# TRANSPORTATION AS A DISEASE VECTOR—A MODELING APPROACH

July 2021

Center for Advancing Research in
**Transportation Emissions, Energy, and Health**
A USDOT University Transportation Center

Texas A&M Transportation Institute
Georgia Tech College of Engineering
Johns Hopkins Bloomberg School of Public Health
College of Engineering The University of Texas at El Paso
UC Riverside CE-CERT

## Disclaimer

# TECHNICAL REPORT DOCUMENTATION PAGE

| 1. Report No. | 2. Government Accession No. | 3. Recipient's Catalog No. |
|---|---|---|
| 4. Title and Subtitle<br>Transportation as a Disease Vector—A Modeling Approach | | 5. Report Date<br>July 2021 |
| | | 6. Performing Organization Code |
| 7. Author(s)<br>Alexander Meitiv, Kristen Sanchez, Joe Zietsman, Tara Ramani, Greg Winfree, and Eva Shipp | | 8. Performing Organization Report No.<br>TTI-04-34 |
| 9. Performing Organization Name and Address:<br>CARTEEH UTC<br>Texas A&M Transportation Institute<br>1111 RELLIS Pkwy, Bryan, TX 77807 | | 10. Work Unit No. |
| | | 11. Contract or Grant No.<br>69A3551747128 |
| 12. Sponsoring Agency Name and Address<br>Office of the Secretary of Transportation (OST)<br>U.S. Department of Transportation (USDOT) | | 13. Type of Report and Period<br>Final<br>March 1, 2020–March 31, 2021 |
| | | 14. Sponsoring Agency Code |

15. Supplementary Notes

This project was funded by the Center for Advancing Research in Transportation Emissions, Energy, and Health University Transportation Center, a grant from the U.S. Department of Transportation Office of the Assistant Secretary for Research and Technology, University Transportation Centers Program.

16. Abstract

Today's interconnected world, linked by transportation networks, plays a major role in the spread of a pandemic such as COVID-19. The virus originated in a single community, but due to the global nature of transportation, it spread to other parts of the world, impacting local communities and repeating this cycle many times over. In the context of disease spread, transportation can be viewed as a *disease vector* because it can spread diseases through at least the following three mechanisms:

- Infected people and goods travel to other locations and can spread the disease along the way and at the final destination.
- People congregate in groups and at higher densities when using public transportation, increasing the chance of passing infection among fellow passengers.
- The surfaces in public transportation and shared vehicles can become infected, potentially spreading infection to others who touch the same surfaces.

Clearly understanding transportation's role in the spread of disease vitally informs decisions that can stop or at least significantly reduce the spread of disease through transportation. This project involved developing a demonstration model to show how transportation can function as a disease vector and how certain policies can reduce the spread of a disease such as COVID-19, specifically through the third mechanism outlined above.

| 17. Key Words<br>Transportation, COVID-19, Disease Vector, Mortality, Policy | | 18. Distribution Statement<br>No restrictions. This document is available to the public through the CARTEEH UTC website.<br>http://carteeh.org | |
|---|---|---|---|
| 19. Security Classif. (of this report)<br>Unclassified | 20. Security Classif. (of this page)<br>Unclassified | 21. No. of Pages<br>20 | 22. Price<br>$0.00 |

**Form DOT F 1700.7 (8-72)** Reproduction of completed page authorized

## Executive Summary

Today's interconnected world, linked by transportation networks, plays a major role in the spread of a pandemic such as COVID-19. The virus originated in a single community, but due to the global nature of transportation, it spread to other parts of the world, impacting local communities and repeating this cycle many times over. In the context of disease spread, transportation can be viewed as a disease vector because it can spread diseases through at least the following three mechanisms:

- Infected people and goods travel to other locations and can spread the disease along the way and at the final destination.
- People congregate in groups and at higher densities when using public transportation, increasing the chance of passing infection among fellow passengers.
- The surfaces in public transportation and shared vehicles can become infected, potentially spreading infection to others who touch the same surfaces.

It is therefore vitally important to clearly understand transportation's role in the spread of disease so that informed decisions can be made to stop or at least significantly reduce the spread of disease through transportation. This project involved developing a demonstration model to show how transportation can function as a disease vector and how certain policies can reduce the spread of a disease such as COVID-19, specifically through the third mechanism outlined above.

The demonstration model uses a stochastic agent-based approach that models local person-to-person and person-to-vehicle infection rates. People are arranged on a square grid with periodic boundary conditions where only nearest neighbors can come into contact with each other, and it is assumed that any person can come into contact with any vehicle with equal probability. People find themselves in the following states: vulnerable, infected (with a variable time-dependent infectivity), recovered, or dead. Vehicles are characterized by their variable time-dependent infectivity. The model simulates person-to-person and person-to-vehicle interactions to imitate the spread of a disease such as COVID-19 through the synthetic population. Variable parameters in the modeling approach include:

- Person-to-person encounter rate.
- Person-to-vehicle encounter rate.
- Vehicle disinfection rate.
- Person-per-vehicle ratio.

These variables simulate policies related to social distancing, sheltering in place, disinfection of public transportation vehicles, frequency of public transportation services, and occupancy rates in public transportation vehicles. The model reveals the importance of key variables in controlling the spread of a disease such as COVID-19 through transportation, with some combinations of the policies more effective than others. The outputs of the model are shown graphically as well as through simulation videos. Simulation videos for each scenario are available via this Dropbox link. The demonstration model shows that transportation can be modeled as a disease vector and that implementing key strategies such as social distancing, sheltering in place, disinfecting public transportation vehicles, and limiting the number of people per vehicle can effectively fight the spread of disease through transportation. The demonstration platform has the potential to be adapted to a transit network, city, metropolitan planning organization, or region. Further, the platform has the potential to more fully inform decision makers as they develop strategies to effectively combat the spread of disease through the transportation system.

## Table of Contents

## List of Figures



## List of Tables

## Background and Introduction

Transportation plays a major role in the global spread of disease, affecting the spread of epidemics in several ways. First, transportation increases the range of movement and the spatial diversity of the infected and exposed individuals by facilitating encounters between people who do not live near each other. Second, public transportation increases the transmission rate by forcing people into prolonged contact in a confined, close environment. Third, public transportation vehicles and infrastructures can become carriers of disease that facilitate the indirect transmission of pathogens. In this study, traditional epidemiological models were extended by specifically addressing the indirect disease transmission mechanism. Infectious people deposit pathogens onto inanimate objects, where the virus can remain viable and active for hours and even days. Infected objects in transportation vehicles and infrastructures, such as seat belts, ticketing booths, armrests, etc., are examples of fomites. This study explored the effect of indirect transmission that occurs when vulnerable people become infected through contact with fomites.

Evidence collected regarding COVID-19 and previous pandemics shows that every possible precaution to minimize disease transmission must be taken, including addressing transportation's role in the spread of disease. This particular role has been discussed to some extent, specifically regarding the spread in vehicles, and includes diseases such as influenza (Browne et al., 2016), severe acute respiratory syndrome (SARS) (Bowen and Laroe, 2006), and tuberculosis (Edelson and Phypers, 2011). Studies have also focused on the enhancement of person-to-person transmission in close quarters (Harris, 2020; Kucharski et al., 2020; Li et al., 2020; Riou and Althaus, 2020) and indirect transmission via fomites (Zhao et al., 2019). However, gaps in understanding the impact of transportation vehicles and infrastructures as additional means of disease transmission still exist. To the researchers' knowledge, there are no models or simulation tools that attempt to quantify the role of transportation vehicles and infrastructures as disease vectors.

## Problem

Across all transport modes, there are gaps in understanding the impact of transportation vehicles and infrastructures in disease transmission, especially during the COVID-19 pandemic. To the researchers' knowledge, there are no models or simulation tools that attempt to quantify the role of transportation vehicles and infrastructures as disease vectors.

## Methodology

The researchers developed a demonstration model using a stochastic agent-based approach that measures infection rates due to person-to-person contact (as in other epidemiological models), while additionally modeling infections caused indirectly (i.e., from vehicles to people). The model includes two types of agents: people and vehicles (representing any form of public transportation). Notably, the model addresses near-range contact between people, but it does not address long-range contact between people or person-to-person contact inside public transportation vehicles. People are arranged on a square grid with periodic boundary conditions, and only nearest neighbors (spatially) come into contact with each other. Also, it is assumed that any person can come into contact with any vehicle with equal probability. Each person is characterized quantitatively by the vulnerability to infection (vulnerable or affected), the onset time of infection, the time-dependent level of infectivity, and the time-dependent level of activity. Vulnerable people can become infected because of contact with an infected person or a vehicle with infectivity, $I$. The probability of infection in such an encounter is assumed to be $P = 1 - e^{-\lambda I}$, where the parameter $\lambda$ is estimated to be 0.018 based on the number of daily contacts and the reproduction number $R_0$ reported in Tang et al. (2020).

The infectivity dynamics of people and vehicles differ. A key assumption is that the infectivity of a person (shown in Figure 1a) rises linearly over a time period, $\tau_1$, estimated to be three days (Guan et al., 2020), to a maximum of 1 and then falls linearly to 0 at time $\tau_2$ after the onset of infection. The mean recovery time, $\tau_2 - \tau_1$, is estimated to be 15 days (Aylward and Liang, 2020). The activity factor determines the rate at which the infected person comes into contact with vehicles and other people. Its dynamics mirror that of infectivity (shown in Figure 1b). Healthy people are characterized by the activity factor of 1. After the onset of infection, the activity factor decays linearly with time and reaches the minimum dictated by the severity of the particular disease instance. The severity of each infection is assumed to be random and uniformly distributed in (0,1). Vehicles are characterized quantitatively by their level of infectivity. The infectivity decays exponentially with the characteristic time scale $\tau_3$, which is estimated to be roughly 0.4 days based on the study of the surface stability of SARS-CoV-2 (van Doremalen et al., 2020).

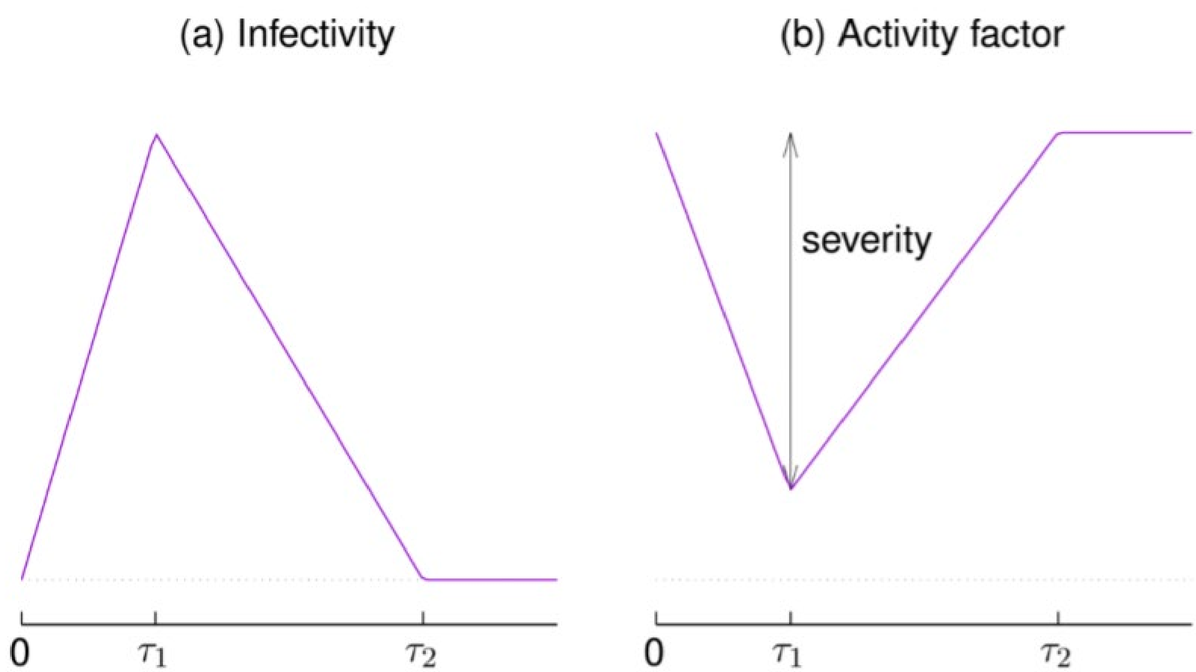



**Figure 1. The infectivity (a) and the activity (b) dynamics of a person. Time 0 corresponds to the time at which a particular person became infected.**

The researchers employed simulation methodology (Gillespie, 1976, 1977) using stochastic sequential processing for four types of events:

- Person-to-person contacts.
- Deaths.
- Person-to-vehicle contacts.
- Vehicle disinfections.

In the simulation, the rate of person-to-person contact is the total human activity, *A*, the sum of all current activity factors, scaled by the person-to-person contact rate, *C*. When a person-to-person contact event is triggered, a random person and his or her nearest grid neighbor are selected with the probabilities proportional to their current activity factors. These two people come into contact. When the contact involves an infected and a vulnerable person, the vulnerable person becomes infected with the probability *P* introduced above. Death occurs at a rate proportional to the product of the difference of the activity factor from 1 and the death rate, *M*, which is fixed at 0.05 to approximate the observed fraction of fatal outcomes for COVID-19. When persons are marked dead, they are excluded from further event processing.

The rate of person-to-vehicle contact is the product of the total human activity, *A*, and the person-to-vehicle contact rate, *V*. In this context, "vehicles" refer to public spaces, including public transportation vehicles and infrastructures, rather than personal vehicles. The person-to-vehicle contact rate does not vary with a specific person's access to personal transportation. When a vulnerable individual comes into contact with a vehicle, the person becomes infected with probability *P* given above, which depends on the current vehicle infectivity. When an infected person comes into contact with a vehicle, the infectivity of that vehicle is incremented by the current infectivity of the infected person. The disinfection rate is the product of the number of vehicles, $N_v$, and the disinfection rate, *D*. When a disinfection event is triggered, a random vehicle's infectivity resets to zero.

The simulation proceeds until the total infectivity of all people and vehicles is zero. At the end of the simulation, measurements are taken of the fraction of the population infected, the fraction of deaths, and the total duration of the epidemic.

Table 1 summarizes all model parameters. Parameters influenced by policy include the person-to-person contact rate, *C*; the person-to-vehicle contact rate, *V*; the number of vehicles, $N_v$; and the vehicle disinfection rate, *D*. For example, decision makers may employ social distancing and/or shelter-in-place orders to limit person-to-person contact and person-to-vehicle contact. Decision makers may also regulate the number of public transportation vehicles available and/or vehicle disinfection schedules.

**Table 1. Model Parameters**

| Parameter | Description |
|---|---|
| $N_p$ | Number of people |
| $N_v$ | Number of vehicles |
| $\tau_1$ | Duration from a person's infection onset to peak infectivity |
| $\tau_2$ | Duration from a person's infection onset to recovery |
| $\tau_3$ | Characteristic time scale for the exponential decay of vehicle infectivity |
| $D$ | Number of disinfections per day per vehicle |
| $V$ | Person-to-vehicle contacts per day per person |
| $C$ | Person-to-person contacts per day per person |
| $M$ | Death rate |
| $\lambda$ | Likelihood of infection during an encounter |

## Results

The simulation started with a single infected individual, while every other person was vulnerable. Due to the stochastic nature of transmission, there was a non-zero probability that just a few other individuals would be infected before the disease ran its course. However, if the number of infected individuals passed a certain threshold, the epidemic spread until a significant fraction of the population had been affected. Therefore, the distribution of the ultimate infected population fraction was bimodal, as shown in Figure 2. The values of the model parameters were specified in the model description except for the person-to-person contact rate, *C*; person-to-vehicle contact rate, *V*; vehicle disinfection rate, *D*; and person-per-vehicle ratio, $R = N_p/N_v$. If both the numbers of vehicles, $N_v$, and people, $N_p$, were multiplied by the same factor, the results remained unchanged, verifying the fact that only this ratio was relevant.

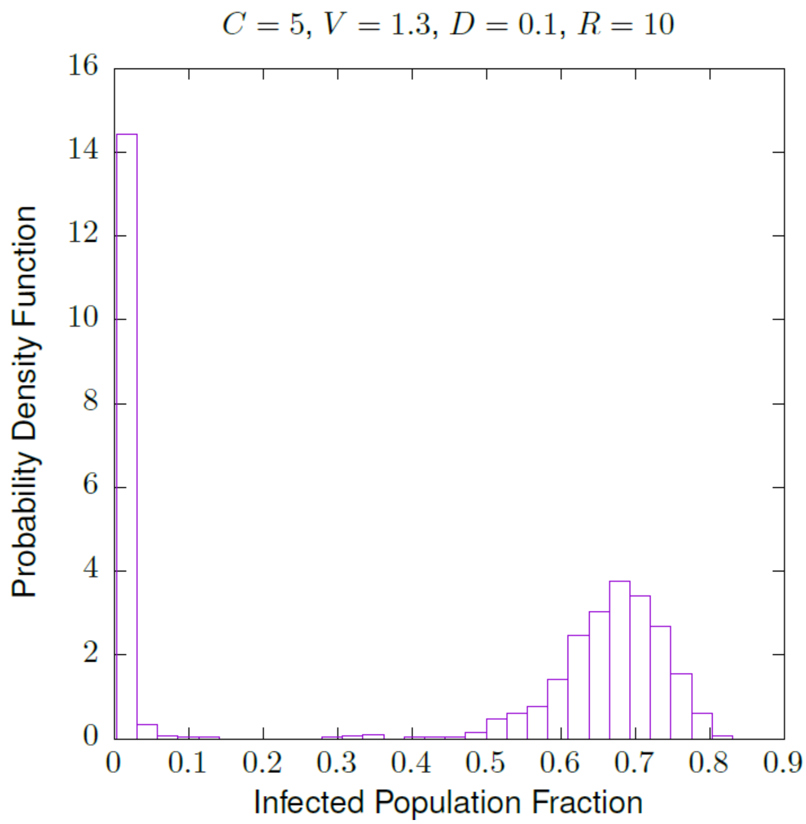



**Figure 2. The distribution of the epidemic size (infected population fraction), which is bimodal in general.**

The epidemic was quantified by computing the probability that a significant fraction (defined as 5 percent) of the population would become infected before the epidemic ran its course. Figure 3 shows the dependence of this probability on the person-to-person contact rate, *C* (Figure 3a); person-per-vehicle ratio, *R* (Figure 3b); vehicle disinfection rate, *D* (Figure 3c); and person-to-vehicle contact rate, *V* (Figure 3d). The growth of the significant epidemic probability with the person-to-person contact rate is self-evident. The qualitative trends in Figure 3b–d can be understood in terms of the vehicle-to-person transmission. Vehicles serve as reservoirs of the pathogen that spread the infection to unaffected parts of the population because every person can encounter any vehicle with equal probability. The average vehicle infectivity declines by increasing the disinfection rate, decreasing the number of people per vehicle, and decreasing the person-to-vehicle contact rate, which leads to the behavior shown in Figure 3. A further quantification of the epidemic's severity is the expected population fraction that will be infected during a substantial epidemic. The results presented in Figure 4 exhibit the same qualitative trends and can be explained via the same mechanisms as the probability of a substantial epidemic shown in Figure 3.

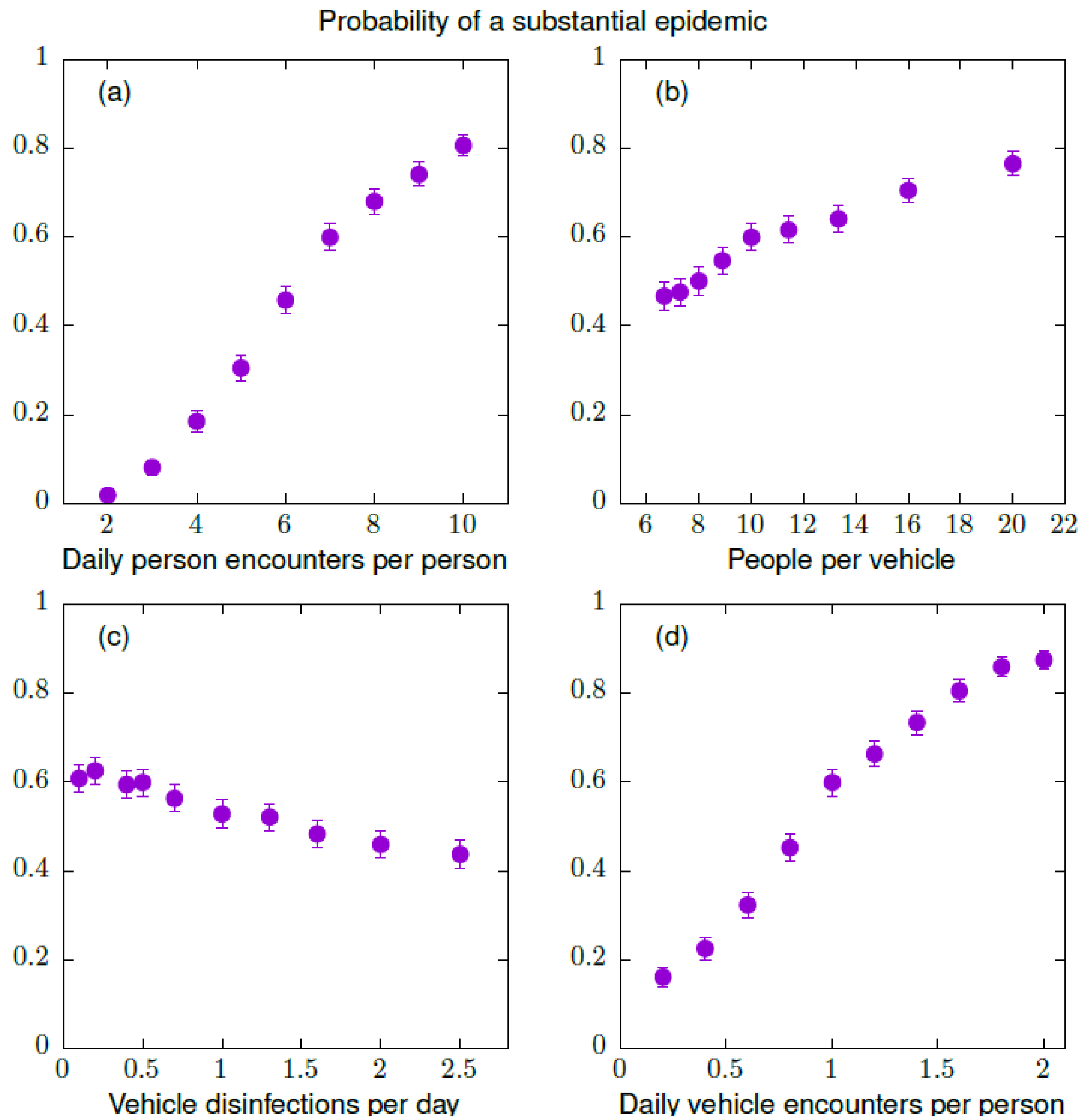



**Figure 3. The probability of a substantial epidemic (in which more than 5 percent of the population is affected) as a function of the (a) person-to-person contact rate, *C*; (b) people-per-vehicle ratio, *R*; (c) vehicle disinfection rate, *D*; and (d) person-to-vehicle contact rate, *V*. The values of the parameters that are not varied in each panel are *C* = 7, *V* = 1, *D* = 0.5, and *R* = 10.**

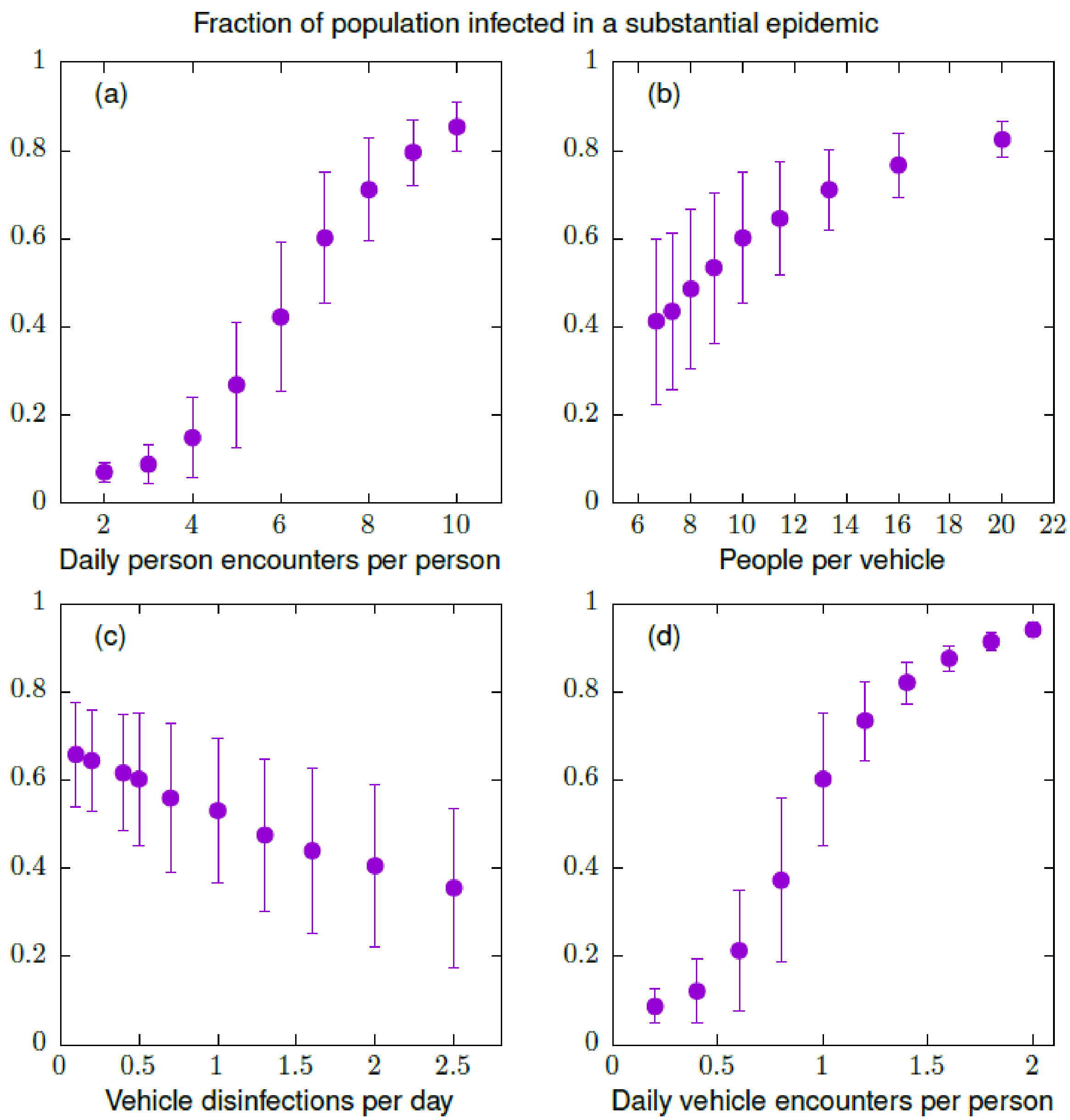


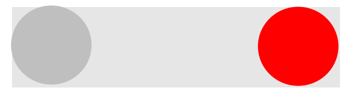
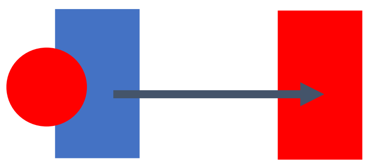
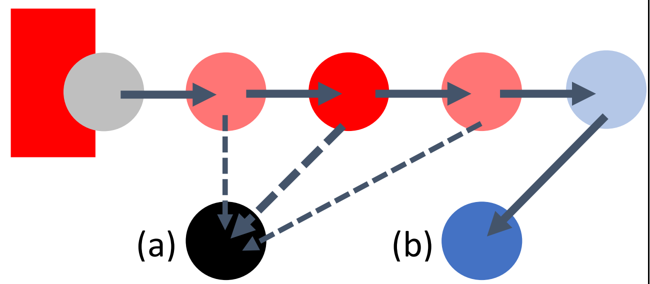
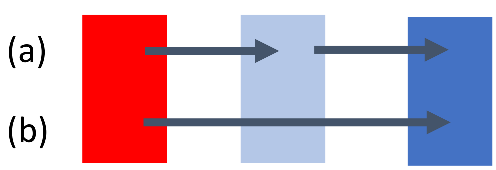
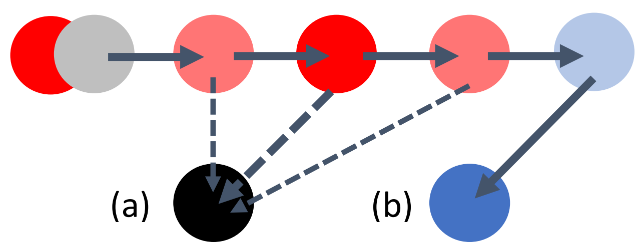

**Figure 4. The average population fraction that becomes infected in a substantial epidemic. The error bars denote one standard deviation from the mean epidemic size.**

The researchers created graphical representations of the results showing the spread of disease under different conditions. Table 2 displays a link to the video of each simulation scenario. In the videos, circles represent people, and rectangles represent vehicles. The color code is explained in Table 3. The parameters that are varied include the person-to-person contact rate, *C*; person-to-vehicle contact rate, *V*; number of people per vehicle, *R*; and vehicle disinfection rate, *D*. In the worst-case scenario, the virus quickly infects everyone, and the vehicles are highly infectious at the height of the epidemic. The rest of the videos show what happens when one or two of the variables are changed to try to mitigate the worst case. Decreasing the person-to-person contact rate to one person-to-person contact per day per person ($C = 1$) works (e.g., social distancing). Decreasing the person-to-vehicle contact rate to one person-to-vehicle contact every 10 days per person ($V = 0.1$) works (e.g., working from home). Increasing the vehicle disinfection rate to five disinfections per day per vehicle ($D = 5$) or decreasing the number of people per vehicle to four ($R = 4$) do not work by themselves, but doing both at the same time has a noticeable effect.

**Table 2. Videos Depicting the Epidemic Graphically**

| Sample Video Simulations | Parameters | Outcome |
|---|---|---|
| Video:<br>Worst-case scenario | 10 person-to-person contacts per day per person ($C = 10$)<br>1 person-to-vehicle contact per day per person ($V = 1$)<br>1 disinfection every 10 days per vehicle ($D = 0.1$)<br>20 people per vehicle ($R = 20$) | Timeline: 156 days<br>Population:<br>92.8% infected<br>88.8% recovered<br>4% died |
| Video:<br>Decrease person-to-person contact rate (*C*) | 1 person-to-person contact per day per person ($C = 1$)<br>1 person-to-vehicle contact per day per person ($V = 1$)<br>1 disinfection every 10 days per vehicle ($D = 0.1$)<br>20 people per vehicle ($R = 20$) | Timeline: 228 days<br>Population:<br>8.3% infected<br>7.9% recovered<br>0.4% died |
| Video:<br>Decrease person-to-vehicle contact rate (*V*) | 10 person-to-person contacts per day per person ($C = 10$)<br>1 person-to-vehicle contact every 10 days per person ($V = 0.1$)<br>1 disinfection every 10 days per vehicle ($D = 0.1$)<br>20 people per vehicle ($R = 20$) | Timeline: 285 days<br>Population:<br>11.4% infected<br>11% recovered<br>0.4% died |
| Video:<br>Increase vehicle disinfection rate (*D*) | 10 person-to-person contacts per day per person ($C = 10$)<br>1 person-to-vehicle contact per day per person ($V = 1$)<br>5 disinfections per day per vehicle ($D = 5$)<br>20 people per vehicle ($R = 20$) | Timeline: 212 days<br>Population:<br>81.9% infected<br>78.3% recovered<br>3.6% died |
| Video:<br>Decrease number of people per vehicle (*R*) | 10 person-to-person contacts per day per person ($C = 10$)<br>1 person-to-vehicle contact per day per person ($V = 1$)<br>1 disinfection every 10 days per vehicle ($D = 0.1$)<br>4 people per vehicle ($R = 4$) | Timeline: 393 days<br>Population:<br>76.9% infected<br>73.6% recovered<br>3.3% died |
| Video:<br>Increase vehicle disinfection rate (*D*) and decrease number of people per vehicle (*R*) | 10 person-to-person contacts per day per person ($C = 10$)<br>1 person-to-vehicle contact per day per person ($V = 1$)<br>5 disinfections per day per vehicle ($D = 5$)<br>4 people per vehicle ($R = 4$) | Timeline: 377 days<br>Population:<br>50.9% infected<br>48.3% recovered<br>2.6% died |

**Table 3. Explanation of the Graphical Representation Elements and the Color Code—Infectivity Increases from Deep Blue (0) to Light Blue to Light Red to Deep Red (>1)**

| Vehicles | People |
|---|---|
| <br>Noninfected vehicle | <br>Vulnerable person Infected person |
| **Person-to-vehicle contact**<br><br>An infected person can infect vehicles while infectious. | **Vehicle-to-person transmission**<br><br>Dead person Recovered person<br>A vulnerable person is exposed to an infected vehicle and becomes infected. Infected persons either die during the course of the disease (a) or recover (b). The probability of death is greatest at peak infectivity. |
| **Vehicle disinfection**<br><br>Vehicle infectivity decays exponentially with time (a) and/or vehicle is immediately uncontaminated by disinfection (b). | **Person-to-person contact**<br><br>Dead person Recovered person<br>A vulnerable person is exposed to an infectious person and becomes infected over time. Infected persons either die during the course of the disease (a) or recover (b). The probability of death is greatest at peak infectivity. |

## Conclusions and Recommendations

The results of this project make a case for transportation vehicles and infrastructures as disease vectors. The researchers developed a demonstration model to show the impact of the person-to-person contact rate, person-to-vehicle contact rate, disinfection rate, and people-per-vehicle ratio on the spread of disease. The findings showed that reducing the person-to-person contact rate or the person-to-vehicle contact rate effectively limits disease spread. Increasing the vehicle disinfection rate or decreasing the number of people per vehicle does not work alone, but doing both simultaneously can have a substantial effect on the epidemic's severity. Simplifying assumptions notwithstanding, the demonstration model shows that transportation can be modeled as a disease vector and that the person-to-person contact rate, person-to-vehicle contact rate, disinfection rate, and people-per-vehicle ratio are important factors to consider when implementing disease control strategies in different transportation modes. Key strategies such as social distancing, sheltering in place, disinfecting public transportation vehicles, and limiting the number of people per vehicle are important in fighting the spread of disease through transportation.

Policy and decision makers, scientific researchers, and practitioners are encouraged to use the concepts presented in this project brief to further explore the role of transportation vehicles and infrastructures as disease vectors and to investigate strategies to limit disease spread in this capacity. Another area for further investigation includes implementing material with antimicrobial properties (e.g., copper [Grass et al., 2011]) on frequently touched transportation surfaces and personal protective equipment. The demonstration platform presented here has the potential to be adapted to a transit network, city, metropolitan planning organization, or region. There is potential for practical applications if the demonstration model is, for example, calibrated with local data such as the structure of contact networks and the patterns of usage of shared spaces in public transportation systems. The platform also has the potential to more fully inform decision makers as they develop strategies to effectively combat the spread of disease through the transportation system.

The findings presented in this project brief pave the way for future research in the area of transportation as a disease vector with the goal of mitigating disease spread through transportation. Interdisciplinary work is warranted to reexamine how best to strengthen transportation assets to minimize the capacity to transmit disease. Transportation engineers, epidemiologists, infectious disease experts, biochemists, materials scientists, and others will need to collaborate to reimagine transportation aspects such as materials of construction and surface preparation. As the world continues to become more interconnected, it is important to continue understanding the impact transportation has on the spread of disease so that informed decisions can be made to stop or at least significantly reduce the spread of disease through transportation.

## Research Outputs, Outcomes, and Impacts

A research output from this project is the publication of a project brief (Meitiv et al., 2020). The project brief document was published on the CARTEEH website in June 2020. Additional research outputs of this project are video products. The spread of disease under different conditions was graphically represented in a video for each simulation scenario. Links to each scenario simulation are included in Table 2. In the videos, circles represent people and rectangles represent vehicles, as displayed in Table 3.

## Technology Transfer Outputs, Outcomes, and Impacts

A technology transfer output from this project is a data story that is hosted on the CARTEEH Data Hub. The data story describes the outcomes of the analysis of a complex agent-based stochastic model of epidemics in which disease can be transmitted either directly via person-to-person contact (i.e., local transmission) or indirectly via person-to-vehicle and vehicle-to-person contact. The details of the modeling approach, the technical summary of the results, and a less-technical white paper are attached to the data story as PDFs. The data story is available at this link. An additional technology transfer output from this project is an open GitHub repository that contains detailed instructions and the C++ code used to simulate a complex agent-based model and visualize the results for each scenario in a video animation. The GitHub repository is available at this link.

## Education and Workforce Development Outputs, Outcomes, and Impacts

Kristen Sanchez, a master's-level student enrolled in the program for Public Health at Texas A&M University, was hired on this project to conduct the literature review and assist with composing the project brief and final report. Kristen co-authored the project brief. Kristen used the knowledge and skills gained from the project in her coursework in the Master of Public Health program in the Department of Epidemiology and Biostatistics as well as in her internship with the Texas Department of State Health Services, where she collected and tracked data on COVID-19 outbreaks in vulnerable populations and facilities.

## References


Aylward, B., and Liang, W. (2020). *Report of the WHO-China Joint Mission on Coronavirus Disease 2019 (COVID-19)*. https://www.who.int/docs/default-source/coronaviruse/who-china-joint-mission-on-covid-19-final-report.pdf

Bowen, J. T., and Laroe, C. (2006). Airline Networks and the International Diffusion of Severe Acute Respiratory Syndrome (SARS). *The Geographical Journal*, *172*(2), 130–144. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7194177/.

Browne, A., St-Onge Ahmad, S., Beck, C. R., and Nguyen-Van-Tam, J. S. (2016). The Roles of Transportation and Transportation Hubs in the Propagation of Influenza and Coronaviruses: A Systematic Review. *Journal of Travel Medicine*, *23*(1). https://doi.org/10.1093/jtm/tav002

Edelson, P. J., and Phypers, M. (2011). TB Transmission on Public Transportation: A Review of Published Studies and Recommendations for Contact Tracing. *Travel Medicine and Infectious Disease*, *9*(1), 27–31. https://doi.org/10.1016/j.tmaid.2010.11.001

Gillespie, D. T. (1976). A General Method for Numerically Simulating the Stochastic Time Evolution of Coupled Chemical Reactions. *Journal of Computational Physics*, *22*(4), 403–434. https://doi.org/10.1016/0021-9991(76)90041-3

Gillespie, D. T. (1977). Exact Stochastic Simulation of Coupled Chemical Reactions. *The Journal of Physical Chemistry*, *81*(25), 2340–2361. https://doi.org/10.1021/j100540a008

Grass, G., Rensing, C., and Solioz, M. (2011). Metallic Copper as an Antimicrobial Surface. *Applied and Environmental Microbiology*, *77*(5), 1541–1547. https://doi.org/10.1128/AEM.02766-10

Guan, W., Ni, Z., Hu, Y., Liang, W., Ou, C., He, J., … Zhong, N. (2020). Clinical Characteristics of Coronavirus Disease 2019 in China. *New England Journal of Medicine, 382,* 1708–1720. https://doi.org/10.1056/NEJMoa2002032

Harris, J. E. (2020). The Subways Seeded the Massive Coronavirus Epidemic in New York City. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3574455

Kucharski, A. J., Russell, T. W., Diamond, C., Liu, Y., Edmunds, J., Funk, S., … Flasche, S. (2020). Early Dynamics of Transmission and Control of COVID-19: A Mathematical Modelling Study. *The Lancet Infectious Diseases, 20,* 553–558. https://doi.org/10.1016/S1473-3099(20)30144-4

Li, Q., Guan, X., Wu, P., Wang, X., Zhou, L., Tong, Y., … Feng, Z. (2020). Early Transmission Dynamics in Wuhan, China, of Novel Coronavirus–Infected Pneumonia. *New England Journal of Medicine*, *382*(13), 1199–1207. https://doi.org/10.1056/NEJMoa2001316

Meitiv, A., Sanchez, K., Zietsman, J., Ramani, T., Winfree, G., and Shipp, E. (2020). *Transportation as a Disease Vector—A Modeling Approach: Project Brief*. https://www.carteeh.org/transportation-as-a-disease-vector-a-modeling-approach-project-brief/

Riou, J., and Althaus, C. L. (2020). Pattern of Early Human-to-Human Transmission of Wuhan 2019 Novel Coronavirus (2019-nCoV), December 2019 to January 2020. *Eurosurveillance*, *25*(4). https://doi.org/10.2807/1560-7917.ES.2020.25.4.2000058

Tang, B., Wang, X., Li, Q., Bragazzi, N. L., Tang, S., Xiao, Y., and Wu, J. (2020). Estimation of the Transmission Risk of the 2019-nCoV and Its Implication for Public Health Interventions. *Journal of Clinical Medicine*, *9*(2), 462. https://doi.org/10.3390/jcm9020462

Van Doremalen, N., Bushmaker, T., Morris, D. H., Holbrook, M. G., Gamble, A., Williamson, B. N., … Munster, V. J. (2020). Aerosol and Surface Stability of SARS-CoV-2 as Compared with SARS-CoV-1. *New England Journal of Medicine*. https://doi.org/10.1056/NEJMc2004973

Zhao, B., Dewald, C., Hennig, M., Bossert, J., Bauer, M., Pletz, M. W., and Jandt, K. D. (2019). Microorganisms @ Materials Surfaces in Aircraft: Potential Risks for Public Health? A Systematic Review. *Travel Medicine and Infectious Disease*, *28*, 6–14. https://doi.org/10.1016/j.tmaid.2018.07.011