Tracking the process of an outbreak to a pandemic via logistical infrastructures: Case study

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ABSTRACT

When a pandemic arises, the health of human beings could be at risk. Even though some businesses can close their doors, due to government sanctions, logistical infrastructures usually keep being active to supply necessary products like food to the population. However, these logistical infrastructures could also be vulnerable to the virus. The spreading of an infectious virus can be hard to control and monitor under certain circumstances. Several studies have shown how viruses spread across the world population, they developed protocols to control such spread by decreasing human interaction. While some studies have researched the impact of logistical infrastructures on the spreading of a virus on a high abstract level, the conclusions of these studies are usually confined to a single infrastructure. The logistical infrastructure sector as a whole could contribute to distributing a virus. Therefore, the objective of this paper is to find out how logistical infrastructures impact the spreading of a virus and if the logistical sector could make some significant changes to the infrastructure to prevent such a catastrophic pandemic. This paper will discuss the results by creating models that simulate real-world logistical infrastructural processes whilst an infectious virus is among the people.

Keywords

Logistical Infrastructures, pandemic, infection-rate, agent-based modeling.

1. INTRODUCTION

People, businesses, and countries were not prepared for the immense impact of the COVID-19 pandemic that continues to rage across the world. The COVID-19 pandemic caused by the SARS-CoV-2 virus has over 5,4 million cases and over 344,000 deaths confirmed across the world as of 26 May 2020 [14]. Preventing more deaths is paramount and governments apply constrictions to everyone in order to accomplish that. Some businesses struggle to stay financially stable due to issues such as supply chain complications and a decline in consumer demand. Finding a method to predict the scale of a potential pandemic could be key in stabilizing the world economy and saving human lives. Logistical infrastructures including airlines and shipping have lost billions of dollars during the COVID-19 pandemic, due to the tremendous decrease in infrastructural traffic and the restrictions that were laid upon them by the representing governments [13]. There are a few techniques, like analytical methods to simulate a virus with a logistical infrastructure environment. In this paper, advanced modeling techniques are used to digitalize a virus-like object. The simulations use different scenarios to get a grasp on the effect of logistical infrastructures. With the help of these techniques, important questions as to how logistical infrastructures have an impact on the spreading of a virus can be answered. Via simulation models, the basis of understanding the impact of mitigation strategies as executed on different logistic infrastructure layers can be found. The simulations will be developed in an agent-based modeling platform GAMMA [18]. Previous related work usually fixates one specific infrastructure for which the research is conducted [12, 4, 7, 10]. In this paper, a model that encapsulate all the different logistical infrastructures is designed, and I introduce a full-scale logistical infrastructure model structure and refine it to a testable hierarchic structure. The main properties of the models are:

- **Autonomous decisions:** the agents in the models must act according to their own will (with set parameters to specify the capability of the agent).
- **Interaction with environments:** The environment set in the models must be interactable by the agents used in the simulation.
- **Emergent behavior :** The agents can interact with objects and humans alike, leading to unpredictable behavior in the system as a whole creating a large impact.

I exemplify the proposed virus spreading model via a proof-of-concept implementation. It is shown how a virus can be spread via logistical infrastructures, with different means of spreading. Experimental results from several sectors run scenarios that represent this method, indicating the viability of the model approach [9, 19, 2]. The aim of this paper is to validate the case study based on the conceptual model presented in this paper. I believe that this contribution can lay a foundation to further research and development of disease prevention technologies. The content of this paper with the use of Peffers design science methodology is as follows, as is shown by the structure of this paper [15]. The problem statement and the impact on the logistical branch have been explained above. Section two covers the necessary background of this paper. Section three presents the requirements of the simulations. Section four presents the reader with the conceptual model on which this research is based. Section five explains the

28^{th} *Twente Student Conference on IT* Febr. 2^{nd}, 2018, Enschede, The Netherlands.

use of our case study and introducing the logistical infrastructures that are going to be simulated. Section six will present the results of the simulations. Section seven will go over the sensitive analyses reflected on the postal infrastructures used in this paper. Section eight reflects on the research paper and limitations. Section nine will conclude this research paper and propose future work.

2. BACKGROUND

Agent-based modeling and simulation, ABMS in short, is a platform on which agents can interact with other agents in a given environment. Agents are components of a model with certain properties and attributes that can follow base-level rules for behavior as well as a higher-level set of freewill behavior. These interactions can lead to influence in their overall behavior, making the agents unpredictable. According to Macal and North [5], "By modeling agents individually, the full effects of the diversity that exists among agents in their attributes and behavior can be observed as it gives rise to the behavior of the system as a whole". Building an agent-based model from the ground up developing each agent individually, self-organization between the agents can be observed in models. Such self-organization is composed of patterns, structures, and behaviors that can emerge, even though those features were not hardcoded in the first place. The above-stated feature of agent-based modeling is key and separate agent-based modeling from other modeling systems. Modeling social systems with agent-based modeling is extremely beneficial, due to the interaction and influence agents could have on each other. Agents learn from each other through experience and adapt accordingly to their environment.

When a virus has embedded itself inside a human body, that person can become infected and can carry over the virus to other people. Usually, these types of viruses start on a small scale, with people in an approximately small circle around the first infected person get infected. In most cases, the presence of the virus is not yet known. Viruses can spread using different means, most commonly airborne and via water. Raspatory protection is extremely important as a mitigation mechanism for an outbreak [16]. Infections that cover a large group, community, or population inside a region of a country is referred to as an epidemic. When a pandemic occurs, the infectious virus covers a much larger group of population spread across multiple countries.

3. REQUIREMENTS

The developed simulations' purpose is to determine how the logistical infrastructures affect the spreading of a virus [9]. The structure of these simulations is built upon the study of Enrique Frias-Martinez et al. who developed a simulation model in which the Mexican H1N1 outbreak was simulated [10]. Their paper researched the impact of the interventions the Mexican government-enforced to prevent the spreading of the H1N1 virus. The simulations were done in an agent-based modeling system with similar agent attributes. In our simulations an agent can deviate between three different states, **Exposed, Infected and Cured** as shown in **Fig. 1**. These states are inspirited by Barrett et al. and follow a similar approach [3]. In **Fig. 1** Δ represents the infection distance of the virus, γ represents the chance an agent is cured after a period of time, and α represents the chance an agent is infected. Once an agent is cured of the disease it creates ant-bodies against the virus. Therefore, it can no longer be infected or infectious, so it will be removed from the simulation. In our model, it is assumed that every agent has the same probability of infection and probability to be cured. The specific changes in these variables are highly dependent on which type of virus is represented. In this paper, the main focus is on the specifics of the virus COVID-19. The further explained properties of the COVID-19 virus used in this paper are the following:

- **Infection distance (Δ):** this variable depicts the distance in which an infected agent can carry over the virus. This distance is different for humans to object respectfully and human to human. According to the Center for Disease Control and Prevention, the minimum social distancing is 6 foot or 1.8 meters [8].

- **Incubation time (γ):** the incubation time is a unit of time after which an infected agent is cured and develops antibodies, after which the agent can no longer be infected or infect other agents. According to the research of Lin Yang et al. the incubation time is roughly: 1-15 days [20].

- **Infection chance (α):** this variable depicts the chance of which a virus can spread between a human or an object. In these simulations the infection chance is approximately: 2,454,452 / 330,944,050 * 100 % = 0.74 percent [14]. This number is derived from taking the country with the highest number of cases and divide those with their total population. As of May 26th, the USA has 2,454,452 reported cases and a population of approximately 330,944,050.

The properties above hold for each logistical infrastructure, the dissimilarity is the environment and the speed in which the agents move around the environment. Each environment is built around the usage of the logistical infrastructure.

- **Human** agents move 4 km/h with 0,1% chance to move during day and 0,001% during night.

- **Postal** agents move 30 km/h with 50% chance to move during day and 30% during night.

- **Ships** move 45 km/h with 50% chance to move during day and 40% during night.

- **Trucks** move 80 km/h with 45% chance to move during day and 40% during night.

- **Airplanes** move 270 km/h with 50% chance to move during day and 50% during night.

The simulation relies on day-night cycles in which certain infrastructures conduct less or more business during certain hours. The day-night cycle is implemented such that between 18:00 and 06:00 (night time) agents have different chances to move than between 06:00 and 18:00 (day time).

In short, the proposed model will be carried out on the simulations of real-life logistical infrastructures. These simulations depict the properties of a virus type like that of COVID-19. The information regarding COVID-19 is still limited due to its recentness. Interventions will be implemented in de simulations, and the effects will be compared in the results.

Figure 1. Transition model rom exposed to cured

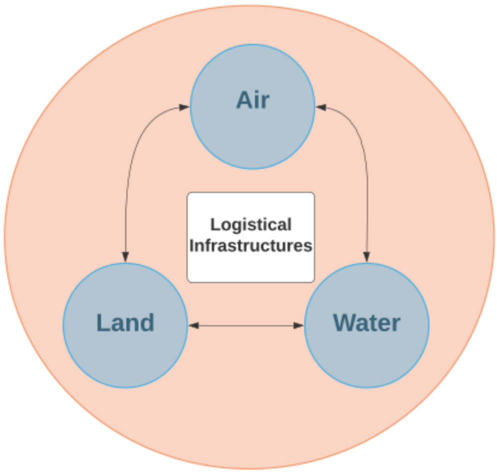

Figure 2. Concept logistical infrastructures

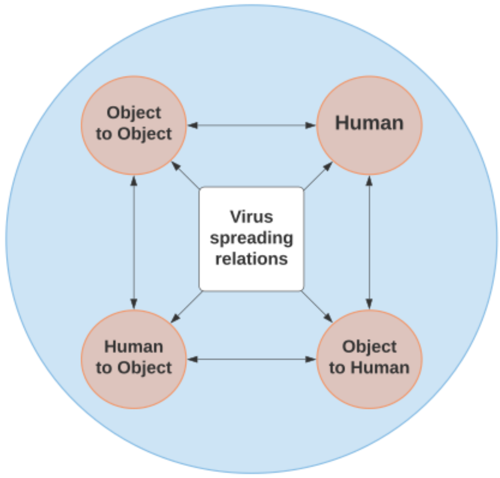

Figure 3. Concept virus spreading relations

4. MODEL

To fully understand and analyze the impact of logistical infrastructures on the spreading of a virus, a look at a bigger picture is needed. First of all, the infrastructures that are included in this category need to be laid-out. The papers of A.J.Tatem, Köstler, K.a, and TimCarter et al. specify the importance of air, land, and water as a means of spreading a virus [1, 12, 4]. To analyze the spreading, our model has to encapsulate all the different logistical infrastructures that are used. Therefore, I have decided that in this paper the term logistical infrastructures will consist of all movement via air, land, and water as shown in **Fig. 2**. The virus grid model should comply with some requirements, including reliability, robustness, and extensibility, to sum up, a few. I only focus on a subset of the controller requirements, to present relevance of the case:

- **Scalability:** Different viruses can affect certain sectors more than others, scalability is of utmost importance to increase or decrease the affected area of the model. The means of spreading and logistical infrastructures are included in this process. The proposed hierarchy already indicated the ability to scale the virus grid into different levels, when the connections between them are known. Yet, even at the scale of a country, a lot of variables are in play and raise the concern of scalability.

- **Multi-agents:** Future use of the virus grid model may want to define additional agents in the model, which may interfere with the virus. In this paper, I conduct a small sample size of agents in our case study. In upcoming cases, different agents must be able to be assigned to the grid and interact properly. These agents may vary in time, depending on the preference of the user at that time.

- **Incremental change:** Technology as a whole does not stand still, everything must be adaptive, and this model is not excluded. Any changes that might be introduced in the future regarding aspects that are presented in this model must be progressive and cannot jeopardize a working system. Therefore, changing large quantities of the model at once is inadvisable and can lead to unusable results. The virus grid model is designed to be progressive and certain aspects and objectives can be changed accordingly.

The model that is proposed in this section indicates the degree the virus will spread in logistical infrastructures. The research of Fanelli D et al. suggests that a virus-like COVID-19 can spread via object and humans alike. Therefore, the proposed model has to define four ways a virus can spread whilst be in transit via logistical infrastructures: **Fig. 3** [7]

- **Human-human:** Infection via human to human contraction of a virus is common and is the fastest and most reliable way of spreading. Humans contract the virus via air, skin, or bodily fluids. The proposed model does not distinguish between those three types of infection.

- **Human-object:** Serves as a bridge between the infection that can occur when a human comes in contact with an infected object. Depending on the type of virus objects can play a certain role in the means of spreading. When objects can transfer the virus to humans, humans can in return infect an object to complete the cycle.

- **Object-human:** Certain viruses can live on objects for an x period, making the objects curial in the infectious cycle.

- **Object-object:** Even though this particular transfer of a virus does not happen that often, it is important to include since this model is scalable and could be used for every type of virus. The connection between each logistical infrastructure is a two-way street, the virus can shift between land, air, and water respectfully. The means of spreading is the same for each logistical infrastructure no matter which of the three categories it is under.

5. CASE STUDY

In the model section, I discussed the conceptual model for the spreading of a virus in logistical infrastructures. I also discussed the aim of this research regarding the significance of logistical infrastructures in the spreading of a virus. The scale of logistical infrastructures in the conceptual model is too large to fully encapsulate in a reasonable time frame. Therefore, in this paper, I decided to carry out a case study with five logistical infrastructures spreading across all three logistical platforms. The purpose of this contribution is to facilitate the ground on which the conceptual model is based. It proves a reusable base on which other logistical infrastructure sectors can be tested. In this paper, only four spreading measures with the same level of importance are considered. However, we believe that the proposed model would also apply to different measures of spreading based on higher importance. Also, this would need to be coded into the model program to indicate the infection percentage of each type of spreading.

5.1 Architecture Overview

In this model, I use agents to simulate the behavior of a virus inside a fixed environment using the logistical infrastructures. The main agents include:

- **The virus agent**
- **The human agents**
- **The shipment agents**
- **The airplane agents**
- **The truck agents**
- **The postal agents**

The views are adopted from the medical field and from the logistical field, to create a good balance infrastructural system that satisfies both parties [11, 6, 17]. Based on that knowledge a logistical infrastructural hierarchy that encapsulates all three of the main types of infrastructures is proposed. The above agents are placed inside a hierarchic structure, which shows the relations between the agents respectively **Fig. 4**.

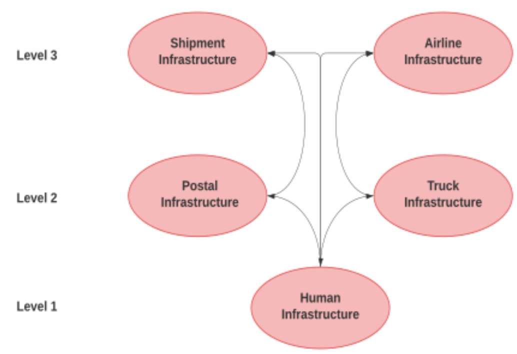

Figure 4. Logistical infrastructures hierarchy

6. RESULTS

The results section will present the obtained findings for each simulation. These results will provide the necessary information to construct a detailed answer to the research question of this paper. The results are categorized into three different scenarios: **the method without logistical infrastructure, the basic method with logistical infrastructure**, and **the mitigation method**. Where the mitigations could be initialized before or during the runtime of the simulation.

6.1 Methods

The properties discussed in the simulation structures apply to all the simulations. This sub-section discusses each simulation scenario separately. The mitigation strategies used in the simulations are derived from the work of Enrique Frias-Martinez et al. [10] who used similar mitigation strategies in their H1N1 model.

6.1.1 Basis without Logistical Infrastructure

This method is the independent simulation, with only human agent interaction without the use of any logistical infrastructure. The set-up phase of the simulation starts with only one infected human.

6.1.2 Basis with Logistical Infrastructure

This method is having the logistical infrastructure implemented. The model starts with one logistical infrastructure agent infected and no initial human infections during the set-up phase.

6.1.3 Mitigations

In each simulation three mitigation methods are implanted. These mitigations consist out of:

- If a human agent is infected, the procedure will be to stay home until the virus is cured.

- If an infrastructure agent is infected, the procedure will be to stop working until the virus is cured

- If the total amount of infected agents crosses the 20 percent mark, the specific logistical infrastructure will cut back 50% off its workers.

These mitigations are used individually or simultaneously on the logistical infrastructure's simulations.

Logistical Infrastrucutres	independent virus spreading model	Virus spreading model with logistical infrastructure	Counter Measurement 1	Counter Measurement 2	Counter Measurement 3	Counter Measurements 1/2/3
Postal	71.14	99.9	86	98.2	97.44	84.62
Airline	56.8	76.22	32.1	12.55	68.72	11.70
Shipment	71.91	98.91	84.32	95.43	96.66	81.89
Truck	76	98.87	86.11	90.65	99.32	80.243

Figure 5. Infection percentages and mitigation strategies

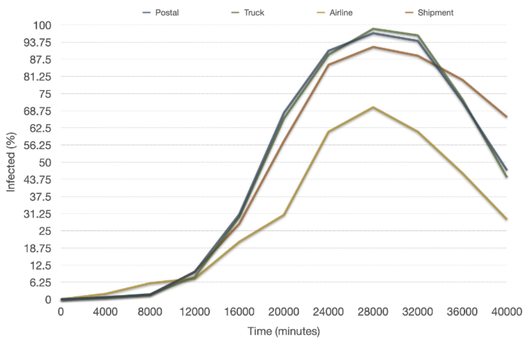

Figure 6. Infections logistical infrastructures

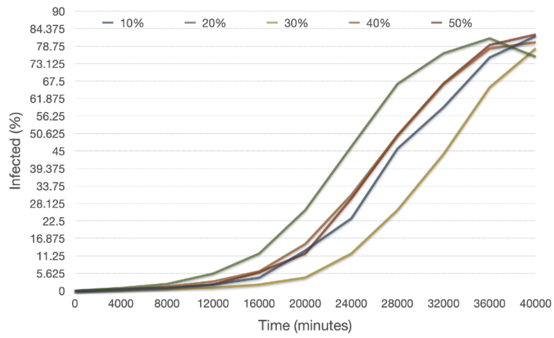

Figure 7. Infections postal infrastructure

6.2 Outcome

The purpose of the presented experiments is to show the effects that the logistical infrastructures are having on the spreading of an infectious virus. They are not meant to validate any of the presented models in this paper, nor to evaluate their performance. In the environments set for the logistical infrastructure simulations, the sample size of the simulations is $N_p = 25000$ which is the average population of a small village in the Netherlands and $N_i = 130$. The runtime of the simulation is 28 days, after which the results will be gathered.

In **Fig. 6** the results of all five of the logistical infrastructures using the model presented in this paper. The logistical infrastructures follow the same pattern of infection rate. The postal and truck infrastructure seems to have the highest infected percentage in 28 days of the simulation, whilst the shipment infrastructure follows close. The reason for this could be due to the postal and truck infrastructure have more human interaction in a short period of time, which could make it easier to give over the virus. Remarkable is the airline infrastructure, which has a significantly lower percentage of infected people at its peak and after 28 days. In all four infrastructures, the decline in infected people after 28000 minutes (19 days) is the result of the incubation time which is 15 days, after which people get cured of the virus.

Fig. 5 shows an overview of the results of the simulations with and without using logistical infrastructures. On the right side of the table, the counter measurements are displayed while using the different logistical infrastructures. At first glance, the logistical infrastructures do not seem to deviate that much from each other, except for the airline whos results lie significantly lower. What is remarkable are the results when using and not using a logistical infrastructure, these results suggest that the logistical infrastructures do have an impact on the spreading of a virus. The airline infrastructure has a lower percentage of infected people on average and it is remarkable that counter measurement one and two are both more effective on the airline infrastructure than on the other logistical infrastructures. On further inspection the results of all three counter measurements simultaneously are noticeable. These counter measurements have a significant impact on all four logistical infrastructures. The airline infrastructure is most affected by the use of all three counter measurements simultaneously.

7. SENSITIVITY ANALYSIS

The results of the simulations are based upon the values set during the initialization phase. In this section, the effect of changing these variables will be discussed. The outcome of each simulation is depended on the chosen variables: **Infection change, sample size, movement speed, change to movement**, to name a couple. Changing these variables in any way could heavily affect the results. With the sensitivity analysis, I want to discuss that the found results are not definitive in any shape or form. The chosen variables are gathered with current information from chosen sources and could change in the future. A sensitivity analysis on the postal infrastructure using the third counter measurement which lets the postal company cut back their staff after a certain percentage of people got infected will be conducted. The threshold of the number of infected people is changed into five scenarios: 10%, 20%, 30%, 40%, and 50%. **Fig. 7** shows the results in a graph with the different thresholds. On immediate inspection the number of infected people after 28 days lies seemingly close to each other. What is remarkable is that 30% has the lowest rate of infections. Whilst 10%, 40%, and 50% seem to follow the same pattern.

8. DISCUSSION

The content of this paper is only a case study of the conceptual model. The reason that this research consists of only a fraction of the logistical infrastructures for this model, lies in the unknown viability of the conceptual model. This model was created to research if logistical infrastructures have an effect on the spreading of a virus in a controlled environment. The data had to be gathered in a short period, which limited the number of infrastructures that could be tested. This paper tries in no way to present the most optimal solution for the proposed problem. The initialization variables set for the simulation are gathered from current research of COVID-19 and could change in the future. Because of the limited time and resources, the environments are smaller than initially proposed, also a more realistic set of environments for the different logistical infrastructures could have been created. The initial design of the simulations could be approved upon, these simulations were modeled with limited to no knowledge about modeling or agent-based modeling. Also, the agents could be made more proactive instead of only following certain rules, for instance, avoiding crowded areas during a pandemic or let everything be delivered so it does not need to leave the house. In this paper, I used agent-based modeling, but it is not the only platform on which such experiments can be conducted, further research could be made on other platforms. With the current knowledge and skills, the logistical infrastructure movement patterns could have been made more realistic with set goals and time frames to further increase the real life environment of the simulations.

9. CONCLUSION AND FUTURE WORK

This paper presented a conceptual model for logistical infrastructures in a virus spreading simulation in the form of a case study. In this paper, I investigate the spread of a virus via logistical infrastructure, based on a conceptual model presented. The purpose of this contribution was to address the connection between logistical infrastructures and virus spreading, including mitigation methods within the case study. Four logistical infrastructures are identified and encapsulated in the conceptual model. I experimented with three different mitigation methods and run on the applied logistical infrastructures. The obtained results indicated the viability of the conceptual model, including most apparent:

- the impact of logistical infrastructure on the spreading of a virus, by integrating logistical infrastructure in the simulation.
- the impact of the combined mitigation methods, when applied to the logistical infrastructure environment.
- the impact in regards of amount of infected are the truck and postal infrastructure.

The results indicate that using counter measurements during a pandemic could reduce the number of people that get infected and with that contain the virus.

There are numerous ways to further improve the current models. The models were created with little knowledge about the modeling world and these models could be created in a different modeling platform. Future work can focus on studying the possibility of expanding the model. This will include the introduction of different logistical infrastructures and mitigation methods, with contrasting variables. Besides, future work can experiment with self-adaptive logistical infrastructures, viruses, and humans, swapping between different mitigation methods to mitigate the spreading of the virus. With the introduction of AI in the model, a more realistic real-world scenario could be made that could have more reliable results.

9.1 Open source

Once the research has been published, all code written for the project will be made publicly available on GitHub. Everybody can acces the code and use it at their own pleasure.

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