting the flights cancelled during the Ebola outbreak) and it is assumed there are no delays.

Table 7-2 Airline network scenarios

	Flight schedule 2019	**Reduced flight schedule 2014**	**Regular flight schedule 2014**
ROB	ROB ‘19	ROB ’14 MIN	ROB ’14 REG
FNA	FNA ‘19	FNA ’14 MIN	FNA ’14 REG
CKY	CKY ‘19	CKY ’14 MIN	CKY ’14 REG
DSS	DSS ‘19	Out of scope	Out of scope
ACC	ACC ‘19	Out of scope	Out of scope

7.3. Hub airports

Within this research, a hub is defined as an airport where passengers can transfer between flights. Hubs can fulfil an important role during epidemics, since bringing together passengers from different origins can accelerate the spreading of the disease (Lawyer, 2016). Within this research, Blaise Diagne and Kotoka Airport are defined as hub airports. Lacking data, the number of transferring passengers at the hub airports is arbitrarily set to ten per cent of arriving passengers.

In the airport model, the possibility will be included to screen passengers arriving from Ebola affected areas for Ebola infection. This applies both to passengers with the hub airport as final destination, as well as passengers continuing their journey. Although exit screening is considered more effective than entry screening, entry screening can be a suitable policy when exit screening is unreliable or screening capacity at the airport of departure is inadequate (Airports Council International, 2009; Centers for Disease Control and Prevention, 2014). By including screening at the hub airports, a policy measure comparable to the entry screening at Brussels Airport during the 2014 Ebola epidemic is included.

7.4. Assumptions and experiments

As in chapter 6, different aspects of the network aspects of the model face a level of uncertainty. This section summarizes the main assumptions that are made and the experiments that will be conducted later in this research.

Assumptions

- Passengers have a stable health status throughout the run of the model.
- 2014 flights schedules are based on the 2019 flight schedule. Flights that were not anymore operated in 2019 are added twice a week.
- There are no delays or changes to the flight schedule throughout the simulation run.
- Load factors are constant and equal to the average African air transport load factors.
- 10% of passengers transfer at the hub airports.

Experiments

- The impact of higher or lower Ebola prevalence
- The impact of the fraction of the population ill with other diseases with fever
- The effect of flight cancellations on the spread of Ebola
- The potential of measures at hub airports

8. Verification and validation

Verification of the simulation model checks if the model adequately covers the entities and relations as defined in the conceptual design (Nikolic & Ghorbani, 2011). Verification consists of verification checks (section 8.1) and verification runs (section 8.2). Verification checks examine the correct functioning of the model during the model construction and runtime. Verification runs cover an analysis of the model outcomes under specific circumstances. Model validation aims to test whether the model produces outcomes that correspond with the observed reality, and is covered in section 8.3.

8.1. Verification checks

The graphical, component-based representation of the system in Simio allows for continuous debugging of the model. Illogical entity flows are easily identified and fixed. This is done throughout the model construction. Adding status labels and plots to the model checks the correct functioning of the entity generation, routing and processing at servers. Hereby, different aspects of the model can be checked, e.g. the number of generated passengers with different health statuses; the operational status of different screening stations; and the number of passengers departing or missing their flight. This way, it is also checked if the number of generated passengers matches the number of passengers leaving the system. Furthermore, the path of an individual entity through the system is checked by using the *Model Trace* function of Simio, which provides the modeller with a detailed report containing every step of the entity. The same is done for the employees staffed at the airport.

8.2. Verification runs

Verification runs are performed by completing extreme value tests and sensitivity analysis. Extreme value tests check for the model functioning under extreme circumstances, to find out if the model reacts as expected. The extreme value tests as shown in Table 8-1 are conducted.

Table 8-1 Extreme value test parameters

		Inputs to be varied	Input values
1	**Staff test**	Check-in workers	0, 1, 100
		Customs officers	0, 1, 100
		Security officers	0, 1, 100
2	**Ebola prevalence test**	Fraction Ebola	0, 1
3	**Sensitivity and specificity test**	Sensitivity	0, 1
		Specificity	0, 1

The results of the extreme value test are summarized here. Firstly the effect of staffing is tested. Zero staff leads to zero departed passengers, since the airport's servers are not operational and passengers cannot pass. A staffing of just one employee at each station results in excessive queuing times and lots of missed flights. By staffing one hundred employees at each station, queueing times are minimal and close to every passenger reaches its destination in time. Some passengers still miss their flights. Extreme value test two varies the prevalence of Ebola. No one infected with Ebola results in zero infected Ebola arrivals. Everyone infected with Ebola result in a number of Ebola arrivals equal to the number of departed passengers – in a scenario without screening measures. Third extreme value test varies the sensitivity and specificity of screening. Extreme values of sensitivity directly impact the number of infected arrivals, whereas the number of false positives is mainly determined by the

specificity. The aforementioned results in the conclusion that the model performs as expected during the extreme value tests.

Sensitivity analysis is performed to understand how sensitive the Simio model responds to changes in parameters. Simio contains a tool to check for the sensitivity of input parameters. Therefore the input parameters are varied for the factors: sensitivity, specificity and percentage Ebola.

The sensitivity analysis shows that the model responds sensitive to a change in the specificity of the screening measures, significantly more than to a change in the sensitivity of screening. This can be explained by the fact that a change in specificity affects the (vast majority) of non-infected travellers, whereas the sensitivity only applies to the few Ebola infected travellers. Therefore a change in the specificity has a significantly bigger influence on for instance the destination in time than the sensitivity.

Interestingly, the strongest decrease in the number of infected arrivals results from a *decrease in the specificity* of fever screening. This feels illogical, since a 'worse' performing fever screening measure results in a 'better' outcome. However, it can be explained when considering the low fever prevalence among Ebola infected passengers due to the long incubation time. Since the majority of Ebola cases does not yet exhibit fever symptoms, a fever screening station which wrongly marks passengers as exhibiting fever symptoms, results in the strongest decrease in infected arrivals. Naturally, this also results in a strong increase of false positives. Decreased specificity results in an increased queuing time, since more passengers are sent through to secondary screening. Unsurprisingly, an increase in the prevalence of Ebola results in an increase in the number of infected arrivals.

Based on the sensitivity analysis it can be concluded that the model behaves responds to changes in the input parameter as expected. However, the impact of changes in the specificity of fever screening indicate a limited effectivity of this screening. This will be researched further in the model experimentation and data analysis chapters.

8.3. Validation

The validity of a simulation model would normally be checked by comparing the outcomes of the model with the situation in reality. Because of multiple reasons, that is complicated for this model. Comparison with historic data from the 2014-2015 outbreak is possible, but complicated by the number of unknowns within the simulation model. The number of infected arrivals in reality is for instance used to calibrate the model by means of adapting the Ebola occurrence rate among airline passengers. This means the indicator is can no longer function as a validation tool. When it comes to future outbreaks, comparing with reality is not possible whatsoever.

Taking into account the difficulties of validation as described above, some of the characteristics of the past outbreak can be checked for. In reality no cases were detected at Brussels Airport, although it is known that (still incubating) Ebola cases passed (Ebola Coordinator Belgium, 2019). This corresponds with the model characteristics: requiring both fever characteristics and Ebola risk factors as indicated by the questionnaires in order to be suspected of carrying Ebola, results in a very low detection rate. The impact of the incubation time on the chance of detection of the disease makes undetected travelling of incubating cases likely. In a more general sense, limited effectivity of Ebola screening measures is in line with the professional opinion of experts and humanitarians in the field.

Although no actual airport information is available, it is expected the model does not show validity when it comes to the staff numbers, since they are very low. Also the amount of passengers making their flight in time would be unacceptable for any airport management.

9. Experiment plan

This chapter describes the experiments to be conducted in order to formulate an answer to the research question. This chapter specifies the inputs and scenarios that will be applied to the simulation model. Section 9.1 explains how the different experiments are specified. Following that section, the experiments are categorized in the following consecutive phases in the subsequent sections:

1. Preparation of models — section 9.2
2. Re-enacting the 2014-2015 outbreak — section 9.3
3. What-if scenario of a new outbreak — section 9.4
4. Innovative options and strategically deployed resources — section 9.5

The individual experiments that are done within these phases are listed in Table 9-1. The outcomes of the experiments as described in this chapter are listed in Chapter 10.

Table 9-1 Categorization of experiments

Section	Flight schedule	Experiment
9.3 Re-enacting outbreak	2014	No screening measures
		3x NCIT screening and questionnaire
		Both NCIT screening and questionnaire suspected required
		Minimal and regular timetable
		Fever prevalence check
		Prevalence other diseases
9.4 What-if scenario	2019	No screening measures
		3x NCIT screening and questionnaire with staff check
		3x NCITC screening and questionnaire with staff check
9.5 Innovation and hubs	2019	RDT screening with/without other screenings
		RDT screening without secondary screening
		Screening at hubs

9.1. Experiment specification

This section specifies how the different experiments are specified and distinguished, by varying the inputs of the models. This is followed by the introduction of a table which is used to list the experiment characteristics for all experiments to be conducted.

Firstly the **flight schedule** is defined. The airport and scenario of interest are determined by the flight schedule. The scenarios of interest are shown in Table 9-2. Since Senegal and Ghana were not the countries which have been most affected by Ebola and their airports did not suffer from large scale flight cancellations, their main airports (DSS and ACC) are not included in the 2014 scenarios.

Table 9-2 Experiment scenarios

	Flight schedule 2019	Reduced flight schedule 2014	Regular flight schedule 2014
ROB	ROB ‘19	ROB ’14 MIN	ROB ’14 REG
FNA	FNA ‘19	FNA ’14 MIN	FNA ’14 REG
CKY	CKY ‘19	CKY ’14 MIN	CKY ’14 REG
DSS	DSS ‘19	Out of scope	Out of scope
ACC	ACC ‘19	Out of scope	Out of scope

The capacities of the airports in the different scenarios in Table 9-2 vary. This is accounted for by specifying the number of employees staffed at the check-in desk, security station and customs control. Since information regarding the actual capacity at these airports is unknown, experiments are conducted to test for these capacities. This is discussed in section 9.2.

Secondly the **prevalence of Ebola** is considered. Based on the disease prevalence within the three main affected countries, the chance of carrying Ebola is calculated. To account for the uncertainty regarding the prevalence of the disease and the reduced chance of an airline passenger to be at risk of having Ebola, the disease prevalence is *multiplicated with a factor* that can be varied over different experiments. Furthermore, the *fraction of Ebola with fever* can be varied, to account for the asymptotic period commencing the illness period.

Third element of interest is the **prevalence of other diseases**. This is an unknown that can influence the effectivity of Ebola detection. Therefore, the *occurrence* of other diseases as well as the *fraction with fever* of persons with other diseases can be varied.

The fourth input factor is the specification of the **screening stations**. The different types of screening (NCIT, NCITC, questionnaires, RDT check and secondary screening) are situated on different locations at the airport (outside the terminal, after check-in, at the gates, for arriving passengers). Furthermore, the (ranges of) sensitivity and specificity are defined. Throughout the model run, the values are varied over the ranges as derived from literature, since the specific values are unknown.

Fifth factor of interest is whether **both or either fever screening and questionnaires** have to raise suspicion of Ebola infection in order to be sent through to secondary screening. Naturally, this is only specified if both these screening stations are included in the model. Sixth factor is the **staffing of the screening stations**. This concerns the number of screeners and nurses working at the airport. Finally, the **indicators of interest** are specified. Not all indicators are researched in every experiment.

Table 9-3 shows the table in which the experiment specification is defined. Each scenario of the model run in Simio consists of ten replications.

Table 9-3 Mock-up of experiment specification

Experiment X: Mock-up experiment specification	
Flight schedule	The flight schedule(s) used, representing the used airports and scenarios
Ebola prevalence	The multiplication factor(s) of the Ebola prevalence; the percentage of Ebola cases with fever
Other disease prevalence	The occurrence of other diseases; the percentage of these cases with fever
Screening stations	The type of screening (if any) deployed at screening station 1, 2, screening at gates, and inbound screening. For all screening stations values for sensitivity and specificity.
1	
2	
gates	
inbound	
secondary screening	
To secondary screening if..	Whether BOTH or EITHER Ebola suspicion by fever screening and questionnaire results in secondary screening. If applicable
Staff deployed	The number of screeners and nurses deployed
Indicator of interest	Which indicators are considered in this experiment

9.2. Preparation of models

Capacity of regular airport operations is represented by the number of staff working there. Therefore, simulations are performed for the different airports and flight schedules as shown in Table 9-2 with different staff numbers. These staff numbers are varied to find the number of staff that is sufficient to make the passengers catch their flight. The resulting numbers for the indicators *People reach destination in time* and *Time in queue* will function as the baseline to test the effects of screening operations on.

In reality, an airport will aim to have every passenger catch their flight. Passengers that risk missing their flight, might jump queues or receive special assistance to make it to their gate in time. In the simulation model this behaviour is not possible. Therefore, within this experiment regular airport operations are deemed to be adequate when 99 per cent of passengers catch their flight. Regular airport operations staffing numbers at hubs are not within the scope of this research.

9.3. Re-enacting the 2014-2015 outbreak

Before policies countering a possible future outbreak are investigated, we have to understand the 2014-2015 Ebola outbreak. The experiments as shown in Table 9-4 are included.

Table 9-4 Experiments 1 to 6

Re-enacting the 2014-2015 outbreak	
Experiment 1	No screening measures
Experiment 2	3x NCIT screening and questionnaire
Experiment 3	Both NCIT screening and questionnaire suspected required
Experiment 4	Minimal and regular timetable
Experiment 5	Fever prevalence check
Experiment 6	Prevalence other diseases

First the scenario without screening is considered, with the reduced flight schedule. Main unknown is the prevalence of Ebola among passengers: on the one hand the underreporting of cases resulting in seventeen to seventy per cent more cases than reported, on the other hand the assumed reduced chance of Ebola cases attempting to travel. Therefore, the prevalence of Ebola is multiplied with factor 1.7, 1.17, 1, 0.5 and 0.1. Single indicator of interest is the number of infected arrivals.

Table 9-5 Specification experiment 1

Experiment 1: 2014-2015 outbreak, no screening measures		
Flight schedule	ROB ’14 MIN, FNA ’14 MIN, CKY ’14 MIN	
Ebola prevalence	factor 1.7, 1.17, 1, 0.5, 0.1	0.283 with fever
Other disease prevalence	0.01 other disease	0.05 with fever
Screening stations	None	
Indicators of interest	Infected arrivals	

Next experiment concerns the deployment of fever screening. Based on the experiences of humanitarians in the region, this screening consists of three fever screening stations, supplemented

with a questionnaire to test for Ebola risk factors. As in the previous experiment, Ebola prevalence is multiplied with factor 1.7, 1.17, 1, 0.5 and 0.1.

In line with previously conducted research, a passenger is regarded suspected and sent through to secondary screening if fever screening or the questionnaire gives reason for Ebola suspicion. Since the impact of staff deployment is not yet focus of this experiment, the stations are staffed with 10 screeners and 10 nurses; this is an overstaffing in the model. Indicators of interest are both *infected arrivals* and *false positives.*

Table 9-6 Specification experiment 2

Experiment 2: 2014-2015 outbreak, 3x NCIT screening and questionnaire		
Flight schedule	ROB '14 MIN, FNA '14 MIN, CKY '14 MIN	
Ebola prevalence	factor 1.7, 1.17, 1, 0.5, 0.1	0.283 with fever
Other disease prevalence	0.01 other disease	0.05 with fever
Screening stations		
1	NCIT screening Sens: Random.uniform(0.8,0.9) Spec: Random.uniform(0.92,0.99)	Questionnaire Sens: Random.uniform(0.2,0.25) Spec: Random.uniform(0.85,0.99)
2	NCIT screening Sens: Random.uniform(0.8,0.9) Spec: Random.uniform(0.92,0.99)	
gates	NCIT screening Sens: Random.uniform(0.8,0.9) Spec: Random.uniform(0.92,0.99)	
inbound	/	
secondary screening	Sens: Random.uniform(0.84,1) Spec: Random.uniform(0.92,1)	
To secondary screening if..	Fever screening OR questionnaire mark passenger as suspected	
Screening staff deployed	10 screeners	10 nurses
Indicators of interest	Infected arrivals; False positives	

The previous experiment's number of infected Ebola arrivals for the different Ebola prevalence rates results in a most likely scenario given the actual detected Ebola cases. The actual number of cases outside of the affected area is 7 (excluding the medically evacuated cases) (Centers for Disease Control and Prevention, 2019). The scenario that correspondents with this amount of infected passengers will be used for the further scenarios, to ease the comparison of the scenarios. This does not mean this fraction is deemed the correct one, it is solely a simplification to make comparing possible.

At Brussels Airport passengers were suspected of having Ebola if *both* fever screening and the conducted questionnaire indicated a possible case of Ebola. Furthermore, given the specificity of the airport screening measures, it is assumed that the scenario where either of the screening stations raises Ebola suspicion will lead to a large number of false positives. Therefore the next experiment is specified as shown in Table 9-7, using the Ebola prevalence factor as found in the previous experiment.

Table 9-7 Specification experiment 3

Experiment 3: 2014-2015 outbreak, both NCIT screening and questionnaire suspected required		
Flight schedule	ROB ’14 MIN, FNA ’14 MIN, CKY ’14 MIN	
Ebola prevalence	As from experiment 2	0.283 with fever
Other disease prevalence	0.01 other disease	0.05 with fever
Screening stations		
1	NCIT screening Sens: Random.uniform(0.8,0.9) Spec: Random.uniform(0.92,0.99)	Questionnaire Sens: Random.uniform(0.2,0.25) Spec: Random.uniform(0.85,0.99)
2	NCIT screening Sens: Random.uniform(0.8,0.9) Spec: Random.uniform(0.92,0.99)	Questionnaire Sens: Random.uniform(0.2,0.25) Spec: Random.uniform(0.85,0.99)
gates	NCIT screening Sens: Random.uniform(0.8,0.9) Spec: Random.uniform(0.92,0.99)	Questionnaire Sens: Random.uniform(0.2,0.25) Spec: Random.uniform(0.85,0.99)
inbound	/	
secondary screening	Sens: Random.uniform(0.84,1) Spec: Random.uniform(0.92,1)	
To secondary screening if..	Fever screening AND questionnaire mark passenger as suspected	
Staff deployed	10 screeners	10 nurses
Indicators of interest	Infected arrivals; False positives	

The experiments as specified so far concern the reduced flight schedule as operated by the airlines in the region as a response to the ongoing epidemic. Therefore it already includes one of the measures: the cancellation of flights. To estimate the effects of this measure, an experiment is included that compares the minimal flight schedule with the regular airline operations in 2014, as shown in Table 9-8.

Table 9-8 Specification experiment 4

Experiment 4: 2014-2015 outbreak, minimal and regular timetable		
Flight schedule	ROB ’14 MIN, FNA ’14 MIN, CKY ’14 MIN ROB ’14 REG, FNA ’14 REG, CKY ’14 REG	
Ebola prevalence	As from experiment 2	0.283 with fever
Other disease prevalence	0.01 other disease	0.05 with fever
Screening stations		
1	NCIT screening Sens: Random.uniform(0.8,0.9) Spec: Random.uniform(0.92,0.99)	Questionnaire Sens: Random.uniform(0.2,0.25) Spec: Random.uniform(0.85,0.99)
2	NCIT screening Sens: Random.uniform(0.8,0.9) Spec: Random.uniform(0.92,0.99)	
gates	NCIT screening Sens: Random.uniform(0.8,0.9) Spec: Random.uniform(0.92,0.99)	
inbound	/	
secondary screening	Sens: Random.uniform(0.84,1)	

	Spec: Random.uniform(0.92,1)	
To secondary screening if..	Fever screening OR questionnaire mark passenger as suspected	
Staff deployed	10 screeners	10 nurses
Indicators of interest	Infected arrivals; False positives; Flights operated	

Other research considers Ebola fever screening as quite effective, successfully identifying 83.4 per cent of the passengers with Ebola (Gold et al., 2019). The hypothesis is that this is due to the disregarding of the incubation time of the disease, resulting in a fever fraction of 85 per cent for all travellers with Ebola. In the following experiment, shown in

Table 9-9, this hypothesis is tested.

Table 9-9 Specification experiment 5

Experiment 5: 2014-2015 outbreak, fever prevalence check		
Flight schedule	ROB '14 MIN, FNA '14 MIN, CKY '14 MIN	
Ebola prevalence	As from experiment 2	0.85, 0.283 with fever
Other disease prevalence	0.01 other disease	0.05 with fever
Screening stations		
1	NCIT screening Sens: Random.uniform(0.8,0.9) Spec: Random.uniform(0.92,0.99)	Questionnaire Sens: Random.uniform(0.2,0.25) Spec: Random.uniform(0.85,0.99)
2	NCIT screening Sens: Random.uniform(0.8,0.9) Spec: Random.uniform(0.92,0.99)	
gates	NCIT screening Sens: Random.uniform(0.8,0.9) Spec: Random.uniform(0.92,0.99)	
inbound	/	
secondary screening	Sens: Random.uniform(0.84,1) Spec: Random.uniform(0.92,1)	
To secondary screening if..	Fever screening OR questionnaire mark passenger as suspected	
Staff deployed	10 screeners	10 nurses
Indicators of interest	Infected arrivals, False positives	

Final experiment of the 2014 scenario concerns the prevalence of other diseases. This is a highly uncertain variable, which is expected to have an influence on the effectivity of Ebola fever screening, mainly by impacting the false positive rate. Therefore two factors are varied: the prevalence of other diseases, and the percentage of the ill population with fever. This experiment is shown in Table 9-10.

Table 9-10 Specification experiment 6

Experiment 6: 2014-2015 outbreak, prevalence other diseases		
Flight schedule	ROB '14 MIN, FNA '14 MIN, CKY '14 MIN	
Ebola prevalence	As from experiment 2	0.283 with fever
Other disease prevalence	0.01, 0.05 other disease	0.05, 0.25 with fever

Screening stations		
1	NCIT screening Sens: Random.uniform(0.8,0.9) Spec: Random.uniform(0.92,0.99)	Questionnaire Sens: Random.uniform(0.2,0.25) Spec: Random.uniform(0.85,0.99)
2	NCIT screening Sens: Random.uniform(0.8,0.9) Spec: Random.uniform(0.92,0.99)	
gates	NCIT screening Sens: Random.uniform(0.8,0.9) Spec: Random.uniform(0.92,0.99)	
inbound	/	
secondary screening	Sens: Random.uniform(0.84,1) Spec: Random.uniform(0.92,1)	
To secondary screening if..	Fever screening OR questionnaire mark passenger as suspected	
Staff deployed	10 screeners	10 nurses
Indicators of interest	Infected arrivals, False positives	

9.4. What-if scenario of a new outbreak

The insights gained in previous experiments will be used to estimate the effects of a new outbreak. The experiments as listed in Table 9-11 are included, with the 2019 flight schedule operational.

Table 9-11 Experiments 7 to 9

What-if scenario of a new outbreak	
Experiment 7	No screening measures
Experiment 8	3x NCIT screening and questionnaire with staff check
Experiment 9	3x NCITC screening and questionnaire with staff check

First the scenario without screening measures will be considered, shown in Table 9-12. The same Ebola prevalence among airline passengers is assumed as in the 2014-2015 scenario.

Table 9-12 Specification experiment 7

Experiment 7: 2019 outbreak, no screening measures		
Flight schedule	ROB ’19 MIN, FNA ’19 MIN, CKY ’19 MIN	
Ebola prevalence	Same as ‘14	0.283 with fever
Other disease prevalence	0.01 other disease	0.05 with fever
Screening stations	None	
Indicators of interest	Infected arrivals	

Next step is the deployment Ebola screening measures, equal to the 2014 scenario. However, this time the airport level logistics are included. This means that staff deployment is a factor of interest. The number of screening staff deployed is varied to investigate the impacts on airport logistics. As shown in

Table 9-13, scenarios with 1 to 8 screeners and nurses will be tested, resulting in a matrix with average *Destination in time* and *Time in queue* for the respective staffing numbers. This number of screening staff might appear limited, but is significant compared to the number of regular airport staff.

Table 9-13 Specification experiment 8

Experiment 8: 2019 outbreak, 3x NCIT screening and questionnaire with staff check		
Flight schedule	ROB '19, FNA '19, CKY '19	
Ebola prevalence	Same as '14	0.283 with fever
Other disease prevalence	0.01 other disease	0.05 with fever
Screening stations		
1	NCIT screening Sens: Random.uniform(0.8,0.9) Spec: Random.uniform(0.92,0.99)	Questionnaire Sens: Random.uniform(0.2,0.25) Spec: Random.uniform(0.85,0.99)
2	NCIT screening Sens: Random.uniform(0.8,0.9) Spec: Random.uniform(0.92,0.99)	
gates	NCIT screening Sens: Random.uniform(0.8,0.9) Spec: Random.uniform(0.92,0.99)	
inbound	/	
secondary screening	Sens: Random.uniform(0.84,1) Spec: Random.uniform(0.92,1)	
Staff deployed	1, 2, 3, 4, 5, 6, 7, 8 screeners	1, 2, 3, 4, 5, 6, 7, 8 nurses
Outcome of interest	Infected arrivals; False positives; Destination in time; Time in queue	

The experiments so far included NCIT screening (forehead screenings) as a fever screening method. However, conducting these individual measurements requires a temperature measurement for each individual passenger by a screener. An alternative is NCITC screening, where passengers walk by and have their body temperature taken. Table 9-14 shows the three NCIT screening stations as in the previous experiment, replaced by NCITC stations. This is done to measure the impact on the performance indicators, using the screening staffing from previous experiment. Due to the shorter processing time, it is expected that less staff is adequate. This is included as a scenario.

Table 9-14 Specification experiment 9

Experiment 9: 2019 outbreak, 3x NCITC screening and questionnaire with staff check		
Flight schedule	ROB '19, FNA '19, CKY '19	
Ebola prevalence	Same as '14	0.283 with fever
Other disease prevalence	0.01 other disease	0.05 with fever
Screening stations		
1	NCITC screening Sens: Random.uniform(0.7,0.9) Spec: Random.uniform(0.92,0.99)	Questionnaire Sens: Random.uniform(0.2,0.25) Spec: Random.uniform(0.85,0.99)
2	NCITC screening Sens: Random.uniform(0.7,0.9) Spec: Random.uniform(0.92,0.99)	
gates	NCITC screening	

	Sens: Random.uniform(0.7,0.9) Spec: Random.uniform(0.92,0.99)
inbound	/
secondary screening	Sens: Random.uniform(0.84,1) Spec: Random.uniform(0.92,1)
Staff deployed	As from experiment 8, experiments with less staff
Indicators of interest	Infected arrivals; False positives; Destination in time; Time in queue; Airport resources

9.5. Innovative options and strategically deployed resources

The aforementioned experiments estimate the effects of the conventional screening methods. This section investigates other options, using the RDT to screen for Ebola, and strategically deploying resources, by focussing on screening at the hub airports that infected passengers travel through. The following experiments are included, with the 2019 flight schedule:

Table 9-15 Experiments 10 to 12

Innovative options and strategically deployed resources	
Experiment 10	RDT screening with/without other screenings
Experiment 11	RDT screening without secondary screening
Experiment 12	Screening at hubs

The first experiment in this section concerns RDT deployment. An RDT screening station is deployed instead of a fever screening station. The RDT scenarios include policies with and without other screening stations operational. This is summarized in Table 9-16.

Table 9-16 Specification experiment 10

Experiment 10: 2019 outbreak, RDT screening with/without other screenings		
Flight schedule	ROB ’19, FNA ’19, CKY ’19	
Ebola prevalence	Same as ‘14	0.283 with fever
Other disease prevalence	0.01 other disease	0.05 with fever
Screening stations		
1	RDT screening Sens: Random.uniform(0.84,1) Spec: Random.uniform(0.92,1) OR RDT screening Sens: Random.uniform(0.99,1) Spec: Random.uniform(0.98,1)	Questionnaire Sens: Random.uniform(0.2,0.25) Spec: Random.uniform(0.85,0.99) OR None
2	NCIT screening Sens: Random.uniform(0.8,0.9) Spec: Random.uniform(0.92,0.99) OR None	
gates	/	
inbound	/	

secondary screening	Sens: Random.uniform(0.84,1) Spec: Random.uniform(0.92,1)
Staff deployed	As from experiment 8 Experiments with only RDT screening only include nurse staffing
Indicators of interest	Infected arrivals; False positives; Destination in time; Time in queue; Airport resources

In the scenarios with improved RDT performance, deployment of secondary screening might have a negative effect on the performance of the system. With a sensitivity of 84-100 per cent and a specificity of 92-100 per cent, secondary performs worse than the more optimistic RDT measures. Therefore, experiment 11 covers scenarios without secondary screening, see Table 9-17. This means a positive outcome of Ebola suspicion at the initial check immediately results in an Ebola suspicion, and a disruption of a passenger's travel plans.

Table 9-17 Specification experiment 11

Experiment 11: 2019 outbreak, RDT screening without secondary screening		
Flight schedule	ROB '19, FNA '19, CKY '19	
Ebola prevalence	Same as '14	0.283 with fever
Other disease prevalence	0.01 other disease	0.05 with fever
Screening stations		
1	RDT screening Sens: Random.uniform(0.84,1) Spec: Random.uniform(0.92,1) OR RDT screening Sens: Random.uniform(0.99,1) Spec: Random.uniform(0.98,1)	Questionnaire Sens: Random.uniform(0.2,0.25) Spec: Random.uniform(0.85,0.99) OR None
2	NCIT screening Sens: Random.uniform(0.8,0.9) Spec: Random.uniform(0.92,0.99) OR None	
gates	/	
inbound	/	
secondary screening	None	
Staff deployed	As from experiment 8 Experiments with only RDT screening only include nurse staffing	
Indicators of interest	Infected arrivals; False positives; Destination in time; Time in queue; Airport resources	

The final scenario considers screening at the hub airports. It is explored if hub screening can be effective, depending on the deployment of screening measures at the airports in the Ebola affected region. Figure 9-1 shows the flights to the hub airports. ACC airport receives flights from both ROB and FNA. DSS only receives passengers from CKY airport.

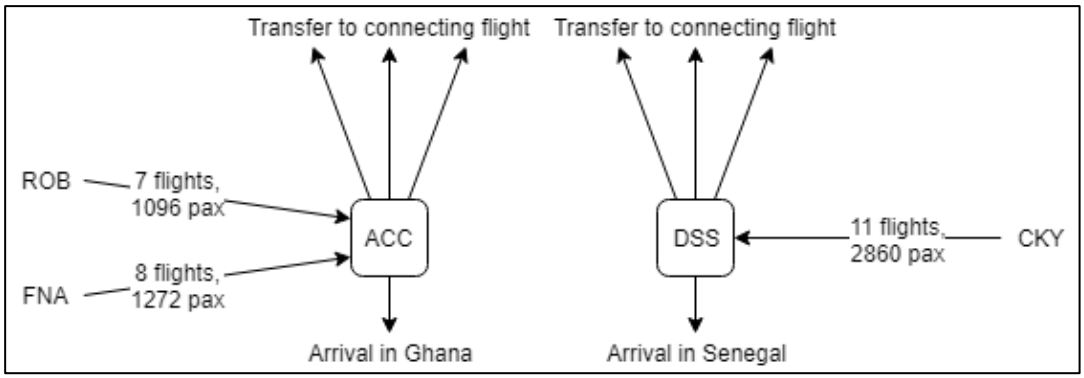


Figure 9-1 Flight operations from the Ebola affected area through hubs

The focus on the hubs within the network attempts to understand the roles of hubs and the feasibility of hub screening in different scenarios. In scenarios where only one or both airports in the affected region conduct screening measures, the effectivity of screening at the hub is assessed. Since DSS airport only receives flights from Guinea, only the effect of screening at CKY airport is considered. The specification of the experiment is shown in Table 9-18.

Table 9-18 Specification experiment 12

Experiment 12: 2019 outbreak, screening at hubs		
Flight schedule	ROB '19, FNA '19, CKY '19, DSS '19, ACC '19	
Ebola prevalence	Same as '14	0.283 with fever
Other disease prevalence	0.01 other disease	0.05 with fever
Screening stations	At hubs	
1		
2		
gates		
inbound	NCIT screening Sens: Random.uniform(0.8,0.9) Spec: Random.uniform(0.92,0.99)	Questionnaire Sens: Random.uniform(0.2,0.25) Spec: Random.uniform(0.85,0.99)
secondary screening	Sens: Random.uniform(0.84,1) Spec: Random.uniform(0.92,1)	
Staff deployed	1, 2, 3, 4, 5 screeners	1, 2, 3, 4, 5 nurses
Indicators of interest	Infected arrivals; False positives; Destination in time; Time in queue; Airport resources	

10. Data analysis

This chapter answers sub question 5: **How do policies for airports and airlines perform during an Ebola epidemic under different scenarios?** This chapter presents the outcomes that result from the experiments as described in chapter 9, and is structured similarly:

1. Preparation of models section 10.1
2. Re-enacting the 2014-2015 outbreak section 10.2
3. What-if scenario of a new outbreak section 10.3
4. Innovative options and strategically deployed resources section 10.4

Sections 10.1-4 summarize the outcomes of the experiments. At the end of each experiment section, the main insight of that experiment is highlighted. This is followed by section 10.5, which presents the practical implications of the outcomes.

10.1. Preparation

Table 10-1 shows the number of check-in, security and customs staff at the three airports of interest for the three scenarios. This is the minimal number of staff to guarantee 99 per cent of the travellers to reach their plane in time. As mentioned before, the number of staff does not reflect actual staff numbers due to model simplifications. It is however usable for relative comparison when deploying staff for screening operations.

Since the staff number reflect the needs at maximum capacity, required staff numbers may be higher for some airports even though aggregated passenger numbers are lower. This is due to required peak capacity to be higher, i.e. flights are less equally spread out over the day.

Table 10-1 Regular airport staffing

	'19			**'14 MIN**			**'14 REG**		
	Check-in	Security	Customs	Check-in	Security	Customs	Check-in	Security	Customs
ROB	4	3	3	5	4	2	5	4	2
FNA	6	4	3	4	2	2	7	6	6
CKY	5	4	2	5	4	2	5	4	2

10.2. Re-enacting the 2014-2015 outbreak

To estimate the effects of measures countering an outbreak, we first have to understand the previous outbreak. This section describes the outcomes of the six experiments that have been conducted, covering the 2014-2015 outbreak.

Experiment 1: 2014-2015 outbreak, no screening measures

Based on the disease prevalence and the (reduced) flight schedule in 2014, an estimation is made of the number of infected passengers travelling from the three airports in the area affected with Ebola, with no screening measures in place. The resulting number of infected arrivals from these airports is shown in Figure 10-1.

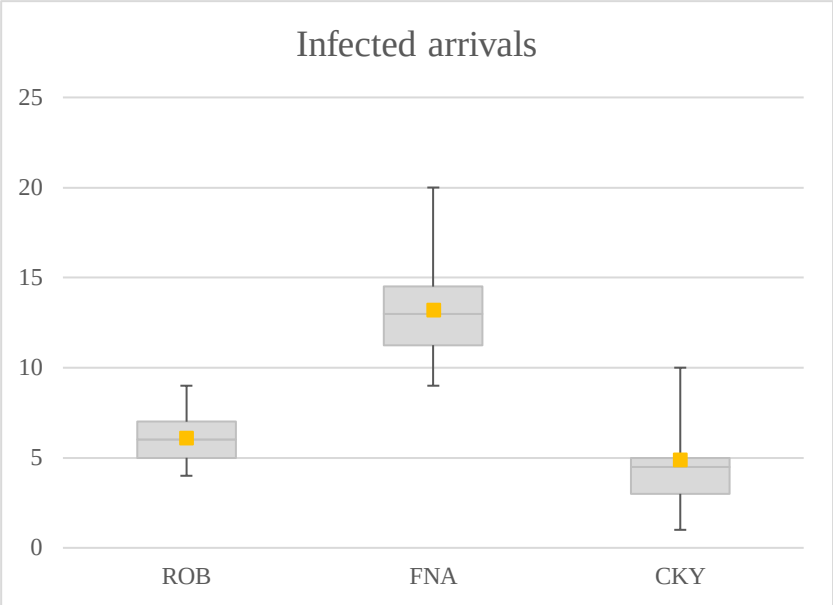


Figure 10-1 Infected arrivals 2014 without screening

The results as shown in Figure 10-1 assume every passenger to have a chance of Ebola infection, based on the prevalence of the disease in the country. To account for the uncertainty regarding the prevalence of Ebola among passengers, Figure 10-2 shows the sum of infected arrivals for an Ebola prevalence multiplied with factor 1.7, 1.17, 1, 0.5 and 0.1.

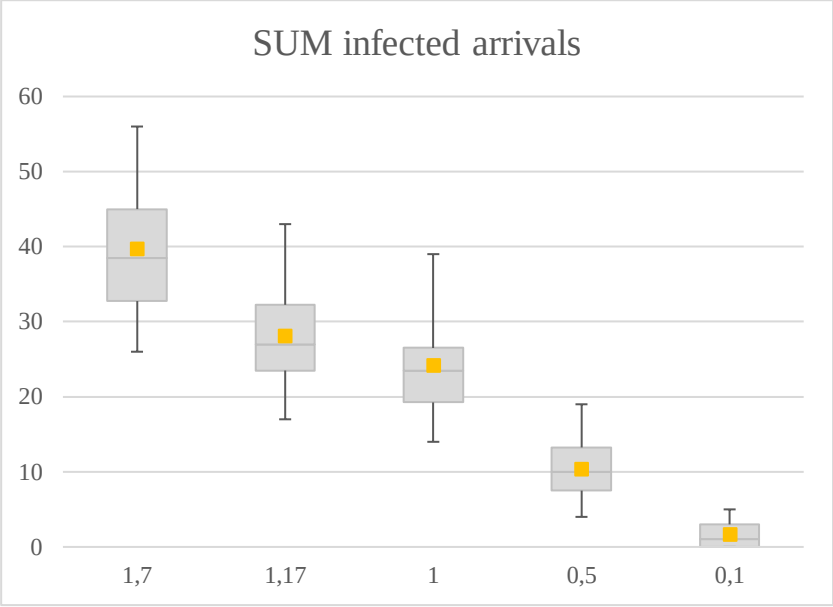


Figure 10-2 Sum of infected arrivals for Ebola prevalence factors

Main insight

Based on the prevalence of Ebola, an estimated number of 14 to 39 Ebola infected passengers will have attempted to board a plane over the course of half a year, of which a large part originating from Freetown Airport. Incorporating the uncertainty related to the underreporting of cases and the assumed lower chance of Ebola cases to board a plane, this range widens to 0 to 56 cases.

Experiment 2: 2014-2015 outbreak, 3x NCIT screening and questionnaire

Figure 10-3 shows the sum of infected arrivals for the different prevalence multiplication factors. Both the situation without screening measures, and deployment of three NCIT (forehead) scanners, supplemented with a questionnaire is included. The graph shows us that screening measures lower the number of infected arrivals, although in most cases the majority of passengers with Ebola pass undetected. In situations with a very low disease prevalence, no reduction in cases is visible.

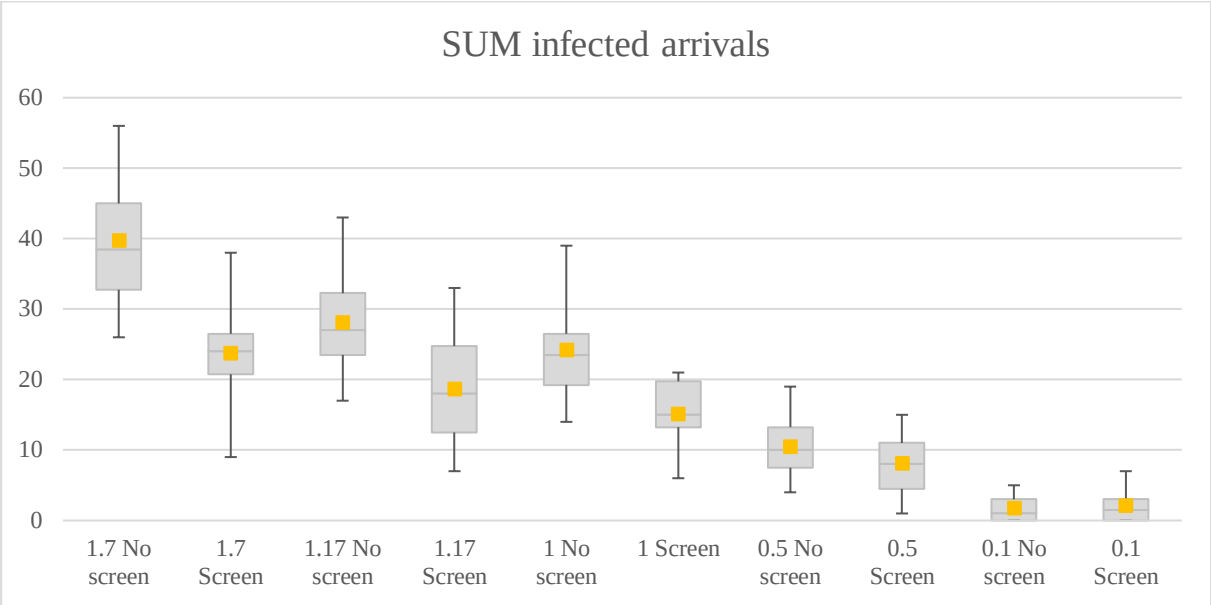


Figure 10-3 Sum infected arrivals 2014 for Ebola multiplication factors without/with screening

The information in Figure 10-3 can be compared with the number of infected arrivals in reality. The actual known number of cases that travelled by plane outside of the affected area is seven (Centers for Disease Control and Prevention, 2019). This means the multiplication value of .5 is regarded the most probable, leading to 1 to 15 cases. This value will be used to compare the different policies. Figure 10-4 shows the expected origin of the Ebola cases from the different airports, using this factor.

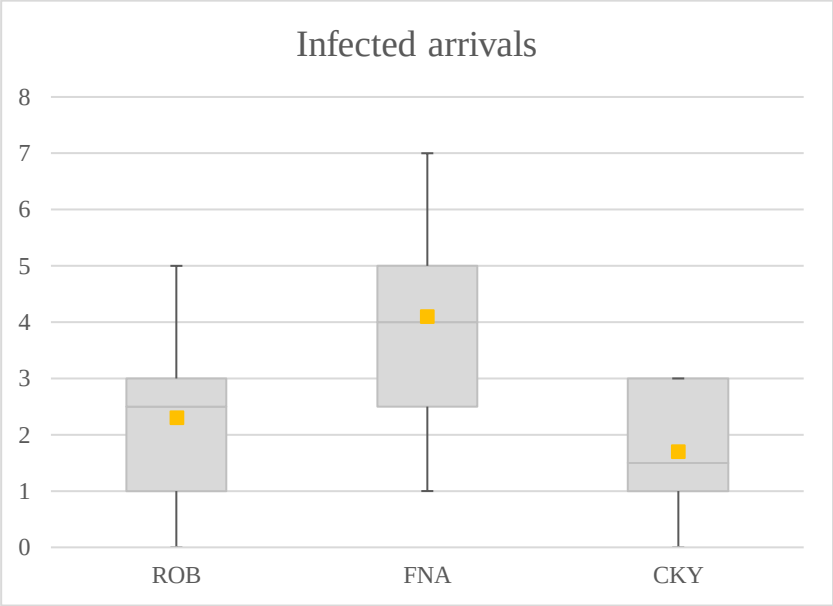


Figure 10-4 Infected arrivals 2014 per airport of origin, factor .5, with 3x NCIT screening and questionnaire

When examining the figures of Figure 10-3, there is a (limited) reduction in infected arrivals resulting from the screening measures. However, screening also leads to false positives. Figure 10-11 shows the number of false positives resulting from screening, which appears to be independent from the amount of Ebola infections.

Figure 10-5 Sum false positives 2014 for Ebola multiplication factors with 3x NCIT screening and questionnaire

The boxplots show the summed numbers at the end of the simulation runs. The number of Ebola infected arrivals and false positives can also be shown over time. Figure 10-6 shows the number of false positives over time, which behaves independent of the prevalence of the disease. The only variance that occurs is expected to be a result of randomness in the model.

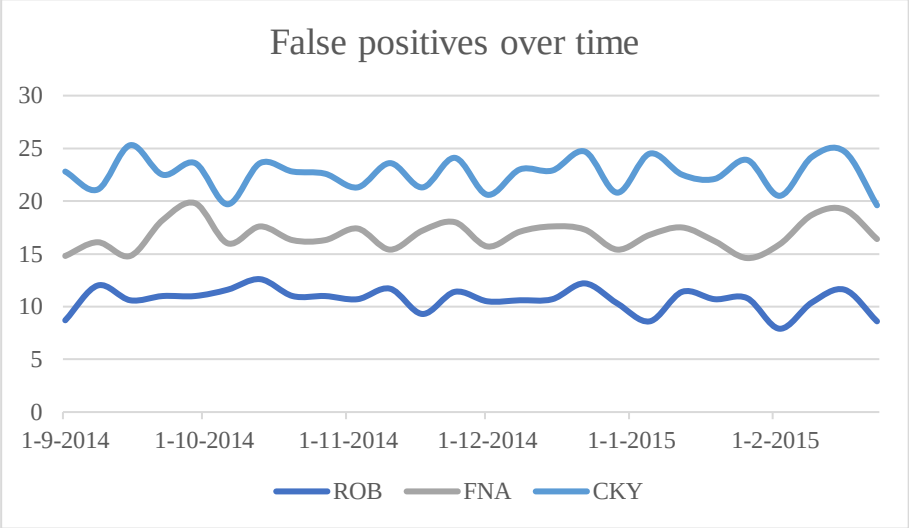


Figure 10-6 Ebola infected arrivals over time

The number of infected arrivals over time from the three airports is shown in Figure 10-7, Figure 10-8 and Figure 10-9. In these figures the average weekly number of Ebola cases is plotted and compared with the number of Ebola cases over time. The results raise suspicion of the number of cases following the course of the disease, but the number of cases is too small to make a well-founded conclusion.

Figure 10-10 shows that the number of infected arrivals from ROB airport over time does in fact follow the course of the disease, by taking a strongly aggravated Ebola epidemic, resulting in a more solid result. This behaviour can be seen at the other airports as well.

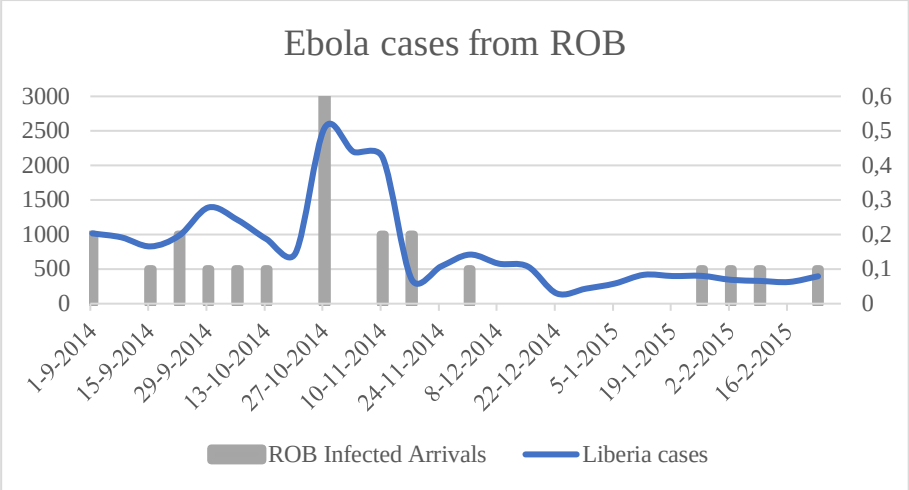


Figure 10-7 Infected arrivals over time ROB

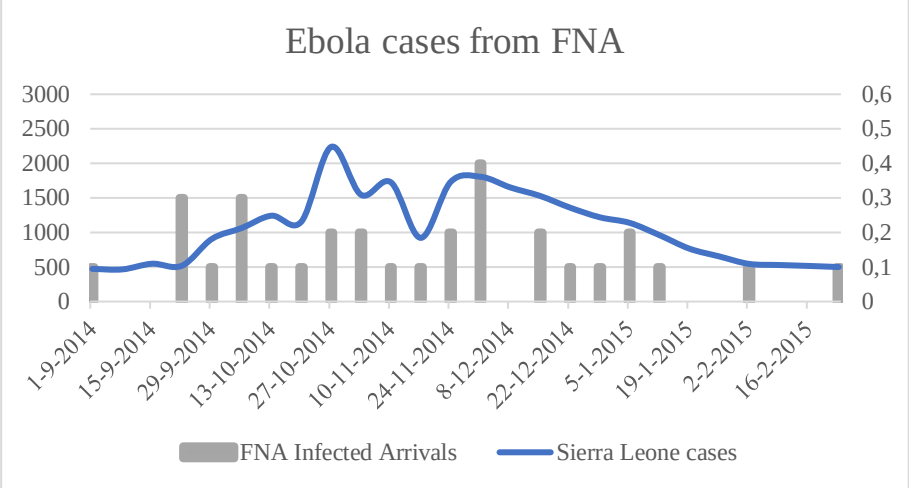


Figure 10-8 Infected arrivals over time FNA

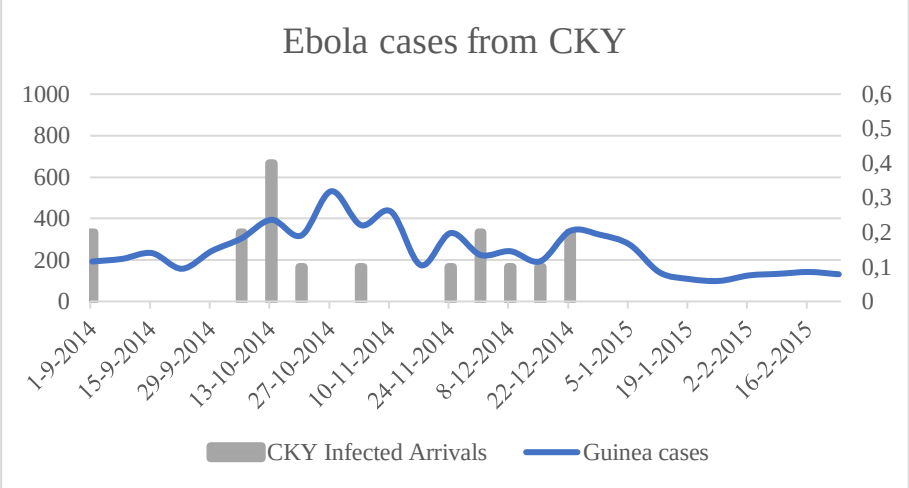


Figure 10-9 Infected arrivals over time CKY

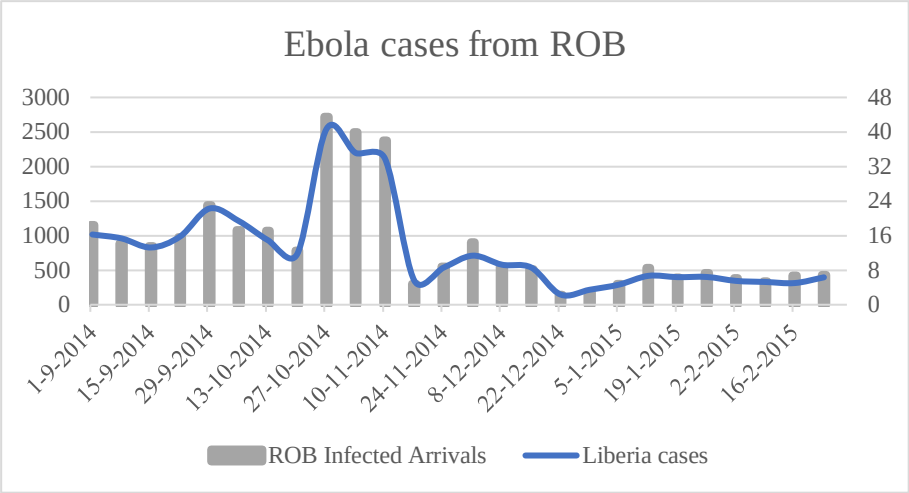


Figure 10-10 Infected arrivals over time ROB, prevalence factor 100

Main insight

Multiplication of the Ebola prevalence with .5 reflects the chance of the infected to board a plane, accounting for the underreporting of cases and the chance of the infected to be an airline passenger.

Ebola screening using fever screening and questionnaires results in a large number of false positives. This is independent of the prevalence of Ebola. The number of infected Ebola arrivals follows the course of the disease over time, the number of false positives does not.

Experiment 3: 2014-2015 outbreak, both NCIT screening and questionnaire suspected required

Experts at Brussels Airport indicated that both fever detection and Ebola suspicion resulting from a questionnaire is necessary in order to detain an individual and denying their onward travel. Figure 10-11 shows the results: a comparison between the number of infected arrivals and false positives of measures in which both or either fever detection and Ebola risk factor detection is necessary in order to prevent an individual from travelling. The results are shown in tabular form in Table 10-2.

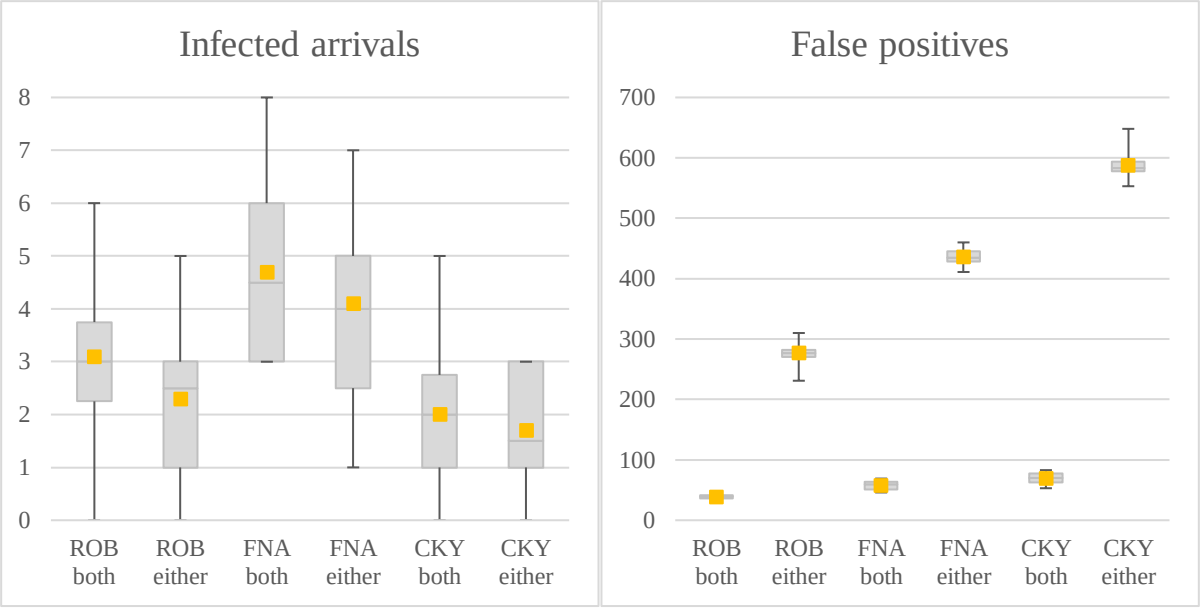


Figure 10-11 Infected arrivals and false positives 2014 per airport of origin, comparing the 'both' and 'either' policy for fever screening and questionnaires

Table 10-2 Comparison of a 'both' versus an 'either' policy for fever screening and questionnaires

	Both		Either		% change	
	Infected Arrivals	False Positives	Infected Arrivals	False Positives	Infected Arrivals	False Positives
SUM	9.8	166.5	8.1	1301.5	-17%	+682%

Main insight

A policy where either fever or questionnaires identify an Ebola suspicion causes 13 to 26 per cent fewer infected arrivals compared to a policy where both are required. However, the number of false positives is about seven times larger. This clearly illustrates the trade-off between specificity and sensitivity.

Experiment 4: 2014-2015 outbreak, minimal and regular timetable

A measure on the network level to reduce the number of infected arrivals is to reduce the number of flights. Experiment 4 is shown in Figure 10-12, with the number of expected Ebola arrivals with the minimal flight schedule as was operational during the Ebola outbreak, compared to a hypothetical situation in which the number of flights was not reduced. Both scenarios deploy three fever screening stations and a questionnaire to prevent the Ebola cases to travel. A clear reduction in infected arrivals can be found, resulting from the reduction of flights. The lack of reduction from Guinea (CKY) is expected to be caused by the limited number of cases, resulting in less solid results.

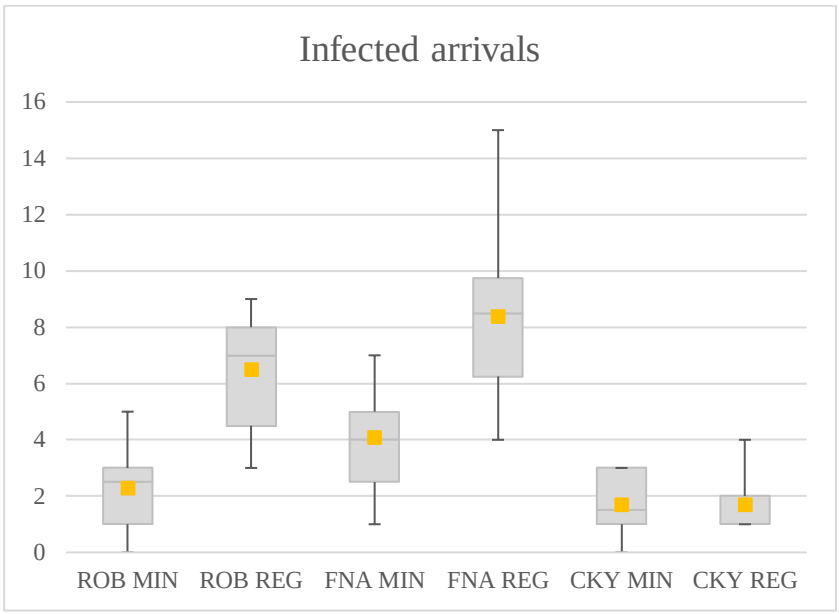


Figure 10-12 Infected arrivals 2014 per airport of origin for the minimal and regular flight schedule

The results of flight reductions are shown in tabular form in Table 10-3. A reduction of the number of flights of on average 62 per cent leads to a reduction in Ebola cases of on average 51 per cent. The boxplot as shown in Figure 10-12 illustrates that the uncertainty is large.

Table 10-3 Weekly departures from the airports of interest in the regular and minimal timetable

	ROB		FNA		CKY		SOM	
	Flights	Cases	Flights	Cases	Flights	Cases	Flights	Cases
Regular '14	41	6.5	34	8.4	37	1.7	112	16.6
Minimal '14	8	2.3	14	4.1	21	1.7	43	8.1
Change	-80%	-65%	-59%	-51%	-43%	0%	-62%	-51%

Main insight

The reduction of flights results in an approximately proportional reduction of infected arrivals.

Experiment 5: 2014-2015 outbreak, fever prevalence check

Previous research shows a significantly higher effectivity of screening measures than shown in this research so far. It is expected that this difference results from the fever fraction, which is assumed to be lower because of the long incubation time of the disease. Figure 10-13 shows the effects of the incubation time on the number of Ebola cases departing from the three airports. The X-axis shows the fraction of Ebola cases with fever: 85 per cent symptomatic cases is the situation without incubation time, 28.3 per cent is the situation with. The figure shows a major influence of the fever fraction on the effectiveness of screening measures.

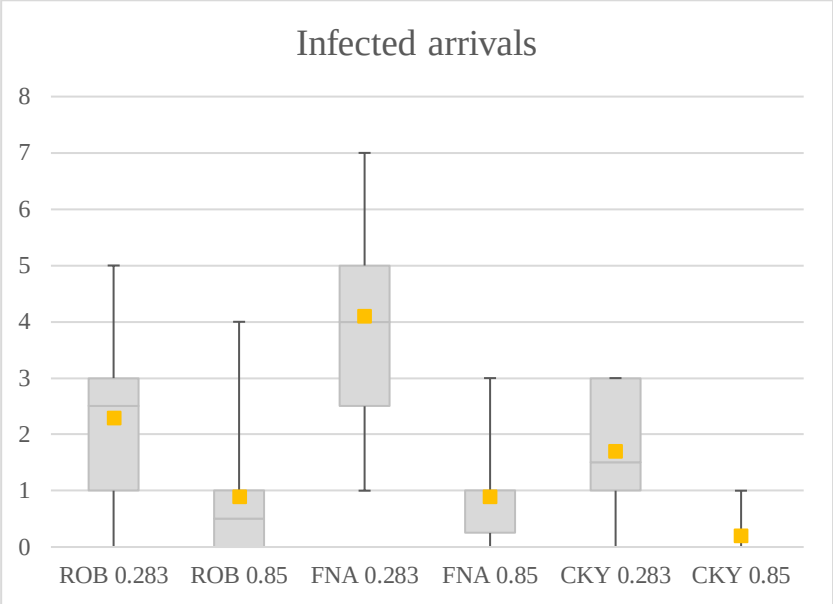


Figure 10-13 Infected arrivals 2014 per airport of origin for .283 and .85 symptomatic fractions

Main insight

The incubation time (representation by the fever fraction) has a major negative influence on the effectiveness of conventional screening measures.

Experiment 6: 2014-2015 outbreak, prevalence other diseases

The prevalence of other diseases is considered a factor that can influence the effectivity of Ebola screening. As shown in Figure 10-14, the number of infected arrivals is relatively stable regardless the prevalence of other diseases or their fever fractions. However, the number of false positives is strongly influenced by the fraction of other diseases.

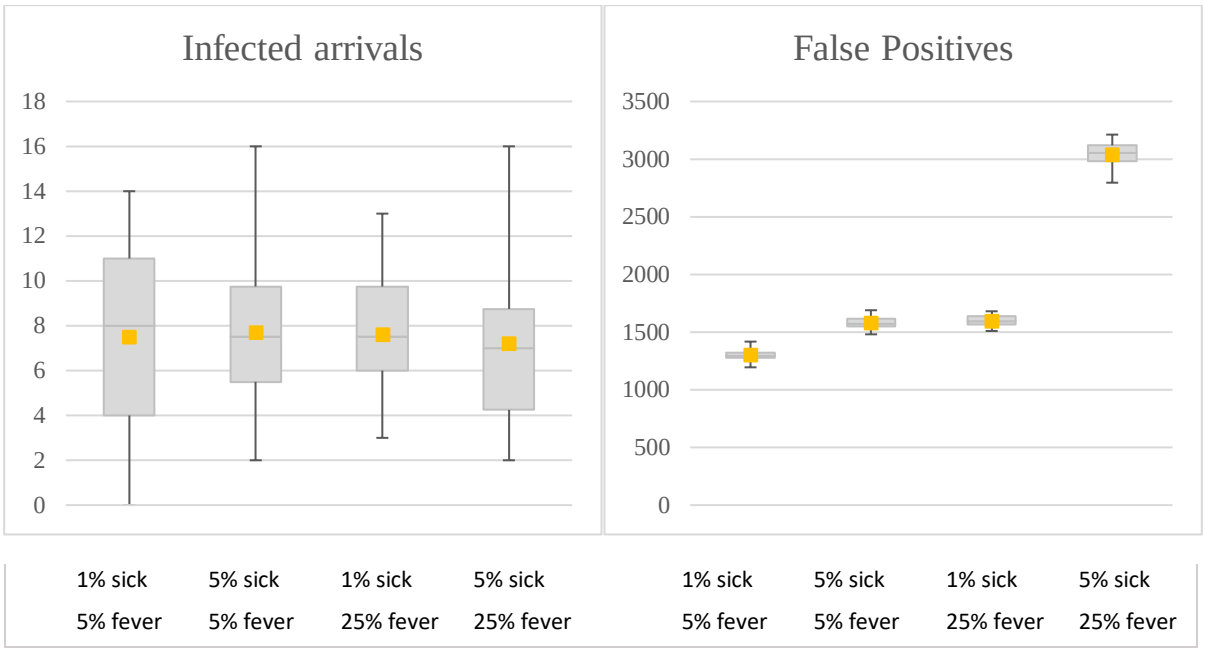


Figure 10-14 Infected arrivals and false positives for other disease and fever fractions

Main insight

The number of false positives is strongly influenced by the prevalence of other diseases with fever. The number of infected arrivals is not.

10.3. What-if scenario of a new outbreak

A new outbreak of Ebola with the current flight schedule in place is analysed in experiment 7, 8 and 9. It shows how an outbreak of a scale of the 2014-2015 pandemic could spread with the current flight operations in place.

Experiment 7: 2019 outbreak, no screening measures

In order to be able to compare this scenario with the previous ones, the multiplication factor of .5 is used on an outbreak of the same magnitude as the 2014-2015 outbreak, but with the current flight schedule. The resulting number of infected arrivals in the 2019 scenario is expected to be considerably higher than in 2014-2015, as shown in Figure 10-15.

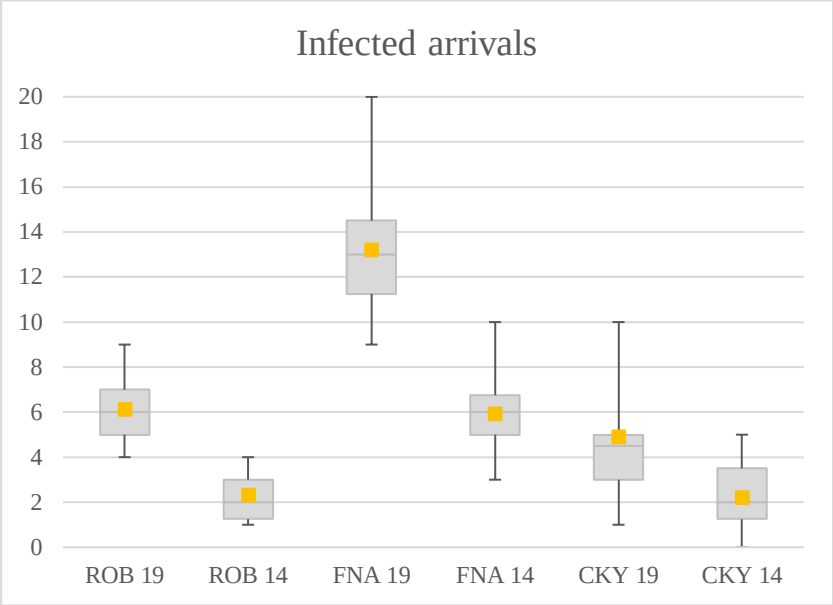


Figure 10-15 Infected arrivals 2019 & 2014 without screening, per airport of origin

Main insight

It is expected that 14-39 infected passengers board a flight if no screening is deployed, a clear increase compared to the 2014-2015 outbreak. This shows, as in experiment 4, the effect of the network operations on the number of infected arrivals.

Experiment 8: 2019 outbreak, 3x NCIT screening and questionnaire with staff check

This experiment assesses the deployment of the screening method of three NCIT screenings supplemented with a questionnaire. This results in the infected arrivals as shown in Figure 10-16. This means that over the course of 6 months of an Ebola epidemic of the scale of the 2014-2015 epidemic with the current flight schedule, 5 to 27 Ebola cases are expected to travel out of the area, with these screening measures in place.

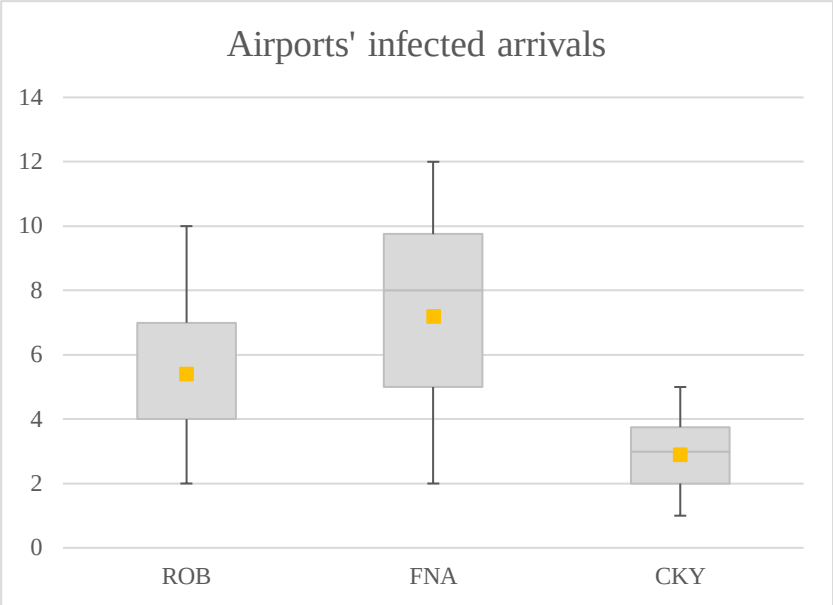


Figure 10-16 Infected arrivals 2019 with 3x NCIT screening and questionnaires, per airport of origin

Next step is to incorporate the outcomes on the operational level. In order to model the airport level operations, firstly the number of screening staff needs to be defined. Experiments are conducted to find a value of staff that results in at least 95 per cent of passengers arriving at their gate in time. This is a relatively low percentage, since in reality the airport will aim to make all passengers catch their flight. However, within this simulation model it is decided to aim for the 95 per cent limit, as at some airports a value significantly higher than that is not attainable with screening measures in place, even with a vast overstaffing.

The screening staff numbers are shown in Table 10-4. They may appear limited, but are, as the regular staff numbers, lower than is expected in reality because of the modelling method. To put the numbers into perspective, the staffing size as percentage of the regular airport operations staffing in the model is shown. Here it shows it is actually a very substantial staffing capacity, with on average an extra staff demand of 73 per cent.

Table 10-4 Screening staff deployed per airport, absolute and as percentage of regular staffing

	Screeners	Nurses	SUM	% of regular staffing
ROB	4	2	6	60%
FNA	7	4	11	85%
CKY	5	3	8	73%

Main insight

There exists a trade-off between deployed resources and the efficient operations on the airport level: inadequate resources result in worse airport performance.

On average, an extra staffing of 73 per cent of the regular airport operations staffing is needed in order to efficiently perform airport screening measures – meaning 95 per cent of passengers arrive at their gate in time.

Experiment 9: 2019 outbreak, 3x NCITC screening and questionnaire with staff check

This experiment compares screening performance with different staffing numbers. For all three airports, six scenarios are included. Screening consists of NCIT screening plus questionnaires, NCITC screening plus questionnaires and NCITC screening only. These screenings are done with the staffing numbers as resulted from experiment 8, as well as with reduced staffing capacity. The outcomes on five indicators are shown for these scenarios. Since all flights are operated, the indicator *Percentage of flights operated* is disregarded. The outcomes are shown in Table 10-5. Because of the amount of data, no boxplots are shown for this experiment, averages are shown instead However, the observations still show considerable variance, in particular when it comes to the infected arrivals.

Table 10-5 Comparison of NCIT, NCITC & questionnaire screening measures per airport

Inputs				**Disease spread**	**Connectedness**		**Airport operations**	
		Sc	Nur	Inf. Arr	False Pos.	In Time	Time in Q	Resources
ROB	NCIT+Qs	4	2	4.9	711	0.96	0.43	6
	NCIT+Qs	3	1	4.1	701	0.83	1.28	4
	NCITC+Qs	4	2	5.6	712	0.96	0.25	6 1)
	NCITC+Qs	3	1	3.7	713	0.94	0.61	4
	NCITC	4	2	5.6	334	0.98	0.19	6
	NCITC	3	1	5.5	337	0.98	0.19	4 1)
FNA	NCIT+Qs	7	4	8.9 2)	993	0.95	0.37	11
	NCIT+Qs	6	3	8.8	1001	0.92	0.56	9
	NCITC+Qs	7	4	8.8 2)	1021	0.96	0.28	11
	NCITC+Qs	6	3	10.6	1012	0.95	0.32	9
	NCITC	7	4	11.4 2)	474	0.98	0.26	11
	NCITC	6	3	9.9	471	0.98	0.26	9
CKY	NCIT+Qs	5	3	3.5	1377	0.95	0.47	8
	NCIT+Qs	4	2	3	1348	0.89	0.87	6
	NCITC+Qs	5	3	2.4	1356	0.96	0.31	8
	NCITC+Qs	4	2	2.5	1376	0.93	0.45	6
	NCITC	5	3	3.9 3)	635	0.98	0.27	8
	NCITC	4	2	2.7	639	0.96	0.27	6

The most interesting outcomes are shown with a blue background in the table and elaborated on here:

1) Removing questionnaires when fever screening is deployed can improve the system's performance, with improved outcomes on all indicators, except for the number infected arrivals, which stays approximately constant.
2) However, in other situations, removal of the questionnaire results in an increase in infected arrivals.
3) Less staff can result in fewer infected arrivals, which is an unexpected outcome. However, it is expected this is caused by infected passengers missing their flight due to understaffing. This is confirmed by the decrease of passengers who reach their destination in time.

In Figure 10-17 the differences between the scenarios are made more explicit. For the airports and staffing scenarios combined, the number of infected arrivals, false positives, destination in time and time in queue is shown, relative to the NCIT+Qs scenario. The following interesting outcomes can be deducted:

1. On average, NCITC screening results in more infected arrivals than NCIT screening.
2. The removal of questionnaires lowers the amount of false positives majorly, but also leads to a small increase in the number of infected arrivals.
3. NCITC screening increases the percentage of passengers reaching their destination in time slightly, and their time in queue majorly, compared to NCIT screenings.

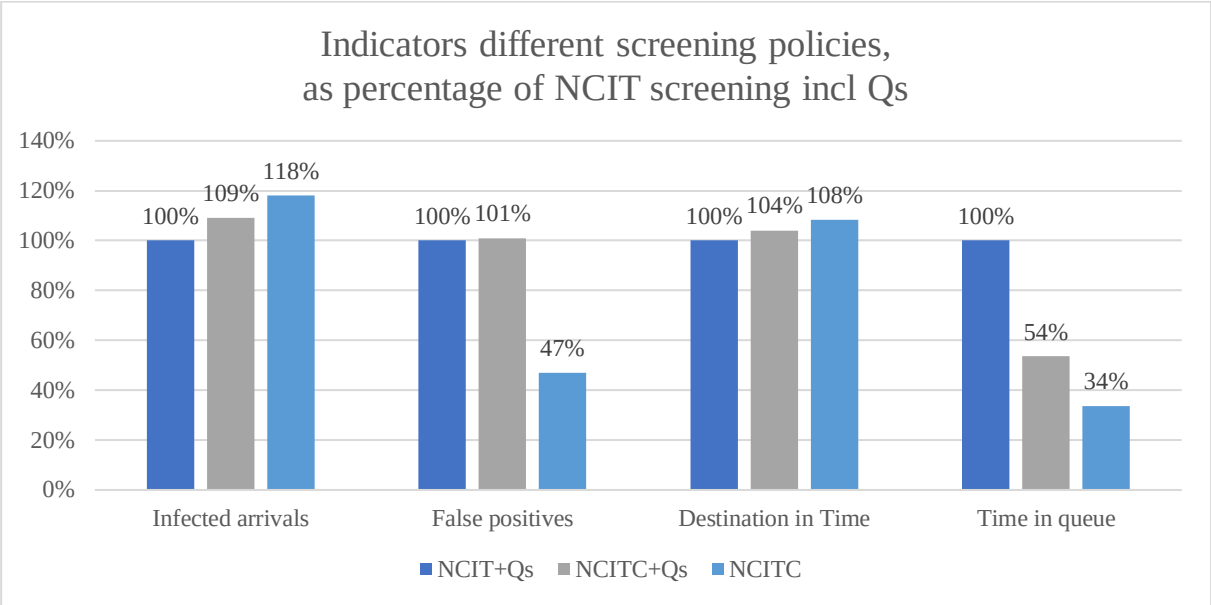


Figure 10-17 Performance screening policies compared to NCIT+Qs

Main insight

The addition of questionnaires can reduce the number of infected arrivals, while increasing the number of false positives, queueing times and required resources at the airport. In other situations, no reduction of the number of infected arrivals is seen.

NCITC screening results in a higher destination in time with a smaller staffing compared to NCIT screening. However, the number of infected arrivals can be higher. This illustrates a trade-off between resource allocation and effectivity of the screening measures. Also the trade-off between false positives and infected arrivals is, again, visible.

10.4. Innovative options and strategically deployed resources

Experiment 10: 2019 outbreak, RDT screening

The RDT is an innovative screening measure that can be incorporated in airport screening operations. This section shows the results of experiment 10, involving different RDT deployments, with and without other screening measures. Furthermore, the characteristics of the RDTs themselves are varied, since, unlike other screening measures, the RDTs do not exhibit a trade-off between sensitivity and specificity: particular RDT screenings function well on both.

When an RDT screening station is deployed, the number of infected arrivals is generally higher than the outcomes of fever screening stations. On the other hand, the number of infected arrivals is considerably lower. This, again, shows the trade-off between sensitivity and specificity.

This section compares different set-ups of RDT screening in combination with other screening stations. Firstly the performance of RDT screening with a sensitivity of 84-100 per cent and a specificity of 92-100 per cent is visualized in Figure 10-18. It takes the situation with just RDT screening as basis, and judges the policies with questionnaires and/or NCIT screening added as well compared to this number. The addition of questionnaires to the RDT screening results in a slight increase of infected arrivals, whereas the addition of NCIT screening reduces this number by 25 per cent. This is accompanied by a vast increase in the number of false positives (the value shown above the bar). The destination in time reduces by 2 to 4 percentage points, and time in queue increases, with more screening staff deployed.

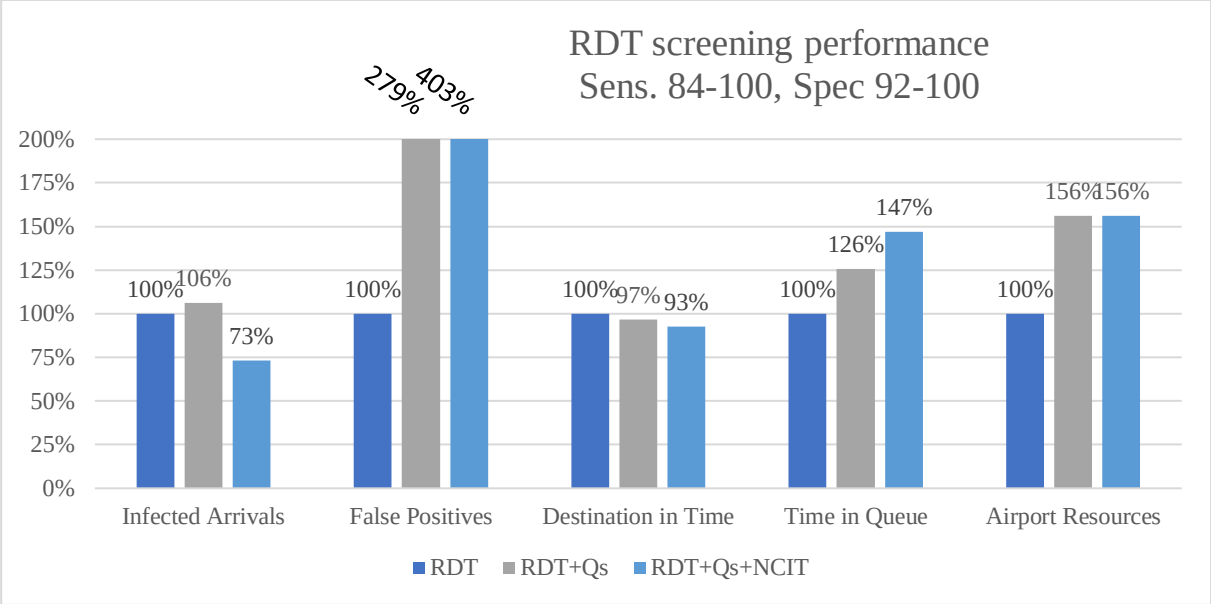


Figure 10-18 RDT screening performance at ROB, wider range

Unsurprisingly, a more sensitive and specific RDT leads to a lower number of infected arrivals. However, if questionnaires or NCIT screening are added in this scenario, the number of infected arrivals does not decrease. This is accompanied by a worse performance in the other indicators, including a considerable increase in false positives. This is shown in Figure 10-19.

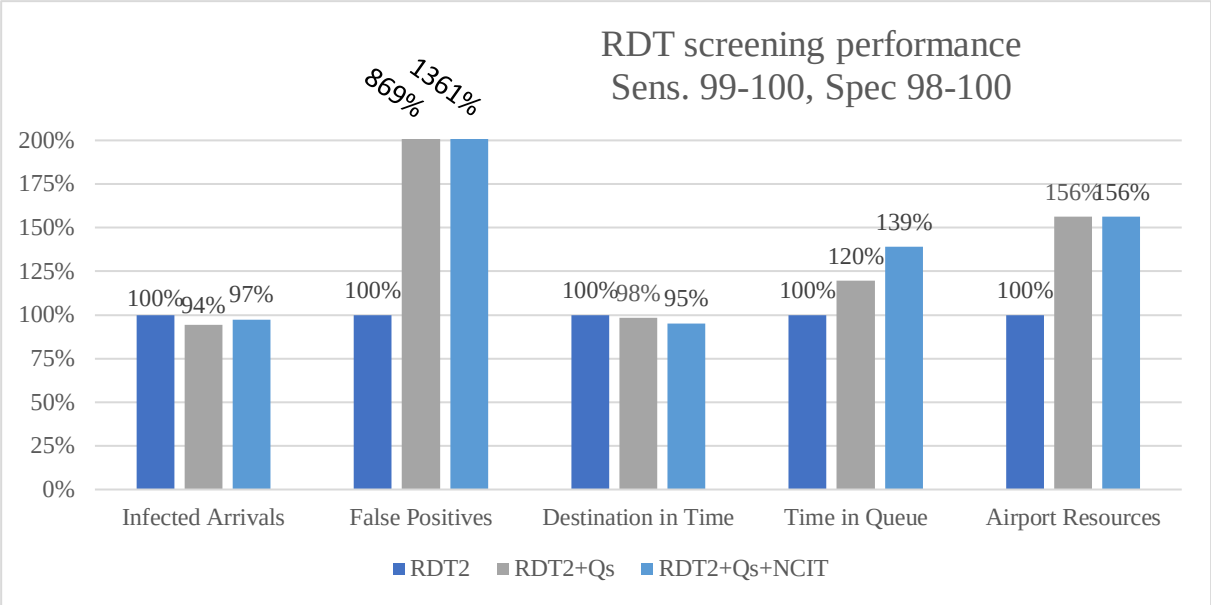


Figure 10-19 RDT screening performance at ROB, narrower range

Main insight

RDT screening results in more infected arrivals, but fewer false positives than fever screening.

The number of false positives increases dramatically when fever screening is added to RDT screening, especially if the difference in screening characteristics is larger.

Experiment 11: 2019 outbreak, RDT screening without secondary screening

In the previous experiment, passengers who were identified as suspected in an RDT screening, were still sent through to a secondary screening before a final judgement was made. This is puzzling, since RDT screening – measuring the actual presence of Ebola – should perform superior to the fever screening the secondary screening consists of. With this extra screening in place, the asymptomatic cases of Ebola that are identified by the RDT station, or dismissed at the secondary screening. Therefore, the secondary screening is removed in this experiment. In Table 10-6, Table 10-7 and Table 10-8 the outcomes are shown for a worse and a better performing RDT screening, with and without questionnaires and NCIT screening.

Table 10-6 Screening measure performance without secondary screening at ROB

Inputs			**Disease spread**	**Connectedness**		**Airport operations**	
	Qs	NCIT	Inf. Arr	False Pos.	In Time	Time in Q	Resources
RDT			0.5 1)	3286	0.90	0.42	4
Sens. 84-100	x		0.4	9305	0.74	0.38	6
Spec. 92-100	x	x	0.1	12086	0.67	0.41	6
RDT			0	815	0.97	0.45	4
Sens. 99-100	x		0	7282	0.80	0.40	6
Spec. 98-100	x	x	0	10292	0.72	0.44	6

Table 10-7 Screening measure performance without secondary screening at FNA

Inputs			Disease spread	Connectedness		Airport operations	
	Qs	NCIT	Inf. Arr	False Pos.	In Time	Time in Q	Resources
RDT			1.1	4694	0.90 2)	0.46	7
Sens. 84-100	x		0.9	13083	0.75	0.40	11
Spec. 92-100	x	x	0.5	17045	0.67	0.39	11
RDT			0.2	1160	0.97	0.51	7
Sens. 99-100	x		0.1	10286	0.80	0.42	11
Spec. 98-100	x	x	0.1	14469	0.72	0.42	11

Table 10-8 Screening measure performance without secondary screening at CKY

Inputs			Disease spread	Connectedness		Airport operations	
	Qs	NCIT	Inf. Arr	False Pos.	In Time	Time in Q	Resources
RDT			0.7	6354	0.90	0.49	5
Sens. 84-100	x		0	17845	0.75	0.43	8
Spec. 92-100	x	x	0	23236	0.67	0.45	8
RDT			0	1592	0.97	0.53	5
Sens. 99-100	x		0	13997	0.80	0.45	8
Spec. 98-100	x	x	0	19754	0.72	0.48	8

The following results can be derived from the analyses:

1. Compared to a situation of RDT screening with secondary screening, the number of infected arrivals decreases strongly. Adding questionnaires and/or NCIT screening reduces this number a bit further.
2. The removal of secondary screening results in an enormous amount of false positives. This is worsened by adding questionnaire and fever screening stations to the RDT check. This is accompanied by a deteriorating fraction of destination in time (expected to be a result of the increase of false positives).

Main insight

The addition of secondary screening to RDT screening decreases the effectivity, measured by the number of infected arrivals, enormously.

Simultaneously, with screening measures which are less than 100 per cent specific, a secondary check is required to limit the number of false positives, even if this check performs worse than the primary check.

Experiment 12: 2019 outbreak, screening at hubs

Final topic of interest is screening at airport hubs. Table 10-9 shows the weekly number of flights and passengers from the airports in the Ebola affected region to the hub airports, from which a part of the passengers will continue to other flights after transferring.

Table 10-9 Weekly flights to hubs

From airport	To hub	Weekly flights	Weekly passengers
ROB	ACC	7	1096
FNA	ACC	8	1272
CKY	DSS	11	2860

First a scenario is tested in which all passengers arriving at the hub airport are screened for Ebola. This results in an enormous number of false positives and prevents about 14 per cent of the passengers to catch their flight in time, even with a screening staff deployment of 100 per cent of the regular airport operations. Therefore, a scenario where all arriving passengers at a hub are screened for Ebola is regarded a non-feasible measure. This means the only scenario of interest is the screening of only the passengers arriving from Liberia, Sierra Leone or Guinea, which is comparable with the measures at Brussels Airport in 2014. This means the arriving passengers from these destinations have to be kept separated from the other passengers. Screening measures in this scenario concern the conventional NCIT measures, not the RDT screening.

Figure 10-20 shows the results of the experiments concerning the flights from ROB and FNA, to and via ACC. The airports are shown in the squares, where a blue marked airport means this airports conducts Ebola fever screening. ROB and FNA airport are shown jointly, although still modelled as separate airports. All arrows and their respective numbers relate to the number of Ebola infected passengers on this route. *Arrival ROW* means the arrival of infected passengers in the Rest of the World.

Screening at the ACC hub reduces the number of cases (both in the country and transferring) by on average 20 per cent. Starting at a situation without screening, it is more beneficial to deploy screening at ROB and FNA rather than deploying it at ACC – also for the stakeholders at ACC airport themselves. Required staffing capacities are low compared with staffing at ROB and FNA, since passenger flows are smaller. However, this is accompanied by a spread to the other 28 airports with destinations other than in Ghana. The randomness of the results has a high impact on the outcomes. Screening at hubs faces similar trade-offs as the screening at airports of origin, like the resulting false positives and queueing times.

From Figure 10-21 it can be derived that screening at DSS can lower the number of Ebola cases as well. The data above probably represents a number too small to make well-founded statements. Even though the number of flights between these airports is significant, the prevalence of Ebola in the Guinea is so low that it is hard to make solid statements.

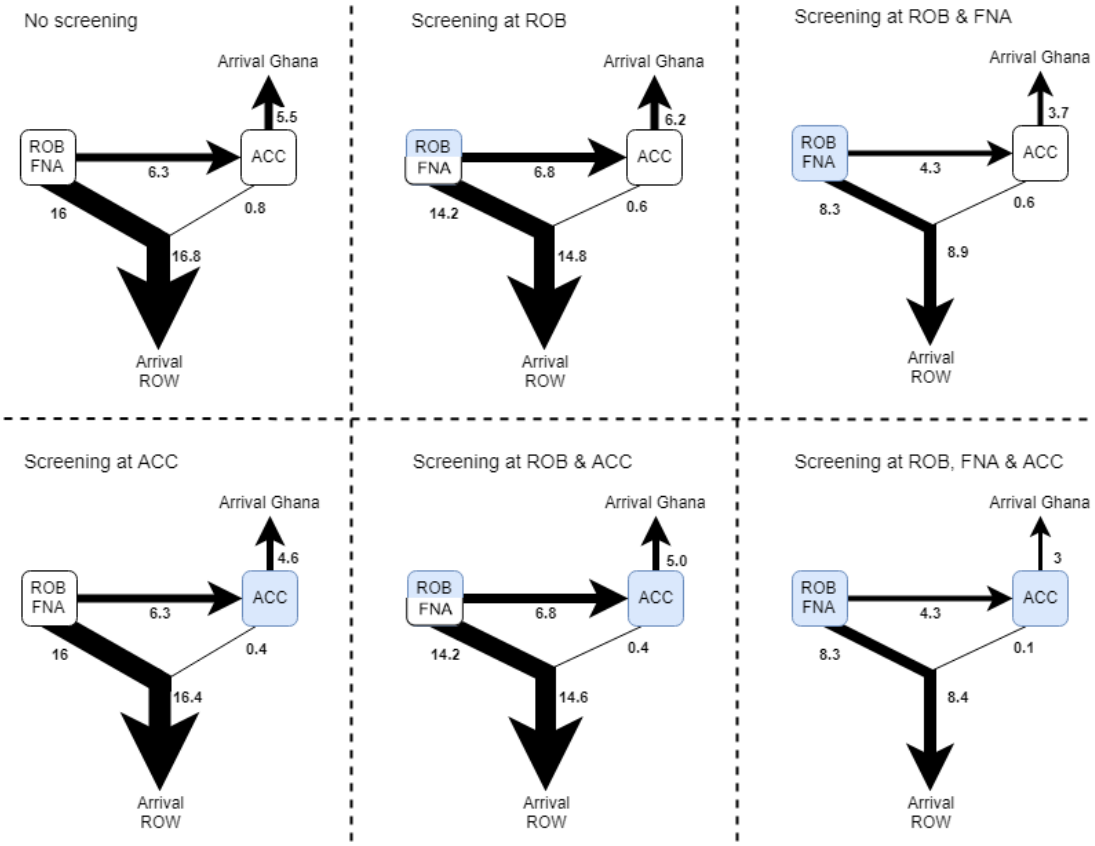


Figure 10-20 Infected arrival flows around ACC hub

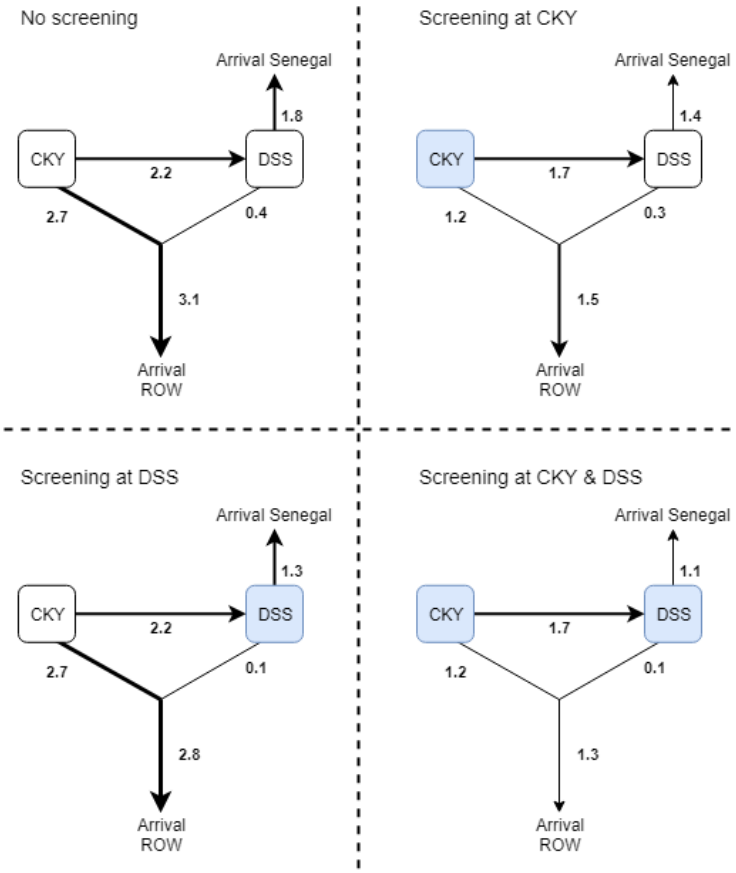


Figure 10-21 Infected arrival flows around DSS hub

Main insight

Screening at airports in the affected region is more effective than screening at hub airports where passengers transfer. Both in the country of the hub airport, as of all airports added up, screening in the affected region results in the fewest infected arrivals.

Screening at hubs can reduce the number of infected passengers, also if (imperfect) screening measures at the countries of origin are deployed. If deploying entry screening, focus on flight from countries with the highest Ebola prevalence, combined with a high number of flights.

10.5. Synthesis

This section combines the outcomes that can be derived from the results of the experiments as described so far. It covers the three different sections similarly to section 10.2, 10.3 and 10.4 of this chapter, followed by a combined overview.

Synthesis experiments 1-6, 2014-2015

The outcomes from the experiments concerning the 2014-2015 epidemic are combined to provide an overview of the measures. Since the airport level characteristics are not yet discussed, only the *Infected arrivals, False positives* and *Flights operated* are topics of interest. Figure 10-22 visualizes these outcomes in a bubble graph. The X-axis concerns the number of infected arrivals, the Y-axis the false positives. The size of the bubble shows the percentage of flights operated. The difference between the policies and environmental factors is important. The scenarios *no screening, 3x screening, both screening* and *regular flight operations* are policy options that can be deployed. The *fever prevalence* and *population ill with other diseases* are external factors that cannot be influenced, but have an effect on the effectivity of screening measures. The numerical results are listed in Table 10-10.

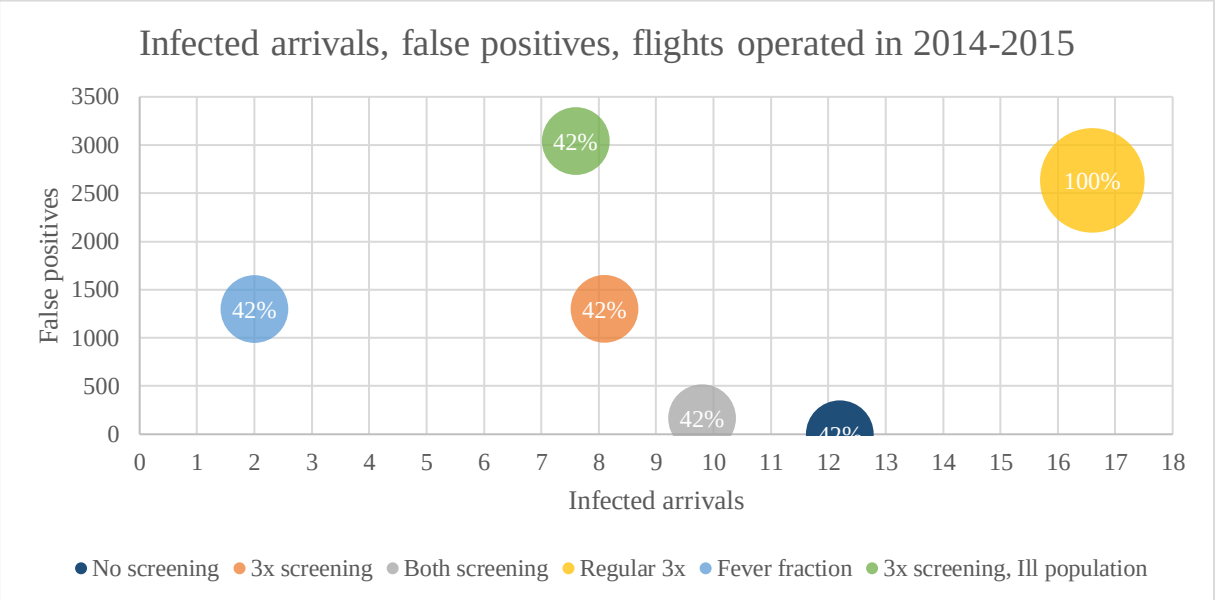


Figure 10-22 Bubble graph infected arrivals, false positives, flights operated 2014 scenarios

Table 10-10 Overview indicators for 2014 scenarios

	Infected arrivals	False positives	Flights operated
No screening	12.2	0	42%
3x screening	8.1	1301	42%
Both required	9.8	239	42%
Ebola fever fraction	2	1299	42%
Ill population	7.6	3041	42%
Regular flights	16.6	2634	100%

The following can be derived from the analyses:

1) *Fever screening measures have limited effectivity and result in many false positives.*

The long incubation time of Ebola results in a reduction of no more than a third of Ebola cases arriving at airports outside of the affected area. Simultaneously, a large number of healthy passengers are falsely identified of carrying Ebola. With fever screening and questionnaires in place, more than three hundred passengers are wrongfully restricted from travelling to prevent one case of Ebola to spread.

2) *A reduction of the false positive rate goes hand in hand with a decrease in effectivity.*

The amount of false positives can be reduced by questioning passengers with fever for Ebola risk factors, and only detaining those that score positive on both. This still results in one hundred false positives for one prevented Ebola case. Furthermore, Ebola detection is reduced from a third to a fifth of all cases. This illustrates the trade-off between sensitivity and specificity: the number of infected arrivals versus the number of false positives.

3) *Higher prevalence of other diseases worsens the performance of the system.*

An increase of the prevalence of other diseases with fever will result an increase of false positives. If 1.25 per cent of the population is ill with another disease with fever, up to 650 incorrect Ebola suspicions appear for each prevented Ebola case.

Synthesis experiments 7-9, 2019

An outbreak of a similar scale as the 2014-2015 outbreak with the 2019 flight schedule in place will, as the previous outbreak, result in the international spreading of Ebola. Fever screening and questionnaires can reduce, not prevent this from happening. The following can be derived from the analyses:

1) *A new Ebola outbreak can result in a spread of cases that is worse than in 2014-2015.*

With similar screening measures in place as in 2014-2015, the number of infected Ebola cases that travel out of the region is expected to more than double. This is a result from the increased connectedness of the countries with the rest of the world, and hereby illustrates the effectiveness of flight cancellations, which results in fewer movements and fewer infected arrivals.

2) *Major investments in staffing and screening measures can limit, not prevent the spread.*

When deploying NCIT screening and questionnaires, an additional staffing of 73 per cent of the regular airport staff is required to allow passengers to reach their flight in time. A clear trade-off exists between deployed resources and the efficient operations on the airport level: inadequate resource deployment results in fewer passenger reaching their flight in time and long queueing times.

3) Screening exhibits trade-offs of effectivity, passenger flow and resource requirements.

Deploying NCITC instead of NCIT screening can result in better performance of the system. NCITC screening results in fewer false positives and smoother airport logistics, while requiring fewer resources. However, the number of infected arrivals can be higher compared to a scenario with NCIT screening. This clearly shows a trade-off between resource allocation and effectivity of the screening measures. Also the trade-off between false positives and infected arrivals is, again, visible.

Synthesis experiments 10-12, innovative measures and strategically deployed resources

The following can be derived from the analyses concerning RDT deployment and the functioning of the hubs:

1) RDT screening measures can result in the least false positives of all measures.

RDT screening in combination without other measures, with a secondary screening results in the lowest number of false positives, and a rate of passengers reaching their destination in time. However, there is no reduction in infected arrivals, compared to the conventional screening measures.

2) RDT screening without a secondary check can result in the fewest infected arrivals.

RDT screening without a secondary screening results in the fewest infected arrivals, but also in a very high number of false positives. Since this policy checks for the actual presence of Ebola, the vast majority of Ebola cases is detected. This makes a secondary check based on the prevalence of fever seem illogical. However, the secondary screening prevents a massive number of false positives, even when the secondary screening has a worse performance than the initial screening.

3) RDT screening leads to increased waiting times but needs less staffing.

RDT screening in general results in high waiting times, due to the 15 minute wait that is required to receive the result of the screening. RDT screening without other measures results in low staffing needs, since the RDT procedures that require staff are limited in time.

4) From the system's perspective, screening at the source is more effective than at the hubs.

Screening at airports in the affected region is the most effective policy option. Both from the perspective of the system as a whole, as for the hub airport itself, the lowest number of infected arrivals is reached when screening is done at airports in the affected region. Only screening at hubs results in a large number of cases that do not pass through the hub airport and arrive in other countries undetected.

5) Screening at hubs can reduce the number of infected arrivals.

Even though screening at the countries of origin is more effective, screening at hubs can still reduce the number of infected arrivals. When considering deploying screening at hub airports, it is necessary that passenger flows from the affected areas are separated from the other arriving passengers to prevent excessive waiting times and false positives. Focus of the measures should be directed to routes from countries with the highest Ebola prevalence, combined with a high number of flights. If the fractions of infected arrivals are very small, screening at hubs is not likely to be effective.

11. Discussion

This chapter critically discusses the setup and results of the study. Section 11.1 discusses the limitations of the simulation model. This is followed by section 11.2: critical assumption in this study. In section 11.3 interesting contrasts with literature are discussed. Finally, section 11.4 highlights the practical implementation of the outcomes of this research.

11.1. Limitations of model

The airport model logic regards every screening station as independent. This means that an undetected fever case can be detected at a later station, as described in this report. This is not necessarily problematic, and information proving otherwise is absent. However, a consequence of it is that passengers can be sent to secondary screening multiple times throughout the model run. In theory, a passenger can go from fever screening, to secondary screening, to a questionnaire, to secondary screening again, etc. This is not realistic and results in unrealistic high values for queueing times, resulting in additional passengers missing their flights.

The interaction between the indicators leads to clouded result. This is caused by the fact that less deployed staff affects the time in the system for the suspected passengers in particular, hereby lowering the number of infected arrivals. Or in other words: only the passengers that are suspected to have Ebola, miss their flight. This is reinforced by the long processing time of the secondary screening. This wrongfully indicates measures with fewer staff, but the same screening measures, as superior.

Staffing is clearly a major simplification, resulting from, amongst other factors, the lack of a physical dimension of staff operations in the model. It would be interesting to investigate what the actual staffing numbers are at the airports, and to incorporate a more realistic representation of the operations by the staff.

The lack of actual network data deteriorates the quality of the simulation model. Most beneficial would be more accurate information regarding the disease characteristics, but that is a major unknown. The limited number of cases makes the estimation of Ebola cases by means of a fraction doubtful. In reality, an estimation of the number of Ebola cases attempting to fly by using a fraction of the passengers is probably not the proper way to approach it. The number of cases is probably too small for this, and were mostly humanitarians. 4 out of 7 infected arrivals abroad were humanitarians. In the scenarios with a very limited number of cases, the factor performs even worse.

11.2. Critical assumptions

A major uncertainty regarding the simulation model are the characteristics of the airport measures. The ranges of the screening measures are wide and have a major impact on the functioning of the model. In most experiments, the values for sensitivity and specificity are varied over the whole range of known values, except for the outliers, which still results in a very broad range. As mentioned in some sources, tropical conditions in particular can deteriorate the performance of disease screening measures.

There is chosen for secondary screening on the basis of fever prevalence since no other data was available, but this seriously reduces the differentiation between different policies and hereby has a major effect on the model functioning. The effectiveness of secondary screening has a large impact on the model run, which is not adequately reflected in this research. A more realistic model would

emphasize the influence of the functioning of secondary screening better. More information regarding this second screening step is required.

The functioning of RDTs is researched to a limited extent in particular. The entire effectivity of RDT screening depends on the ability of detecting Ebola during the asymptotic period. In the simulation runs, the detection of non-symptomatic individuals is precisely the biggest difference between the fever screening and RDT deployment. If the functioning of the RDT deteriorates when taking into account the incubation period as well, then there is very limited benefit over fever screening. Furthermore, the addition of secondary screening based on fever prevalence after an RDT screening is deployed, means neglecting the main argument for RDT screening: the identification of the asymptomatic.

The assumption that questionnaires are dominantly filled in untruthfully, results in a low effectivity of this measure. There is very limited scientific basis for this, with only one research concluding from a (limited) research among passengers with influenza at an airport.

11.3. Contrast with literature

This section discusses the outcomes of this research in relation with the results of previous research in the field of screening measures. The conclusions that are confirmed or rejected by this research are shown in Table 11-1, with a short explanation. The conclusions that are somewhat true, are indicated with the "≈" sign.

Table 11-1 Contrast of outcomes with literature

Source	Conclusion	Confirmed or rejected by this research
Bitar et al., 2009	Limited efficacy of NCIT to detect passengers at early stages of a pandemic influenza, when passengers' fever prevalence would be =<1%.	✓ NCIT screening is unable to successfully detect ill passengers when the prevalence of fever is low.
Brigantic et al., 2009	Potential in both exit and entry screening, although need for identification of asymptomatic passengers. Screening measures require significant resources and can result in delays.	✓ Exit screening in particular can reduce the spread of cases. The number of asymptotic cases complicates screening. Any screening method requires major staffing and results in delays.
Gold et al., 2019	Ebola screening is able to detect 83.4 per cent of cases.	X Incubation time results in low effectivity of fever screening.
Gold et al., 2019	Additional screening at connecting airports provides marginal benefits.	✓ Screening at hubs can reduce the number of infected arrivals slightly, but exit screening contributes more.
Gold et al., 2019	The false alarm rate is independent of the fraction that is sick with other diseases than Ebola.	X Higher prevalence of other diseases with fever results in a strongly increased number of false positives.
Gostic et al., 2015	Due to the incubation time of Ebola, the majority of detected cases was sick with another disease.	✓ Prevalence of other diseases with fever results in false positives
Read et al., 2015	Exit screening for Ebola is more effective than entry screening.	✓ With exit screening, more cases of Ebola are detected.
Read et al., 2015	Exit screening is expected to only detect 35,6% of Ebola infected passengers.	≈ Conventional screening measures detect 14 – 34 per cent of cases.

St John et al., 2005	Entry screening for diseases with a very low prevalence is ineffective, with a positive predicted value (precision) of zero, with major financial investments required.	≈	Screening for Ebola is not completely ineffective, but has a very low effectivity. Major investments in (staff) resources are required.

The conclusions that are not confirmed by this research are elaborated on further. The conclusions of Gold et al. are interesting, since their research is very similar when it comes to the case study and the method used. They conclude that Ebola screening measures are able to detect the vast majority of cases, an outcomes disputed by this research. An explanation is that Gold et al. take the fever prevalence of Ebola over the course of the disease as a fixed value at any point in time, hereby disregarding the incubation period. This leads to unrealistic, overoptimistic outcomes of the model. When diving deeper into the research by Gold et al., more interesting findings can be done. An example is that in their research, NCIT screening is able to detect half of the Ebola cases that *do not* exhibit fever symptoms. No justification is given for this remarkable assumption. In the light of these assumptions, it is unsurprising that this research leads to different conclusion.

Furthermore, their conclusion that the false alarm rate has no relation with the prevalence of other diseases is disproven as well. The explanation that this has no impact on the effectivity in the model of Gold et al. is assumed to be a result of very low variances in the model parameters, leading to small changes that are regarded insignificant. However, when examining the prevalence of malaria in the countries of interest, one can only conclude that a high prevalence of other diseases with fever is plausible.

Read et al. conclude with a value that is a close approximation of the outcomes of this research. Their 35.6 per cent detection rate comes close to the outcomes of this research that assume 14 to 34 per cent of the cases being detected. The difference is assumed to result to the addition of secondary screening in this research, leading to an increase in the number of infected arrivals, but also reduces the number of false positives. The latter are not researched by Read et al.

Finally, St John et al. conclude that screening for diseases with a low prevalence is ineffective. This is not confirmed by this research, although measures have a very low effectivity. The conclusion that major investments are required to conduct these screenings can be confirmed.

11.4. Practical considerations

The experiments result in outcomes that all show the trade-off between detection rate and false positive rate. There are no policies that function well on both. This means it is expected that a new outbreak of the scale of the 2014-2015 epidemic will result in more infected arrivals than arrived before. To reduce the spread of infected arrivals, measures are required that will in all cases result in false positives, fewer people reaching their destination in time, more queueing time for passengers and more required airport resources. The addition of secondary screening plays a large role in this: it reduces the number of false positives but increases the number of infected arrivals.

The trade-off between effectivity and false positives can be made explicit by representing the false positives as the number of *false positives that is required to prevent one case of Ebola to arrive.* This calculation shows that a more effective policy will result in a vast decrease of the efficiency of the measure. The values are shown in Table 11-2.

Table 11-2 False positives per prevented infected arrival for different policies

	None	NCIT	NCITC	RDT incl. secondary screening	RDT excl. secondary screening
Infected arrivals	24	16-17	17-21	14-20	0-2
False positives per prevented infected arrival	/	370-450	230-420	130-380	150-2220

The outcomes from this study result in two main considerations for policy makers, when the decision is made to deploy screening measures at airports:

1. A decision for a screening measure should be made considering the number of infected arrivals as well as the accepted number of false positives for each prevented case of Ebola.
2. The choice for screening measures is restricted by the available resources of the airport. NCITC screening can for instance be nearly as effective as NCIT screening, but results in fewer false positives, less waiting time and fewer required (staffing) resources. RDT screening also requires less staffing, but results in long waiting times.

When deciding on a screening measure, the specificity of the policy is of major importance. A policy with a 99 per cent specificity results in 6500 false positives over the course of half a year from the region, in a scenario where no secondary screening is deployed. This number increases on the network level if hub or entry screening is added. The options of screening with a lower than 100 per cent specificity are:

1. Accepting the wrongful suspicion of Ebola cases, resulting in the fewest infected arrivals, but a vast amount of false positives, fewer people reaching their destination in time.
2. Refer all suspected cases to secondary screening, hereby reducing the number of false positives, but vastly increasing the number of infected arrivals, more time in queues and more required airport resources. By conducting this secondary screening, the sensitivity of the initial measurement is compensated by conducting another screening.

Therefore, a measure that successfully indicates 50% per cent of the Ebola cases, but does not wrongly identify passengers could work better in practice than a measure which indicates 95% of cases with Ebola and is 99 per cent specific. This is a result of the fact that the latter would require a secondary screening to prevent an excessive number of false positives, but significantly lowering the sensitivity of the measures combined.

When deploying screening measures, passengers should be advised to arrive at the airport of departure early. The average waiting time for passengers with fever screening is .43 hours, which is not excessive. However, the highest individual waiting period amounts to almost 4 hours. This will result in a passenger missing its flight. Optimized operations, required early arrivals at the airports or allowing these passengers to skip the queues might resolve this issue.

However, of all possible policy options, the question is if investments in screening measures are the best allocation of money and resources. It is an extensive policy to only identify a few individuals. Focussing on combatting the disease in the region could be a considerably better investment of resources. Additionally one can think of closely following the health statuses of humanitarians, since

they represented four of the seven cases of Ebola that travelled out of the area. On the other hand, it is possible that the sole presence of screening measures prevented Ebola cases to attempt to board a flight, hereby perhaps preventing the spread more than the actual screening measures themselves.

12. Conclusion

This section presents the conclusion to this research. Section 12.1 answers the sub questions, contributing to an answer to the main research question, which is covered in that same section. Section 12.2 describes the societal contribution of this research, followed by the scientific contribution in section 12.3. The suggestions for further research that follow from conducting this study are the topic of section 12.4.

12.1. Answer to the research questions

This section contains the answers to the research question based on the results from this research. First the sub questions are answered, leading to an answer to the main research question:

How can airports and airlines prevent the spread of an infectious disease through the passenger airline network while maintaining efficient operations?

Sub question 1: How to evaluate the effects of airport and airline policies aimed at the prevention of infectious spreading?

Based on expert interviews, literature and other disease screening simulation models, a list of indicators is composed that rate the performance of disease screening measures. These indicators can be categorized in the fields of interest that reflect the interactions between the dimensions of this study: the prevention of the spreading of an infectious disease, the aim to maintain connectedness of the area, and the smooth operations at the airport level. These indicators are called *Disease spreading*, *Connectedness* and *Airport operations*.

The indicators and their unit of measurement with the desired direction of this indicator, as well as their respective focus areas, are shown in Table 12-1.

Table 12-1 Key performance indicators and focus areas

	Disease spreading	**Connectedness**	**Airport operations**
Infected arrivals (Total cases, MIN)	X		
False positives (Total cases, MIN)		X	
Flights operated (Percentage of flights, MAX)		X	
People reach destination on time (Percentage of passengers, MAX)		X	
Time in queues (Average minutes per passenger, MIN)			X
Airport resources (Screening staff deployed, MIN)			X

Sub question 2: What are policies that airports and airlines take to prevent the transit of infected individuals, and what is their effectivity?

Based on literature regarding airport screening measures and general disease screening, the characteristics of screening measures by airports and airlines are derived. At the airport level, policies aimed at preventing infected passengers to travel screen for either fever symptoms, Ebola risk factors, or the presence of the Ebola virus. Fever screening is done by non-contact thermometers, such as the Non-Contact Infrared Thermal Camera (NCITC), which screens passengers as they pass the range of the camera, or the Non-Contact Infrared Thermometer (NCIT), which screens the passenger's forehead. Questionnaires are conducted to assess if a passenger has been in contact with the disease. The Ebola Rapid Diagnostic Test (RDT) checks for the actual presence of the Ebola virus. Finally, the single policy by airlines concerns the cancellation of flights.

The policies and their characteristics are shown in Table 12-2. The effectivity of policies is measures by their sensitivity and specificity. Sensitivity refers to the percentage of cases it successfully detects. Specificity refers to the correct identification of the non-symptomatic. Since observations from literature vary greatly, ranges are used in this research. The ranges are shown in the table and exclude outliers.

Table 12-2 Disease screening characteristics

Policy	**Screens for**	**Sensitivity (%)**	**Specificity (%)**
NCITC	Fever	70-90	92-99
NCIT	Fever	80-90	95-99
Questionnaire	Ebola risk factors	20-25	85-99
RDT	Ebola virus	84-100	92-100
Flight cancellation	/	100	0

Each policy has a sensitivity and specificity in *detecting the Ebola characteristic it screens for*. This means for instance that the NCITC station successfully detects 70-90 per cent of the individuals exhibiting fever symptoms. Similarly, the RDT station detects 84-100 per cent of the passengers with the Ebola virus. Flight cancellations are a special kind of policy, since they do not screen for any Ebola characteristic, but instead deny every passenger to fly. Hereby this policy has optimal sensitivity but no specificity: all Ebola cases are prevented travelling, just as everyone else.

Sub question 3: How can passenger flow logistics at airports with regards to infectious spreading be formalized and modelled using Discrete Event Simulation?

Discrete Event Simulation allows for a close representation of the actual airport layout by means of a simulation model. Individual passengers can be visualized as they pass through the airport model. A basic layout represents *every* airport of interest in this research, solely accounting for the differences in capacities by varying the number of employees that staff the stations.

Passengers pass through screening stations where disease screening takes place, exhibiting a chance of being marked suspected of carrying the disease. In that case, a passenger is sent through to a secondary screening station where another check takes place. A positive result here as well results in the disruption of the passenger's travels. Scenarios are included that dismiss the secondary check.

Sub question 4: How do airports interact with the system during infectious spreading?

Now the airport models are operational, their functioning is aggregated to the system level. There are three identified ways in which airports interact with their system during a situation of infectious spreading:

1. Flight schedules
2. Passengers and their states
3. Hub airports

The flight schedules represent the magnitude with which the system can spread the infectious disease, and the specific destinations to which the disease can spread. The operated flights are the policy option the airlines have to try to prevent the spread of the infectious disease. Three different flight schedules are considered: the regular 2014 flight schedule, the reduced 2014 flight schedule at the height of the pandemic with cancellations in place, and the current, 2019 flight schedule.

The passengers that board a flight have an allocated health status. Based on the prevalence of Ebola in the country of origin, passengers have a chance of being infected with Ebola. Of the infected, only a part exhibit fever symptoms. 85 per cent of the Ebola infected exhibit fever over the course of the disease, but only after the incubation period of the disease. The remainder of infected passengers has no fever. Passengers can also be sick with another disease, with or without fever symptoms. Alternatively, they are considered healthy.

Hub airports are airport where passengers can transfer to another flight. Within the model, this concerns the airports at Accra and Dakar. At the hub airport, passengers arriving from Ebola affected areas can be screened. This applies both to passengers with the hub airport as final destination, as well as passengers continuing their journey. The latter allows for a further spreading of the disease over the airline system.

Sub question 5: How do policies for airports and airlines perform during an Ebola epidemic under different scenarios?

Fever screening measures have a limited effectivity and result in many false positives. This is a result of the long incubation time of Ebola, resulting in many asymptomatic Ebola cases. A reduction of the false positive rate goes hand in hand with a decrease in effectivity. This illustrates the trade-off between the infected arrivals and the false positives. When other diseases with fever are common in the country of departure, the performance of the system worsens.

A new Ebola outbreak of the scale of the 2014-2015 outbreak, with the current flight schedule in place, can result in a spread of cases that is worse than in 2014-2015. The severity of the disease is approximately proportional to the amount of flights that is operated, illustrating the effectivity of flight cancellations. Major investments in staffing and screening measures can limit, not prevent the spread. Conducting screening measures exhibits trade-offs of effectivity, passenger flow and resource requirements. Measures that require fewer resources and result in less queueing time, result in more infected arrivals.

RDT screening measures can result in the least false positives of all measures. If no secondary screening is deployed, RDT screening can result in the fewest infected arrivals of all measures. However, this also leads the a high number of false positives. RDT screening leads to increased waiting times for passengers but requires less staffing compared to fever screening measures. Screening measures in

general exhibit a higher effectivity at the source of the disease than at the hubs. Also from the hub's perspective, the number of infected arrivals can be reduced the most by conducting screening at the source. However, screening at hubs can still reduce the number of infected arrivals.

Main research question: How can airports and airlines prevent the spread of an infectious disease through the passenger airline network while maintaining efficient operations?

Screening measures can reduce the spread of infectious diseases, but are unlikely to prevent the spreading entirely. All screening measures show a trade-off between sensitivity and specificity of the disease, resulting in either a high number of infected arrivals, or of false positives. The efficiency of a set of screening measures at an airport can be estimated by determining the amount of false positives for each prevented infected arrival. The policies resulting in the least infected arrivals, also result in the most false positives per prevented case. In practice, it is difficult to calculate this number because of the uncertainties during infectious spreading.

To successfully deploy screening measures, a focus on the specificity is expected to be more important than the sensitivity of the measure. The specificity determines if a policy is a viable option, with the impact it has on the number of false positives and on the airport logistics. If the specificity is low and secondary screening is required to prevent an excessive number of false positives, the number of prevented infected arrivals will be reduced as well. The rarer the disease, the more important a high specificity is.

Fever screening measures should be deployed taking into account the incubation time of the disease, the prevalence of fever among symptomatic individuals and the overall prevalence of fever in the country. Furthermore, the availability of (staff) resources restricts the deployment of screening measures. When few resources are available, less accurate policies with smaller resource requirements may be deployed, preventing excessive queueing times at the airport and passengers missing their flight. However, this can lead to more infected arrivals.

Screening measures not focussing on common disease characteristics like fever, but rather the actual presence of the virus can reduce the number of false positives. For this measure to be successful, it needs to be effective also for non-symptomatic individuals, early in the course of the disease. Resulting from the time required before the test provides an outcome, waiting times at the airport increase. Furthermore, this screening method is relatively intrusive if it requires a body swab or blood test to perform the screening.

Disease screening at the airport of origin is the most efficient and effective method of screening. Additional screening at hub airports can reduce the spread of the disease slightly. Air cancellations reduce the number of infected arrivals approximately proportional to the number of flights, but do not prevent the disease from spreading and have negative impacts on the affected countries. Likely explanation of the relatively limited spread of infectious diseases over the airline system is that ill people simply do not attempt to fly, whether that is because of their illness, because these diseases often affect the lower income population, or because the deployment of screening measures prevent passengers from attempting to travel.

12.2. Societal contribution

Based on the results of this study, airports and airlines are expected to be able to make better founded decisions when it comes to the deployment of screening measures. Before deploying fever screening, policy makers should be informed regarding the incubation time of the disease, the prevalence of fever among the symptomatic and the general prevalence of fever in the country.

The sensitivity if a policy is important, since it answers the question: Will the measure prevent the disease from spreading? However, the specificity is at least as important, since it answers the question: Is this measure a viable option? The trade-off between the infected arrivals and the associated number of false positives, represented by the false positives per prevented infected arrivals, should be considered before deployment of the measures.

Furthermore, the results from this research should incentivise decision makers to collaborate on a network level to prevent the spread of a disease: it is better to have well-functioning screening measures at the source, than to have worse-functioning screening measures at multiple airports.

12.3. Scientific contribution

This results that are derived from conducting this study result in to the following scientific contributions:

The interaction between the infected arrivals, false positives, people reaching their destination on time, time in queues and airport resources is made explicit for different screening measures. Different airport's capabilities and resource availabilities lead to different optimal strategies when it comes to which screening measures to deploy.

Evaluating screening measures by the number of false positives per prevented false negative allows for the comparison of the operational feasibility of different screening measures. It makes the trade-offs between sensitivity and specificity explicit, and illustrates the different trade-offs that can be made based on the prevalence of the disease. The rarer the disease, the more critical a high specificity is. The potential deployment of secondary screening has a major influence on this.

The importance of screening at the source, also for the functioning of the hub proves the role of the network: the best outcome for a hub airport is screening at the airport at the source of the disease. This illustrates the function of the airline network and shows the connection of the multiple modelling levels.

12.4. Future research suggestions

Conducting this research gave rise to further research related to this work. This section describes five possible future research suggestions.

First suggestion is making this research more realistic by obtaining more information regarding the actual system. This includes information regarding the precise airport layouts, the flight times and load factors of the airplanes during the Ebola crisis, and a more realistic representation of airport and screening staff at the airports. Ideally, field research at the airports of interest would be conducted to have first-hand information from the area, supplemented with interviews with the local staff involved during the outbreak. This can be supplemented with more accurate information regarding the Ebola prevalence during the outbreak. Preferably, exact information regarding the fever screening devices'

characteristics would be included. This research could further include the practical requirements for a successful deployment of RDT screening.

A second suggestion is an extension of the model with a more sophisticated disease spreading model. This would allow for a more accurate representation of the network function of the airports. Incorporated effects could include the reinforcing effects of infected passengers' arrivals on the spreading of the disease. By connecting this model that distributes infected passengers over the system, with for instance a system dynamics based disease spreading model, these effects could be incorporated (Pruyt, Auping, & Kwakkel, 2015).

Third suggestion is adapting the model logic to represent a different disease with other characteristics. An example would be a flu-like, more contagious disease, which is transferrable by passengers on the airport or during their flight. This would require a model in which passengers interact with each other and exchange disease states, for instance to be modelled using Agent Based Modelling (Badham et al., 2018). Functioning of the system then also depends on other factors. For instance, a highly transferable disease can result in disease transfer during screening for the disease. Furthermore, a high prevalence of disease characteristics like fever can make detection easier. Finally, a less harmful disease can lead to a different trade-off regarding the need for screening measures. A possible case study for this scenario could be the H5N1 outbreak (Centers for Disease Control and Prevention, 2018).

A fourth suggestion would be to research ways to improve the functioning of questionnaires during outbreaks. By identifying asymptotic cases of the disease, questionnaires can be a very cheap and effective disease screening method – if filled in honestly. By developing ways to incentivise people to fill in this form in an honest way, the effectivity of screening might be improved dramatically. This would bring a major improvement to disease screening facilities.

Fifth suggestion concerns the adaption of this model to improve screening measures at other facilities than airports, like hospitals in the area affected by the epidemic. Interviews with experts and humanitarians made clear that most public facilities, like hotels and government offices, in the Ebola affected region had a form of entry screening which was conceptually comparable to the screening at airports. Research concerning screening at hospitals could prevent disease spreading at these crucial facilities with vulnerable people.

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Appendix A: Interview Crisis Management Officer Belgian Ministry of Health

What did the entry screening at Brussels Airport look like?

The temperature measurement took place with a forehead scanner. This takes a few seconds. A problem was that waiting in the cold jet bridge can lower the body temperature, making the measurement less effective. A solution for this is to create a queue in the terminal. We had underestimated that employees really need to be trained on how to use the scanner. Passengers should clean their forehead from sweat with a handkerchief and wipe hair from their face. Then the measurement takes place. These measurements were more difficult than expected. The measuring equipment had a relatively large margin of error. At that time, better equipment was available than the equipment used at Brussels Airport. Currently, there will be even more accurate equipment on the market. Occasionally, measurements had to be taken several times. This slows down the process and makes people impatient.

If the measured value is less than 38 degrees, the passenger is allowed to continue, otherwise he will be referred to a nurse. The nurse examines the passenger location card (PLC) in detail, asks a number of questions from a checklist and conducts two new temperature checks. Questions concern the location of the traveller, possibly contact with Ebola patients, whether he has stayed with a local family, etc. After this, a doctor on duty is contacted, who has the responsibility to make the diagnosis.

The check-up by a nurse takes around 10-15 minutes. This also depends on the language barrier. Sixteen questions are asked, the PLC is run through, and a checklist is completed. There are also two temperature checks. This can easily be conducted with two possible patients on a flight, with seven or eight cases the waiting time increases rapidly. Often the initial measurement appears to be too high, and there is no fever when the (better trained) nurse conducts the screening.

Can you tell something about the exit screening procedures in West Africa?

These are similar to the controls in Brussels and are carried out in a reasonably similar way. The temperature is recorded at the terminal entrance. The quality of the measuring instruments and measurements varied greatly. In part, I felt that exit screening in particular was more to reassure people that something was being done, rather than being a watertight measure. Attempts were made to perform the checks as well as possible, but the quality was very variable. That was an important reason for entry screening by the Belgian government, in addition to the possibility of developing fever while travelling to Belgium.

Do you expect the inspections to have allowed a large number of Ebola cases to pass?

I think this chance is small. Although it is hard to say, I suspect not. The passengers of these flights concerned the more well-off population. They had better access to health care and information, and could protect themselves better. It is easier to protect yourself against Ebola if you live in a house than in a slum. This means there is a selection of who boards such a flight. I do not base this on scientific information, but I suspect that the two largest risk groups on flights are the health workers and the lower middle income class. The first group comes into contact with Ebola patients a lot because of the work they perform. The second group concerns people who do have the means to travel by plane, but who may also come into contact with potential Ebola patients in public transport, at work, etc.

Appendix B: Interview Belgian Humanitarian aid worker

To what extent do you have knowledge of screening measures at airports during the 2014 Ebola crisis?

Only practical experience, in my role as a passenger at the airports of Freetown and Brussels. Temperature screening takes place with forehead scanners, a questionnaire must also be completed, which is issued when the temperature is measured. Upon departure at Freetown Airport the temperature is taken, and during the process by the airport two or three times. The final check was when boarding the aircraft. This happens every time with forehead scanners at 31 degrees Celsius, so it seems doubtful what the efficiency of these screenings is.

On the way to Brussels on the plane, an information note is distributed with an explanation of the controls that have been set up, together with a questionnaire to be completed. Temperature control takes place at Brussels Airport when you leave the jet bridge. That process is quite similar to the screening procedures at Freetown Airport, but somewhat more structured.

Also on the plane with destination Sierra Leone a document was distributed explaining that we were on our way to a country where Ebola was present. It focused on what is expected from travellers when they leave the region again.

Appendix C: Interview Australian Humanitarian Aid Worker

What are your experiences regarding screening measures on airports in West Africa?

In Sierra Leone temperature was taken individually on the forehead. This happened upon entering the airport, just outside the airport terminal.

What are your experiences regarding screening measures at Brussels Airport?

There was temperature screening after returning from West-Africa. On arrival at Brussels Airport temperature was screened and a few questions had to be answered on a form. Questions included whether you had travelled to certain countries; do you have a fever; do you have a cough etc.

What do you know about the effectivity of airport screening?

It is not effective. With fever screening you only capture that specific moment. If someone is sick with Ebola you would not capture it by just taking the temperature. If it does not show up with a regular thermometer, an infected passenger can still be on a plane. Actually, someone infected with Ebola does not transmit the disease during the first three days of fever, so this individual would still be able to safely get on a plane and travel in these three days.

Alternative measures would be to incorporate more questionnaires. It is better to have a more elaborative questionnaire to check if passengers are okay and to know what the screening staff is looking for. The second time I flew out of Ebola the fever screening measures we set up better. This does not mean they were going to find the passengers with Ebola. But people's understanding of the Ebola screening was better. Still, more education is needed.

Do you think any additional cases were missed?

I do not think so. We know about the ones that slipped through because they went back to their country and it became a major thing in the media. So I think no one was missed besides the known cases.

Do you have experience with the Ebola Rapid Diagnostic Test?

Not the first time I was in the region. The second time the test was operational. It worked really well, it gave a result within two hours. This was in 2015, when the rapid test was officially accepted. In 2014 we had to wait nearly 24 hours for a result.

Appendix D: Interview Belgian Head Nurse Ebola

What did screening at Brussels Airport look like?

After connecting the jet bridge, the passengers came to the arrival hall, at the end of the A-terminal. Passengers handed over the papers with their details filled in, and then an infrared measurement on the passenger's temple was taken to get an idea of the person's temperature. If that measurement was elevated (> 38 degrees), a second measurement was conducted. If it was high again, the passenger was sent to an interview room where the passenger was further questioned with regards to the case definition. This includes questions concerning whether you came from the risk area, you had contact with people that were sick, you worked there, you attended funerals. There was an entire checklist by the medical services at the airport. I suspect that if a passenger was found to have fever, but no Ebola risk factors were detected in the questionnaire, the passenger was allowed to continue their journey.

How many employees were involved?

Four people took a measurement, two of them with a thermometer and two collect documents and record the temperature on the PLC. In addition, in an enclosed space, there was a nurse of the airport's medical service. Also someone from the Ministry of Health was present. Temperature measurement is done in seconds. Focus on the temple, press the button, and a fraction of a second later you have a temperature.

Do you know anything about the accuracy of the measurement?

At that time, it was probably the most feasible, fast and safe way to do it. There is also a measurement which involves a wipe over the forehead and a check behind the earlobe, but that is a contact measurement. The airport authorities certainly did not want to go for that. Forehead screening was the most obvious measurement. In the future, the screening might be 10 to 20 meters past the jet bridge, because people cool down in the jet bridge. The reverse can be true in Africa when it is hot.

Was there an Ebola case in Belgium?

No, no Ebola case in Belgium that was positive. A few suspects, but no confirmed patients. In our neighbouring countries there were cases, which suggests that these patients did pass through Brussels but were not detected (or were not yet ill) at the time of transit.

Do you have an idea of the effectiveness of the screening?

There has been rumours about it not being reliable, etc. Everything depends on the measuring equipment. Someone with a really high fever and who is sick may get filtered out. It is not a 100% guarantee, but a way to keep your focus. It requires a bit of manpower, but I think that given the circumstances it was good towards public opinion, it brings peace.

What do you know about the screening in West Africa?

Upon entering the airport and just before boarding there was a temperature check. All measures can help, but it is never a 100% guarantee, because if someone has taken anti-fever medication you will not detect fever. When I was in Africa, not Ebola related, there was a body scan that colours according to the body temperature. There was one operator behind the screen who monitors the measurement

Appendix E: Interview Ebola coordinator Belgium

What can you tell me about Ebola screening at Brussels Airport?

On the 17th or the 19th of October the Ebola screening initiated at Brussels Airport. Main reason for deployment was the unrest among passengers and staff, as well as by the general public. Therefore, the main aim was to reduce the unrest. We were aware of the fact that the accuracy of the test was very limited. It was only one step of a ten step plan to handle the outbreak. Other parts of the plan included for instance the development of procedures for ill passengers on board.

An alternative would have been the cancellation of the flights between West Africa and Brussels. This was disregarded, since this connection was considered a lifeline for the region and there was no scientific consensus justifying this measure. Nevertheless, the flight can still be considered a gateway to let ill people in the country.

Firstly the arriving passengers were screened for fever and the questionnaire they filled in was checked. If this gave reason for concern, the passenger was sent through to a nurse, who conducted another fever screening and a questionnaire. Difficulty during the questionnaire was the functional illiteracy of some passengers, as well as passengers who for instance only spoke Chines. This was more of an issue than the untruthful filling in of questionnaires. Less than five per cent of the arriving passengers had a body temperature of over 37.5 degrees.

Do you know how the screening in West Africa was conducted?

One or two fever screenings were conducted, possibly a questionnaire as well. It was common that passengers would take paracetamol to hide signs of fever. On the other hand, passengers that were clearly ill were usually not fit to fly and would not attempt to take a flight.

Do you think any cases were missed?

I know about the American passenger that flew out of the region and was diagnosed with Ebola in the United States. Upon departure at West Africa as well as during transfer at Brussels Airport, he was not yet showing signs of fever.

Appendix F: Screening characteristics

Table F-1, Table F-2 and Table F-3 list the effectivity of the different screening methods. Table F-1 lists the screening characteristics of fever screening measures, Table F-2 shows the source of questionnaire screening effectivity and Table F-3 contains the RDT screening characteristics. Not all research mentioned in the main text is included in these tables, as for the calculation of sensitivity (an estimation of) the number of total infected is required, which is often missing since this is the unknown factor in the screening process.

Table F-1 Fever screening characteristics per source

Source	Screening	Sensitivity (%)	Specificity (%)	Comments
(Tay, Low, Zhao, Cook, & Lee, 2015)	NCITC STE ITDS	44,1	99,1	Under tropical conditions
(Tay et al., 2015)	NCITC Omnisense ITDS	89,7	92,0	Under tropical conditions
(Gostic et al., 2015) based on (Bitar et al., 2009)	NCIT	70	/	
(Gold et al., 2019) based on (Gostic et al., 2015) & producer	NCIT	90 fever, 50 Ebola no fever	99,5	
(Tay et al., 2015)	NCIT Handheld infrared thermoscope ITDS	29,4	96,8	Under tropical conditions
(European Centre for Disease Prevention and Control, 2014)	NCIT	80-99	75-99	
(Kuan, Lin, Chuang, & Wu, 2010)	NCIT	45	/	Of dengue with fever
(Bitar et al., 2009)	NCIT	89,6	94,3	
(Bitar et al., 2009)	NCIT	85,4	95	
(Bitar et al., 2009)	NCIT	82,7	98,7	
(Bitar et al., 2009)	NCIT	89,4	75	
(Bitar et al., 2009)	NCIT	75	99,6	
(Bitar et al., 2009)	NCIT	82	77	
(Malone et al., 2009)	Fever screening, unspecified	80 symptomatic, 6 non-symptomatic	/	Of pandemic influenza

Table F-2 Questionnaire screening characteristics

Source	Screening	Sensitivity (%)	Specificity (%)	Comments
(Gold et al., 2019)	Questionnaire	20 (Ebola no fever) 25 (Ebola fever)	85 (sick fever) 90 (sick no fever) 100 (healthy)	Assumptions

Table F-3 RDT screening characteristics per source

Source	Screening	Sensitivity (%)	Specificity (%)	Comments
(Semper et al., 2016)	RDT Xpert Ebola assay on blood	100	99,5	
(Semper et al., 2016)	RDT Xpert Ebola assay on swab	100	100	
(Dhillon et al., 2018)	RDT GeneXpert	>99	>95	
(Dhillon et al., 2018)	RDT ReEBOV	100	92	
(Dhillon et al., 2018)	RDT OraQuick	84	98	
(Broadhurst et al., 2015)	RDT ReEBOV	100	92,2	Of symptom. indivs
(Jean Louis et al., 2017)	RDT	84	98	
(VanSteelandt et al., 2017)	RDT	100	98	
(Semper et al., 2016)	RDT	100	95,8	

Table F-4 contains the information regarding processing times of the screening measures, as derived from literature and expert interviews.

Table F-4 Processing times screening

Source	Screening	Processing time
(Gold et al., 2019)	Questionnaires	30 sec av, exp
(Gaber, 2010)	Questionnaires	Up to 2 mins
(Brigantic et al., 2009)	Primary fever screening	Triangular 10,12,30 secs (av 17,33)
(Gold et al., 2019)	NCIT	5 sec av, exp
Crisis Management Officer Belgian Ministry of Health	NCIT	Few seconds, but necessary to clean forehead. Sometimes multiple screenings needed.
Belgian Head Nurse Ebola	NCIT	Matter of seconds
(Gaber, 2010)	NCIT	With questioning/without documentation: 5 mins
(Gaber, 2010)	NCITC	With questioning/without documentation: 5 mins Without questioning: less than 15 secs
Australian Humanitarian Aid Worker	RDT	Within 2 hours
(Jean Louis et al., 2017)	RDT	In minutes
(Brigantic et al., 2009)	Secondary fever screening	Triangular 3, 5, 15 mins (av 7,67)
Crisis Management Officer Belgian Ministry of Health	Secondary screening	10 – 15 mins

Appendix G: Ebola prevalence

Table G-1 shows the Ebola prevalence as used in the model runs, assuming a three week curing time. The fraction of the population infected with Ebola is shown for the weeks throughout the model run, so September 2014 until February 2015. This number represents the chance for each individual traveller to be infected with Ebola.

Table G-1 Weekly Ebola prevalence

	Liberia	**Sierra Leone**	**Guinea**
Week 1	0,000232	0,000108	0,000044
Week 2	0,000218	0,000106	0,000047
Week 3	0,000189	0,000125	0,000053
Week 4	0,000225	0,000118	0,000036
Week 5	0,000317	0,000206	0,000055
Week 6	0,000276	0,000242	0,000069
Week 7	0,000213	0,000283	0,000090
Week 8	0,000167	0,000263	0,000072
Week 9	0,000579	0,000510	0,000121
Week 10	0,000500	0,000352	0,000084
Week 11	0,000481	0,000393	0,000099
Week 12	0,000080	0,000210	0,000040
Week 13	0,000122	0,000394	0,000075
Week 14	0,000162	0,000411	0,000051
Week 15	0,000132	0,000376	0,000055
Week 16	0,000122	0,000348	0,000044
Week 17	0,000034	0,000309	0,000077
Week 18	0,000049	0,000278	0,000073
Week 19	0,000066	0,000259	0,000062
Week 20	0,000095	0,000219	0,000032
Week 21	0,000091	0,000174	0,000025
Week 22	0,000091	0,000149	0,000023
Week 23	0,000078	0,000124	0,000029
Week 24	0,000075	0,000120	0,000030
Week 25	0,000071	0,000117	0,000032
Week 26	0,000090	0,000114	0,000030

Appendix H: Airline timetable specification

Different methods have been used to obtain the necessary data for the airline networks. The data distraction process is described for the three scenarios: 2019 operations; 2014 regular operations; and 2014 minimal operations.

2019 operations

1. Flight data is obtained from FlightAware.com. The data contains the arrival and departure times to and from the five airports of interest, as well as the operating airline and aircraft (FlightAware, 2019). The flight schedule of one week in May 2019 is used as proxy for the timetable of the simulation time.
2. Private, cargo and undefined flights are filtered out of the dataset. Only passenger flights are regarded relevant.
3. To estimate the number of passengers on each flight, the maximum aircraft capacity as found on airlines' websites is multiplied with the average load factor for flights in Africa in 2018, which is 0.782 (International Air Transport Association, 2018).
4. The timetable of the week in May is extrapolated to cover the simulation period of half a year.
5. Flights departing on the first day of simulation are deferred until after 2:30 AM in order to have the first passengers of this flight enter the terminal from 12:00 AM on – the first passengers arrive 2.5 hours in advance of flight departure. This dismisses the need for a warming up period within the model.

2014 regular operations

1. Flight data is obtained from the Openflights database, which is last updated in June 2014 and therefore contains the flight operations at that moment (Openflights.org, 2014). However, this database only contains the flown routes including equipment, not the arrival and departure times and days of the week.
2. To construct a complete timetable, the data from the 2019 operations is used as basis of the regular 2014 timetable. Flights that were not yet operated in 2014 are removed from the timetable.
3. Flights that are not operated in 2019, but were operational in 2014 are added. Based on the average frequency of the other flights, these flights are added twice weekly. These flights are scheduled throughout the day at random.
4. To estimate the number of passengers on each flights, the maximum aircraft capacity is multiplied with the average load factor for flights in Africa in 2014, which is 0.675 (International Air Transport Association, 2015).

2014 minimal operations

1. To construct the timetable of 2014 with minimal operations, the data from the regular 2014 operations is used as basis of the 2014 timetable.
2. From the regular 2014 timetable, flights that have been cancelled during the Ebola outbreak are removed. This information is obtained from airlines' updates, news articles and online forums. This means the timetable probably does not exactly mirror reality, but is expected to be a close estimation.