Corona spread in public trains

Design of Multi-Agent Systems (D27)

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Abstract

COVID-19, caused by SARS-CoV-2, is spreading across the globe. This calls for efficient mitigation options to slow down the spreading of the virus. Previous research showed that increasing social distance and applying different boarding strategies decrease the infection risk in planes. In this research, we look at the effectiveness of several measures that can be applied in the carriages of a train. These measures are a minimal pathway distance while moving though the pathways, ventilation techniques, creating pathways within a carriage and keeping a portion of the seats empty. In this approach, agent-based modelling is used to simulate these measures in a train compartment.

Unfortunately, we were unable to implement a realistic model for the infection probability. This forced us to focus our attention on the effect of the mitigation measures on the social distance instead of infection probability. Our results show that the checker seating mode is most effective in increasing the social distance within individuals. Other mitigation options had a limited effect.

Github repo: `https://github.com/Daankrol/D27-DMAS-Corona-spread-train`

1 Introduction

The disease, now commonly known as coronavirus 2019 (COVID-19), has spread rapidly around the world and quickly became a pandemic. For obvious health concerns, the spread of the causing virus (SARS-CoV-2) has to be decreased as much as possible [Li+20]. One of the most effective techniques used in societies around the globe to decrease the spread is social distancing. This technique requires individuals to keep a 'safe' distance from one another, which may vary from 1 to 2 meter [LL20] to decrease the chance of getting infected. However, as mitigating measures are lifted gradually, social distancing becomes more difficult in public transport. The inability to maintain distance might result in a risk for passengers of public transports, such as trains. In this research, we will address the problem of the coronavirus spread in trains in the Netherlands. By designing a simulation, we measure the effects of 5 different measures.

1.1 Problem

To reduce the spread of the virus, the Dutch government obliges travellers to wear masks, in all public transportation. People in the Netherlands are also obligated to maintain 1.5m social distance at all times [Alg20]. Some seats in the public trains have to remain empty to also have social distance while passengers are being seated. However, as of 1 July 2020, all seats are available again in trains [NS]. Additionally, the citizens from the Netherlands show decreasing compliance with the measures for the safe-distance [Rei+20]. This makes it difficult for passengers to maintain the advised 1.5 meters within a train and could increase the risk of infection during a train journey. Aside from the general rules, including wearing a face mask and maintaining distance, there are no rules for boarding and alighting a train. Normally, when people are boarding and alighting a train, they do this in clusters and use all doors simultaneously [Wig01a]. During this process, people increasingly struggle to maintain the precautionary 1.5m social distance [Rei+20].

1.2 State of the Art

Cotfas et al. compared different boarding techniques of airplanes, by looking at the effect on the spreading of SARS-CoV-2 [Cot+20]. They came to the conclusion that best boarding strategies made use of a predetermined path that caused minimal interaction between passengers with a single entrance door. They also compared the infection risk for different distances and found that the risk at 1m physical distancing is marginally higher than the risk at 2m. The distance could be obtained by leaving rows of seats empty between the passengers.

In [SZ20] the efficacy of social distance in different public transportation methods, such as trains and busses, was evaluated. They also looked at the effect of ventilation and extended the Wells-Riley model, so it can more accurately predict the infection probability by an airborne virus.

1.3 New Idea

In this paper, we look at the effect on the spreading of SARS-CoV-2 of different measures in NS trains in the Netherlands. In short, we try to answer the following research question: "What are the effects of social distancing, ventilation rate, predetermined pathways and seat modes on the infection probability in an agent-based simulation of a train compartment?"

Social distancing is seen as one of the most effective measures to counteract the spread of SARS-CoV-2 [SA20; Chu+20]. We expect that increasing the amount of social distance will result in less spread and out of our three social distance options (0m, 1m, 2m) the two meter will result in the least amount of spread.

As the spreading of SARS-CoV-2 is modelled through air transmission, another way of mitigating the spread of the virus is by reducing the number of virus particles in the air. A more efficient ventilation system is better at removing those virus particles from the carriage and thus reduce the probability of spreading the virus.

We expect that the usage of a compulsory path, leading from a single entrance door to and a single exit door will reduce the spreading of SARS-CoV-2 since this might reduce contact.

Leaving certain seats empty, will increase the social distance between seated passengers. We expect that the checkerboard will have the least amount of spread since this is the set-up with the largest minimal distance.

2 Method

2.1 Simulation model

To measure the effect of the different regulations on the spreading of SARS-CoV-2, we build a simulation with MESA, an agent-based modelling framework written in Python.

2.1.1 Train

The environment of the simulation consists of one train compartment with 78 seats, two doors and one aisle. This compartment is a simplified grid version based on a blueprint of the Intercity Materieel (ICM) received by the Dutch Railway Company (NS). The simplified grid is shown in Figure 1. In this

Figure 1: The grid representation of a train. The gray squares represent seats. Circles represent agents. The doors are shown as a cell without a seat on both the bottom left and the bottom right.

grid, a square represents a $1m^2$ surface. White squares are open spaces. The bottom left and bottom right squares represent the doors of the train. The grey squares represent available seats. When a seat is unavailable, it will turn red. When running the simulation, the time lapses using ticks. For convenience, we chose that 1 tick represents one second.

2.1.2 Passengers

The passengers are represented by agents. Each agent uses behaviours. When a behaviour fails it can fall back to previous behaviour. When it succeeds it can continue to the next behaviour. This behaviour-based approach ensures that the simulation will not get blocked by agents and can successfully run. Agents are visualized using circles. They can enter the train, select an empty seat and move along the aisle to go to their seat. When boarding the train at a station, every time step an agent enters the train. This is based on the average boarding speed of 1 person per second [Wig01b]. Agents do adhere to the social distancing setting. They can only enter the train when there is enough social distance to other agents at the entrance. The agents can move in the train with a speed of 1 square per time step. This is equivalent to $3.6km/h$, which, we believe, is a realistic walking speed in a train. Once the train has arrived at a station, some agents leave the train and navigate to the door. The colour of the circle representing the agent is determined by the agent's current state. If an agent is looking for a destination (an empty seat or a door), the colour is yellow. When the agent is navigating towards a seat, it will turn blue. Once it's seated, the agent will turn green. When an agent is navigating towards the exit, it will turn red. Some passengers are infected and have a probability of infecting other passengers in the train. This probability is computed using the Wells-Riley model, extended by [SZ20]. We further discuss this model in the Parameters section below.

This basic simulation is similar to the airplane simulation of [Cot+20]. There also is only one aisle, but passengers in one row can have one seat between each other. Also, in this simulation, passengers can immediately be seated and do not have to store luggage and therefore do not take additional time. Another difference in this simulation is that no different boarding strategies can be applied as passengers may already be seated when a train arrives at a station, which would result in a strategy that is almost always similar to the random boarding strategy in [Cot+20].

2.2 Parameters

A number of parameters are implemented that can influence the risk of infection by a passenger:

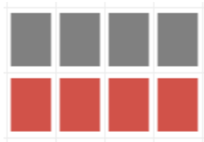
Method	Window	Empty rows	Checkerboard
Visualization			

Table 1: Different seating methods. The squares represent seats. Red squares indicate that a seat is restricted. In this comparison the aisle is located at the bottom of the table.

- **Minimal Pathway Distance:** As it is shown that social distancing reduces the risk of transmission [Chu+20], we will investigate the effect of individuals keep more or less distance while moving around in the aisle of a train carriage. This distance between agents may vary between 0 (no distance), to 1 or 2 meters. However, passengers may pass seated passengers, who occur within their social distance range, while walking down the aisle.
- **Ventilation:** Ventilation has shown to be a reducing factor in the spread of the virus in both buildings, but also public transportation methods [SZ20]. Different air ventilation techniques bring with them different distribution patterns and thus different efficiencies. The Dutch Railway Company could not provide us with the specifics of their ventilation system as this is considered classified. Therefore we will use the efficiencies of several standard cases found by [MMA19], as cited in [SZ20]. These values are expressed as factors with respect to the base case where cool air is supplied at ceiling level. This base case has a ventilation factor, also referred to as air distribution effectiveness (E_z), of 1.0. We will consider a carriage with a worse E_z, for instance, where warm air is supplied at floor level and returned at ceiling level ($E_z = 0.7$), and a carriage with a better E_z, for instance a supply of cool air at approximately 1.4m above the floor and ceiling return ($E_z = 1.5$)
- **One-way movement:** As shown in [Cot+20], a boarding strategy decreases the risk of infection, due to the decrease in exposure time between passengers. A directed pathway may also decrease the number of crossings between passengers, decrease the exposure time and, therefore, decrease the infection risk.
- **Empty seats:** Some seats are left empty to increase/maintain the social distance. This can be done in three different ways: Only using window seats, keep every other row empty or use a checkerboard. Examples of these settings are shown in Table 1.

Additionally, the Wells-Riley model is the most classic and widely used prediction model for infection risk ([RMR78; Wel+55], as cited in [Cot+20]). Therefore, the infection probability of an agent is calculated by using the extended Wells-Riley model designed by the authors of [SZ20], which is specifically designed for the prediction of transmission of COVID-19. Using the extended model, the probability of infection, P_I, for an agent is calculated as follows:

$$P_I = \frac{C}{S} = 1 - exp(-P_d \frac{Iqpt}{Q \cdot E_Z}) \tag{1}$$

where C is the number of new cases, S is the number of susceptible individuals, I is the number of source patients, q is the quantum generation rate factor, p is the pulmonary ventilation rate of passengers, t is the time in seconds, Q is the room ventilation rate, E_Z is the air distribution effectiveness and P_d is the social distance index. P_d is calculated by:

$$P_d = \frac{(-18.19 \ln(d) + 43.276)}{100} \tag{2}$$

where d is the average distance in meters. In addition, d is calculated using:

$$d = \frac{D_{total}}{T_{total}} \tag{3}$$

where D_{total} is the summed minimal distance between an agent i and other agents over a period T_{total}. T_{total} is the total number of time steps an agent spent in the train compartment.

This model assumes that there is a single infected individual inside the carriage at all times. As we model the infection probability over the entire train journey and not the infection from passenger to passenger, it is unimportant to know which individual is initially infected and whom it infects.

2.3 Implementation details

The simulation in the project is made using Python 3.8 and Mesa (v3.3.2). In the simulation are passengers, who board a compartment of a train using either one or two doors, depending on the state of the pathway (i.e. directed or undirected). Every agent has a risk of getting infected based on Equation 1. The time is measured in so-called "time-steps", which are the number of iterations in the simulation. In our simulation, the time-steps represent the time in seconds. In every iteration, an agent is either created, moving to a seat, seated or exiting the simulation.

If an entrance is free a human agent can board the train. Depending on the predetermined pathway distance human agents might have to wait until there is enough social distance near the entrance. Upon entering the train the human agent looks for a free seat. Seats closer to the agent have a higher chance of being chosen than seats further away from the agent. The agent will first look for completely empty rows. If there are none it will find a free seat next to another agent in the row. Do note that this is only possible in the normal and empty rows seat modes. Using the breadth-first search algorithm the shortest path is found to the seat. The human agent will move to the seat will adhering to the predetermined distance to other human agents on the aisle. While traversing through the train to the seat the agent will continually check if the seat is still free. If another agent gets to the seat earlier the agent will fall back to a behaviour to find a new seat.

2.4 Experiment design

To test the effect of the different measures, we ran the simulation model multiple times while tuning different parameters. These parameters with their optional values are summarized in Table 2.

Parameter	**Options**
Minimal Pathway distance	0m, 1m, 2m
Air distribution effectiveness factor	0.7, 1.0, 1.5
One-way movement	True, False
Empty seats	Window seats only, empty rows, checkerboard

Table 2: The different parameters and their options

2.4.1 Trajectory

We simulated different stops from a train ride from Groningen to Den Haag Centraal. At every station, some passengers will leave the train and some new passengers will board the train. To reduce the complexity of the simulation, we decided to have a fixed number of agents entering and exiting the train at each station. By doing so, we assure that the train has a fixed occupancy percentage. This reflects the implementation of the research of [SZ20]. No precise information on the number of passengers per compartment in a train could be found. But then again that would also go beyond the scope of this research. In the simulation, every tick represents one second. The time between each station can be found in Table 3. 5 seconds before reaching the next station passengers can already move to the aisle to prepare for leaving the train while adhering to the social distancing measures.

Station	**Passengers Boarding**	**Passengers Alighting**	**Time to next station (min)**
Groningen	39	0	23
Assen	10	10	51
Zwolle	20	20	26
Lelystad Centrum	20	20	16
Almere Centrum	20	20	20
Amsterdam Zuid	20	20	8
Schiphol	20	20	37
Den Haag Centraal	0	ALL	NA

Table 3: Trajectory information

3 Results

For every level of a parameter, we ran the simulation 10 times leaving the other parameters at their default setting. We measured the minimal social distance of each individual and estimated the infection probability, using the modified Wells-Riley model discussed in subsection 2.2. Finally, we compared the results of 25% of the total number of seats in train carriage being occupied to an occupancy of 50%.

3.1 Seating mode

The seating mode has a clear effect on the minimal social distance of the individual agents with 25% occupancy as shown in Figure 2. The checker seating mode results in the highest mean value (mean = 1.87), followed by the empty rows seating mode (mean = 1.58). While the spread of the results of only window seems the be higher than the normal seating mode, the only windows has only a marginally higher mean value (1.42 versus 1.39).

The multi-modal character of the distributions can be explained by the grid-like architecture used in the simulation. Agents will most likely be seated either one, two or three seats apart from each other. For the checker seating mode, the square root of two also shows a peak in occurrences. This can be explained by the agents sitting diagonally in front or behind each other.

With 50% occupancy shown in Figure 3, the results are similar. Again, checker seating mode (mean = 1.95) outperforms the other seating modes. The variability in the data is substantially reduced. There is a significant difference in the distribution of the means in normal, empty rows and only windows seating mode (Kruskall-Wallis: Chi square = 99.12, p = .00, df = 2). The effect is however very small (mean normal = 1.06, mean empty rows = 1.04, mean only windows = 1.02).

3.2 Minimal pathway distance

The effect of maintaining distance while travelling within the pathways is very limited for both 25% occupancy and 50% occupancy (Figure 4). Maintaining 0.0 minimal pathway distance (mean = 1.39) does not decrease the minimal social distance with 25% occupancy compared to maintaining a 1.0 (mean = 1.39) and a 2.0 (mean = 1.38) minimal pathway distance.

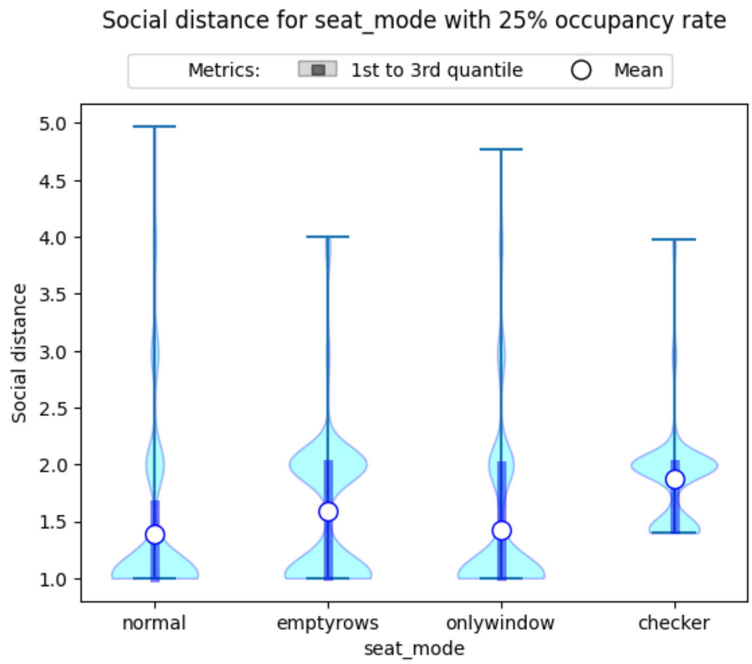


Figure 2: Minimal social distance for differing seating modes with 25% occupancy

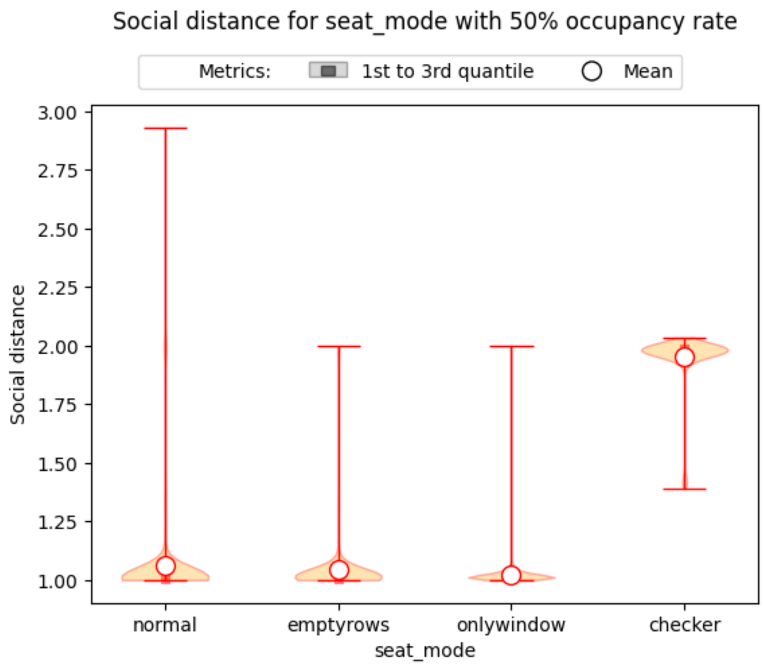


Figure 3: Minimal social distance for differing seating modes with 25% occupancy

Having a 50% occupancy rate mainly reduces the mean value of the minimum distance for each level of minimal pathway distance (mean 0.0 = 1.04, mean 1.0 = 1.06, mean 2.0 = 1.07). Again, the differences between these mean values are minimal.

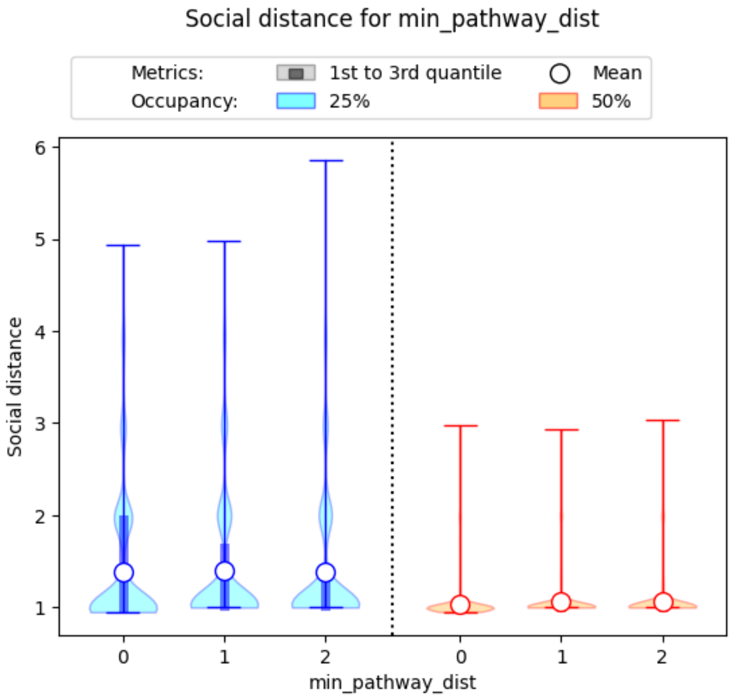


Figure 4: Minimal social distance for differing minimum pathway distances

3.3 One-way movement through pathways

Having enforced walking directions did not substantially influence the minimum social distance in our model with 25% occupancy. Figure 5 shows that even though the 1^{st} to 3^{rd} quantile has a larger range (from 1.01 to 1.64) with the one way movement through carriages turned off compared to the range for it being turned on (1.02 to 1.13), the difference in mean value is minimal (mean = 1.39 for both True and False setting).

Figure 5 also shows that again the main effect of increasing the occupancy to 50% is the reduction of the social distance. Again, the mean values (mean True = 1.09, mean False = 1.06) do not substantially differ.

3.4 Infection Probability

The results produced by the modified Wells-Riley model proposed by Sun and Zhai [SZ20] contained grave abnormalities. These results are discussed in detail in Appendix A. Even after consulting one of the authors, professor J. John Zhai, we were unable to produce results that resembled the results found by Sun and Zhai [SZ20]. Our frame of reference is the scenario in which there is a single infected passenger in a high-speed train carriage with 50% occupancy over the course of a three-hour trip. The infection probability was determined to be 28.4% [SZ20]. However, our model produces an infection probability of 91.7% under similar circumstances.

In our correspondence with professor J. John Zhai, it became apparent that the ventilation rate Q is expressed in m^3/h instead of the m^3/s used in the original Wells-Riley model. Even though explicitly mentioned in the paper to use the time-unit of seconds, we also expressed it in hours to account for the possible change of representation of the ventilation rate. These results are shown in Appendix B. This did not provide the results we had hoped for as the infection rate dropped to 0.0% for all parameter settings we tested.

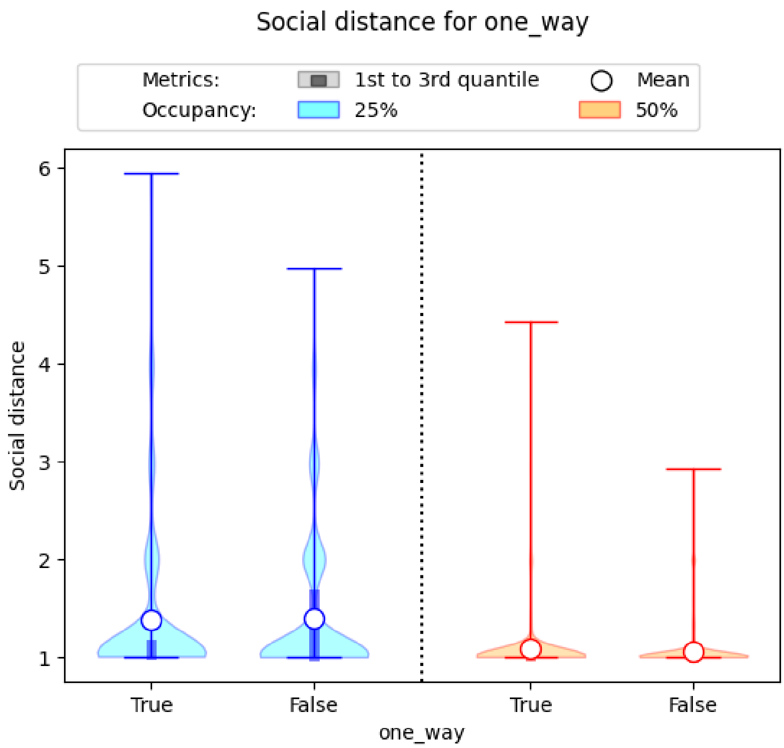


Figure 5: Minimal social distance for using enforced walking directions

3.5 Ventilation efficiency

The ventilation efficiency only effect the affects the infection probability as an input parameter for the extended Wells-Riley model. As the results from our implementation of this model were difficult to relate to empirical data, the effect size of the ventilation efficiency cannot be determined using our simulation. There is no use in comparing differences in the minimal social distance between individuals using different ventilation rates as it does not affect the minimal social distance. Therefore these results are omitted.

3.6 Interpretation of findings

We are not able to say anything useful on the precise infection probabilities produced by our implementation of the Wells-Riley model. It is however safe to assume that the chance of infection is reduced if individuals are seated in the checker seating mode. Both with a 50% and a 25% occupancy, it showed a substantial reduction in the social distance between the individuals compared to other seating modes. Other mitigation techniques did show a small effect, but not enough to be considered a valid mitigation option.

4 Conclusion

4.1 Discussion

Unfortunately, we were unable to reproduce the results of [SZ20] of the extended Wells-Riley model. We contacted the authors but were still unable to make their model work. Therefore, the results that we produced using their model in our own experiments, might be invalid. This is also contributed to the reason for measuring the social distance as a result of our experiments. However, the minimal social distance might not be an optimal measurement, as this is mainly influenced by the seat mode (see Figure 2 and Figure 3).

Passengers move in clusters while they are boarding and alighting a train [Wig01a], which may result in an increased risk of infection at that exact moment. However, the average social distance is measured during the full trip. Boarding and alighting are a relatively small portion of the trip. Consequently, this action has little to no effect on the average social distance between passengers and pales in comparison with the time that passengers are seated.

During our simulation, agents enter and leave the train on every station. During this process, we set the maximum occupancy rate, so it's the same for different experimental setups. This makes sure that it does not influence the results. For similar reasons, we also chose a fixed amount of agents that leave and enter the train on intermediate stations. However, we came up with these numbers ourselves, since we were not able to find actual data. This may have made of our simulation less realistic.

In our simulation, we did not simulate any walls or other objects that would influence the air stream in the train. We used a generalized environment, where the ventilation efficiency is the same for all positions. However, we think that objects, such as the backrest, could influence the spread of SARS-CoV-2 to the front and rear neighbours of an agent.

Our simulated environment consists of one train carriage. The agents only move inside the train, and are disregarded as soon as they touch the door. Therefore, we do not measure the spreading of SARS-CoV-2 outside the train. When people are waiting to board the train they wait in clusters on the platform in front of the door [Wig01a]. In these clusters, it is often difficult to maintain social distance. Therefore, we expect that these situations also might influence the infection rate. Unfortunately, since Mesa works with a grid-based system, we were unable to realistically implement the entrance areas.

Another disadvantages of using Mesa is that the agents are only able to move through the grid in fixed steps. This way we were only able to implement minimal social distances in the pathway of fixed real values. We were, therefore, unable to implement a minimal social distance of 1.5 in the pathways, which is the current measure in the Netherlands [Alg20].

4.1.1 Future improvements

As discussed above, we were unable to find accurate data for all our different parameters. For example, we had to estimate the ventilation efficiency and the number of passengers entering and exiting the train. The NS was not willing to provide us with these details. It would therefore be interesting to improve our research, by using more realistic data.

We based our infection rate on the extended Wells-Riley model. It would also be interesting to compare these results, with results of different models. A dose-response approach is another way to measure the spread of infectious diseases [SC10]. Implementing the dose-response approach would be interesting, since it also considers other ways of infection, besides the airborne rout.

Furthermore, there are some points where our simulation in Mesa does not reflect a realistic environment. It would therefore be interesting if there is a different kind of model, which, for example, does not limit agents to stand on certain gird points. Using such a continuous environment would enable the usage of more specific minimal social distances in the pathway. Not using a grid system, would even make it possible to implement more realistic traffic indoors and on station platforms. Using a 3d model would also be interesting since that enables implementation of realistic airflow.

4.2 Relevance

In this work, we have implemented an agent-based model of a train compartment in Mesa. Using the extended Wells-Riley model we tried to obtain the infection probability when passengers are in a train compartment. However, our implementation of the Wells-Riley model could not provide with results form which we can draw clear conclusions for the infection probability. Still, the difference in mean distance for the seat modes could be relevant for a railway company to investigate further, as an increase in social distance is related to a lower infection probability. Additionally, we have shown that more accurate data is necessary to use the Wells-Riley model properly in our simulation.

4.3 Team Work

During this project, we were also affected by the coronavirus. We could not meet up in person and thus we made heavy use of online video conferencing every week. We would discuss our current progress and the findings of other research. Work was split up early to efficiently implement and research this topic. Using Github issues could be tracked and by making use of the branching functionality the virus model and the actual train simulation could be developed independently. Table 4 shows the division of the work between all team members.

	Implementation	Research and report
Daan	Train model	Contact with NS
	Agent model	Experiments
	State-based behaviours	Methods
	Simulation UI	Discussion
	Code cleanup	
	Code documentation	
	Model visualisation	
Jeroen	Stations	Parameters
	Agent behavior	Corona Measures
		Introduction
		Methods
		Experiments
		Discussion
		Future Improvements
Julian		Parameters
		Corona Measures
		Introduction
		Methods
		Experiments
		Discussion
		Relevance
Ritten	Virus model	Abstract
	Batch running	Corona measures
	Data structuring	Results
	Run instructions	Discussion

Table 4: Work division

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A Infection rate with time in seconds

The infection rate when using seconds as a measuring unit for time is shown in Figure 6 for differing occupancy rates and seating modes. It shows that the checker seating mode is optimal in both the 25% occupancy (mean = 0.79) and the 50% occupancy (mean = 0.88). These numbers are however substantially higher than what we were to expect from the modified Wells-Riley model [SZ20]. This model predicts an infection probability of 28% for a three-hour high-speed train trip with 50% occupancy. When looking at the 25% occupancy in Figure 6, this means that our simulation produces an infection probability about trice as high, while only having half the occupancy. This is by no means realistic and thus these results are highly debatable.

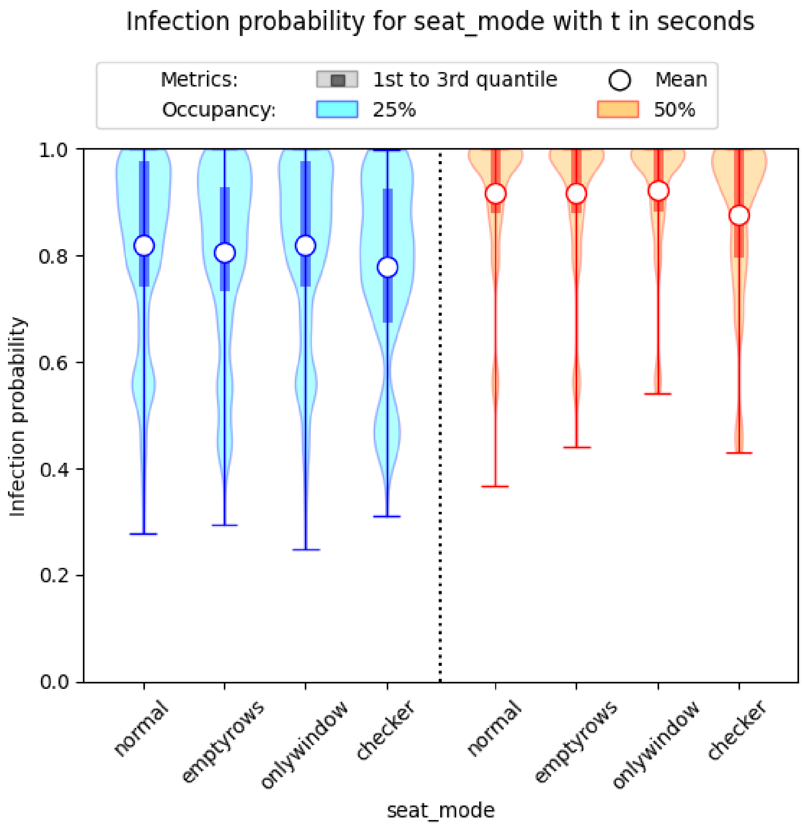

Figure 6: Infection probability with differing occupancy rates and seating modes, measured with seconds as the unit of time

B Infection rate with time in hours

As a possible solution to our unrealistic infection probability, we also took a look at the usage of hours instead of seconds the measuring unit of time. This was done since the modified Wells-Riley model uses m^3/h as a measuring unit for the ventilation factor, instead of m^3/s which is used in the original Wells-Riley model. These results are shown in Figure 7. These results are however even less realistic as all infection probabilities approach 0.

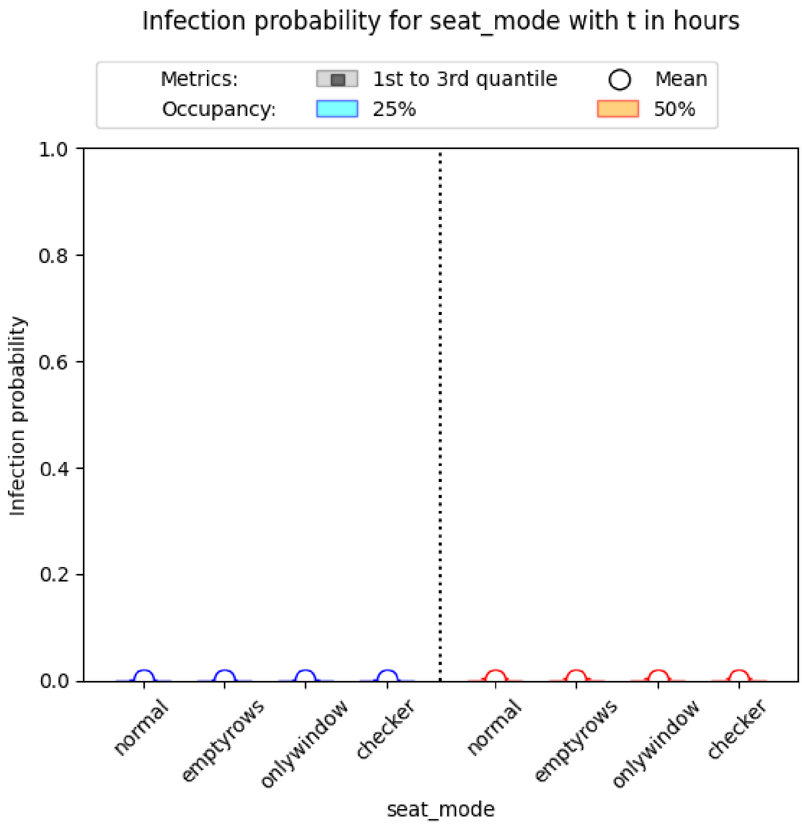

Figure 7: Infection probability with differing occupancy rates and seating modes, measured with hours as the unit of time