Multiscale Model for Pedestrian and Infection Dynamics During Air Travel

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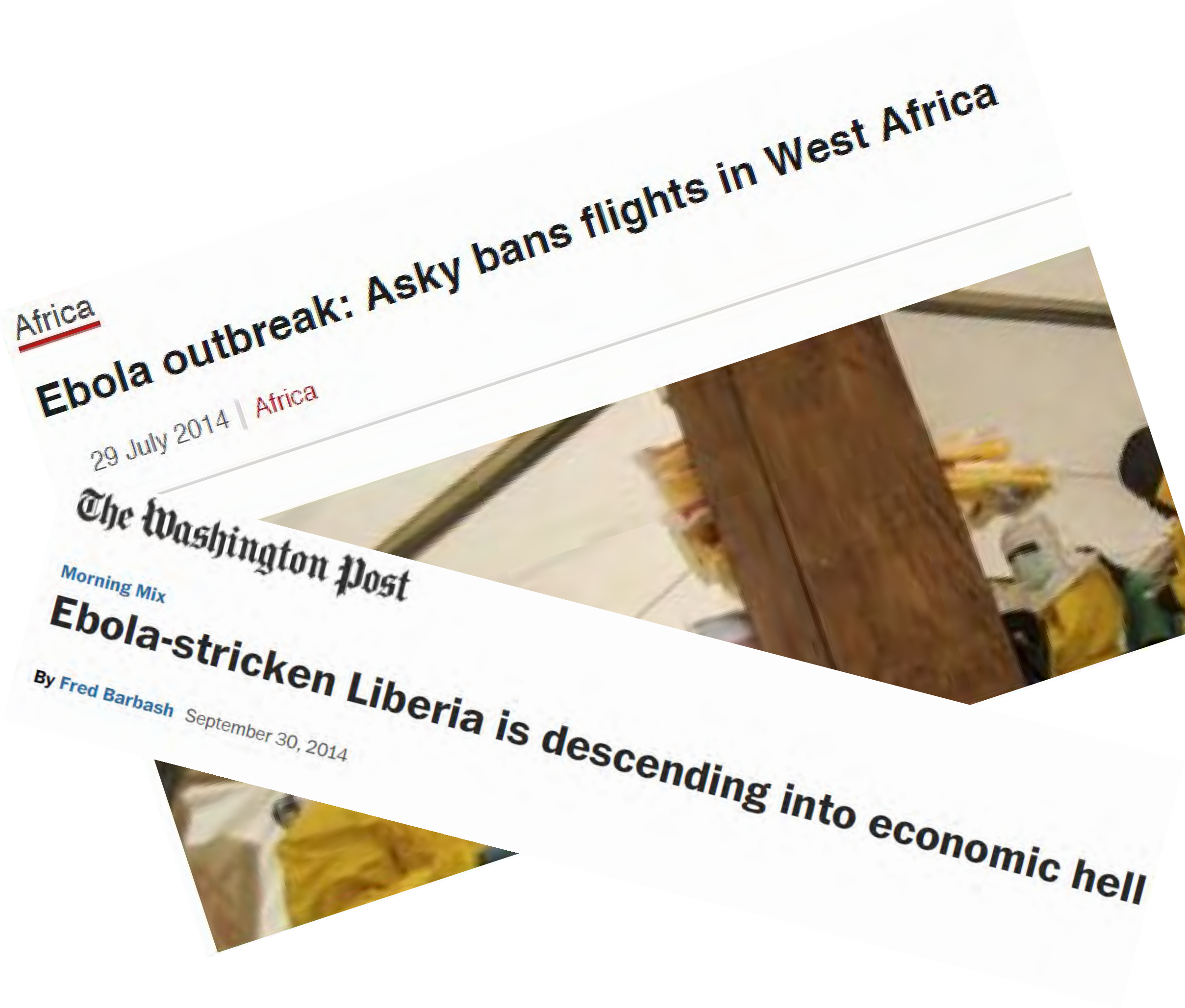
http://www.cs.fsu.edu/vipra/

Motivation

- Infection transmission during air travel for many diseases
- There has been ban on flights from Ebola infected areas
  - Such measures early on can have large human and economic impact
  - **Travelers with Ebola on passenger airplane in US**
  - **SARS transmitted during air travel**
  - **Evidence for many other disease transmission on airplanes**
- Fine-tuned policy prescriptions for air-travel can be as effective
  - Reassures the public that action be being taken
  - Avoids negative human and economic impacts



Objectives

- Develop a modeling framework that will analyze impact of policies decisions on spread of diseases through air-travel
    - Will provide insight to decision makers on consequences of policy choices
- Current work focused on Ebola/SARS and pedestrian movement within Airplane
    - Extension to Airports and other Infectious diseases in progress

Modeling Approach

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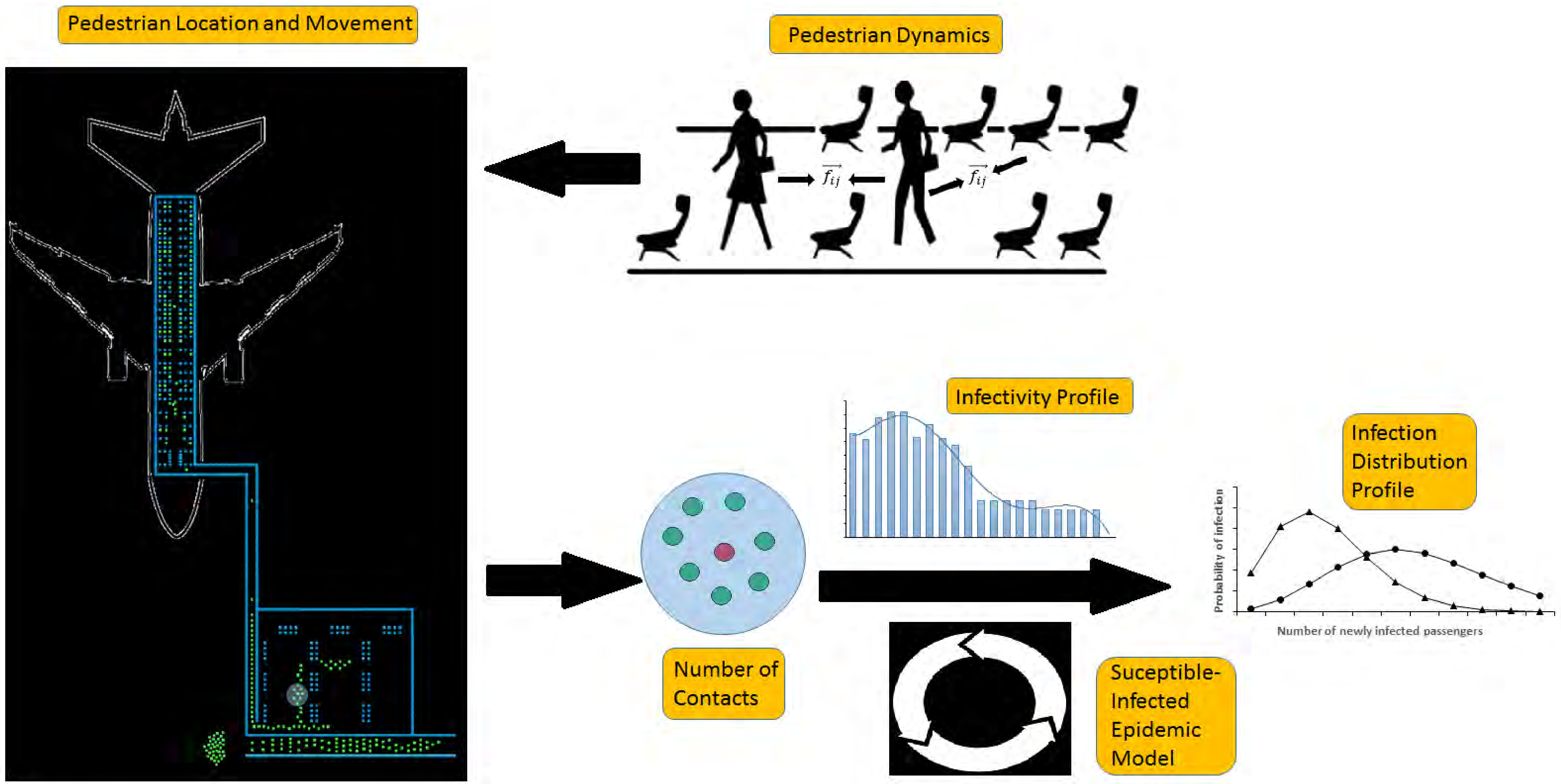
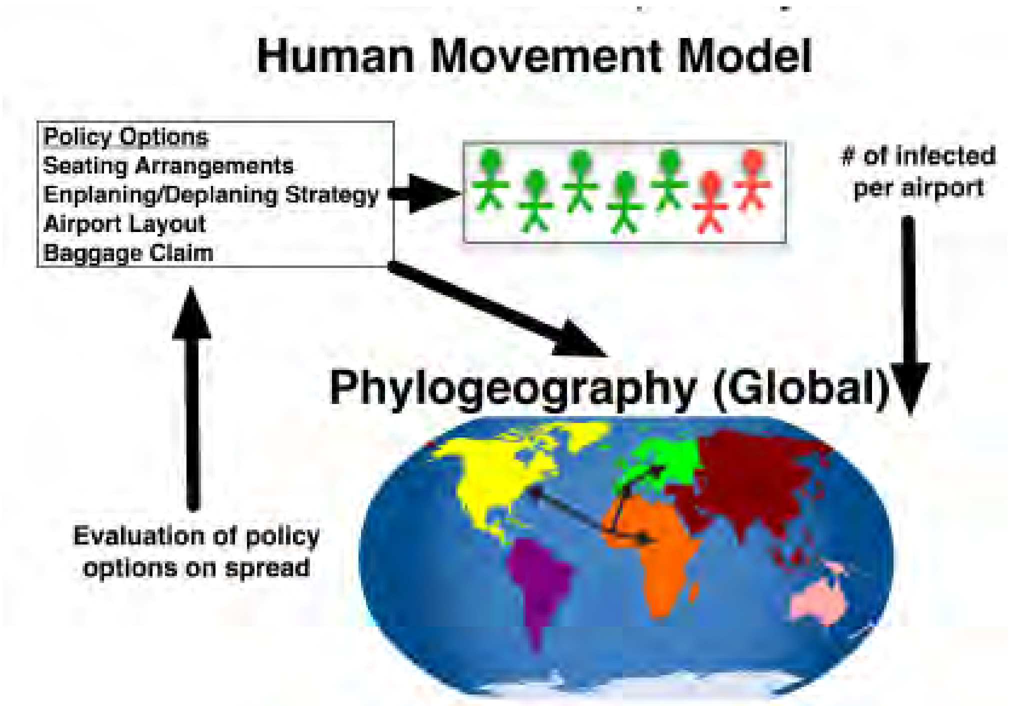


Modeling Approach

- Pedestrian movement model for movement of people within Airplanes and at Airports
- Combine pedestrian movement with stochastic infection models (SI models)
- Evaluate the effect of changes in pedestrian movement on potential infection spread
- Extension to global scale using phylogeography (Collaborators: Mathew Scotch, ASU) – Decision support system using chainbuilder (Rob Pahle , ASU)



Pedestrian Movement Models

- Different approaches to model pedestrian movement
  - Studies based on social psychology
  - Fluid flow based models for pedestrian movement
  - Geometric models to determine route through obstacles
  - Pedestrian movement based on cellular automaton
  - **Social force model proposed by Helbing (2000)**

- **Social Force Model**
  - **Based on molecular dynamics and discrete element methods**
  - **Positions of people evolve in time based on interaction forces between other people and walls**

$$m_i \frac{d\mathbf{v}_i}{dt} = m_i \frac{v_i^0(t)\mathbf{e}_i^0(t) - \mathbf{v}_i(t)}{\tau_i} + \sum_{j(\neq i)} \mathbf{f}_{ij} + \sum_W \mathbf{f}_{iW}$$

Social Force Model

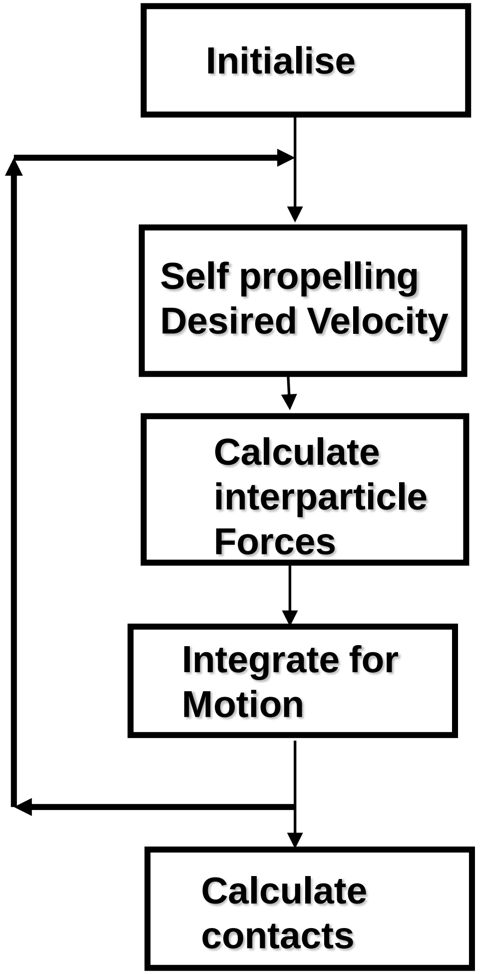
- Molecular dynamics is a mature simulation method in materials science and chemistry and serves as a framework for the model

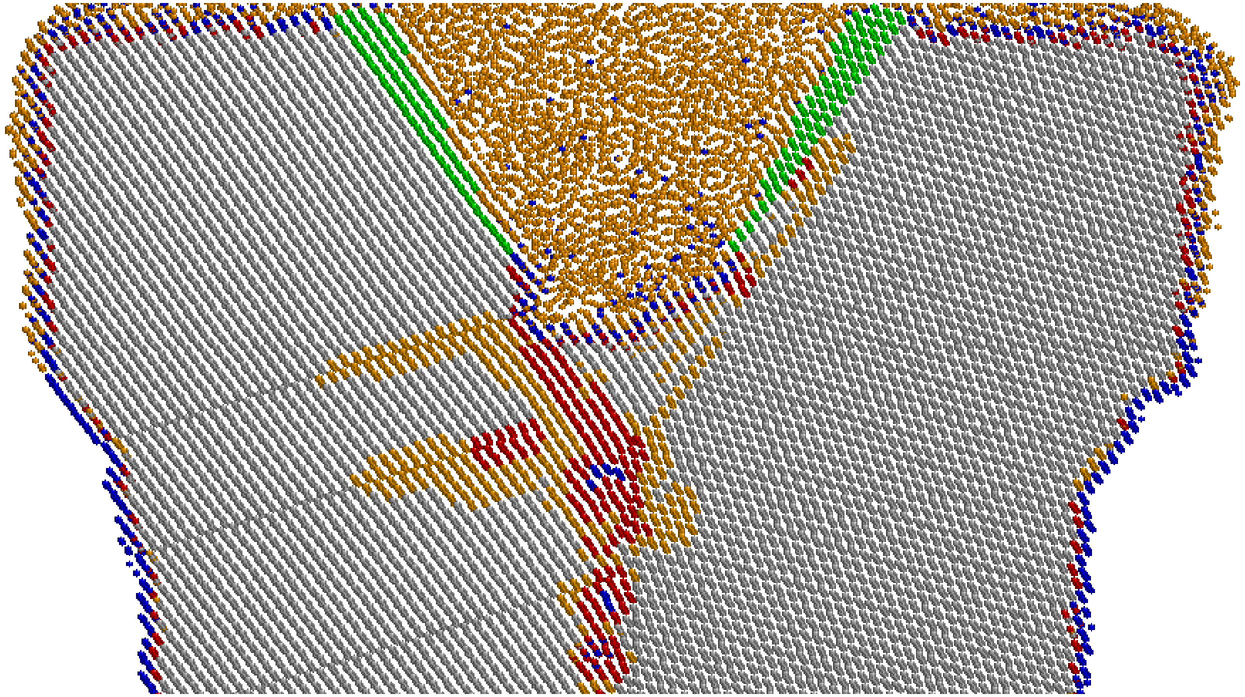
$$\bar{f}_i = \frac{m_i}{\tau}\left(\bar{v}_o^i(t) - \bar{v}^i(t)\right) + \sum_{j \neq i} \bar{f}_{ij}(t)$$

- We introduce location feedback
  - Location feed back on desired velocity
  - Effect of pedestrian density incorporated

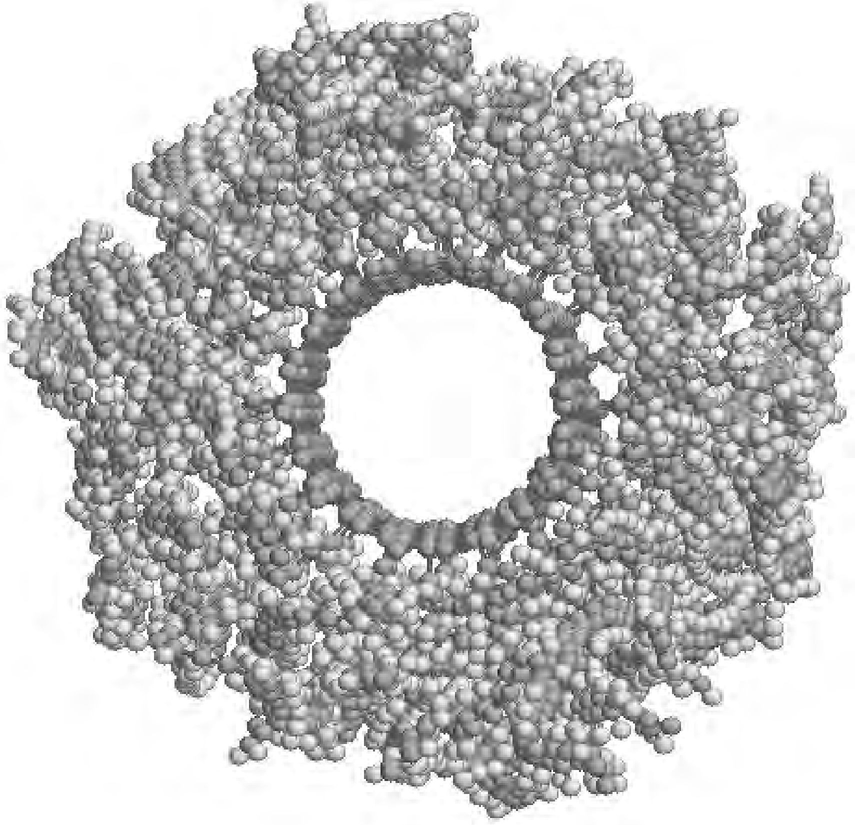
$$\bar{v}_o^i(t).\hat{e}_1 = \left(v_A + \gamma_i v_B\right)\left(1 - \frac{\delta}{\bar{r}_i \hat{e}_1 - \bar{r}_k \hat{e}_1}\right)$$

  - Parallel computing for parameter reduction





Crack propagation and dislocation emission during Liquid metal embrittlement in Al-Ga system – Namilae (2008)



Nanotube composite interface molecular dynamics model - Namilae (2006)

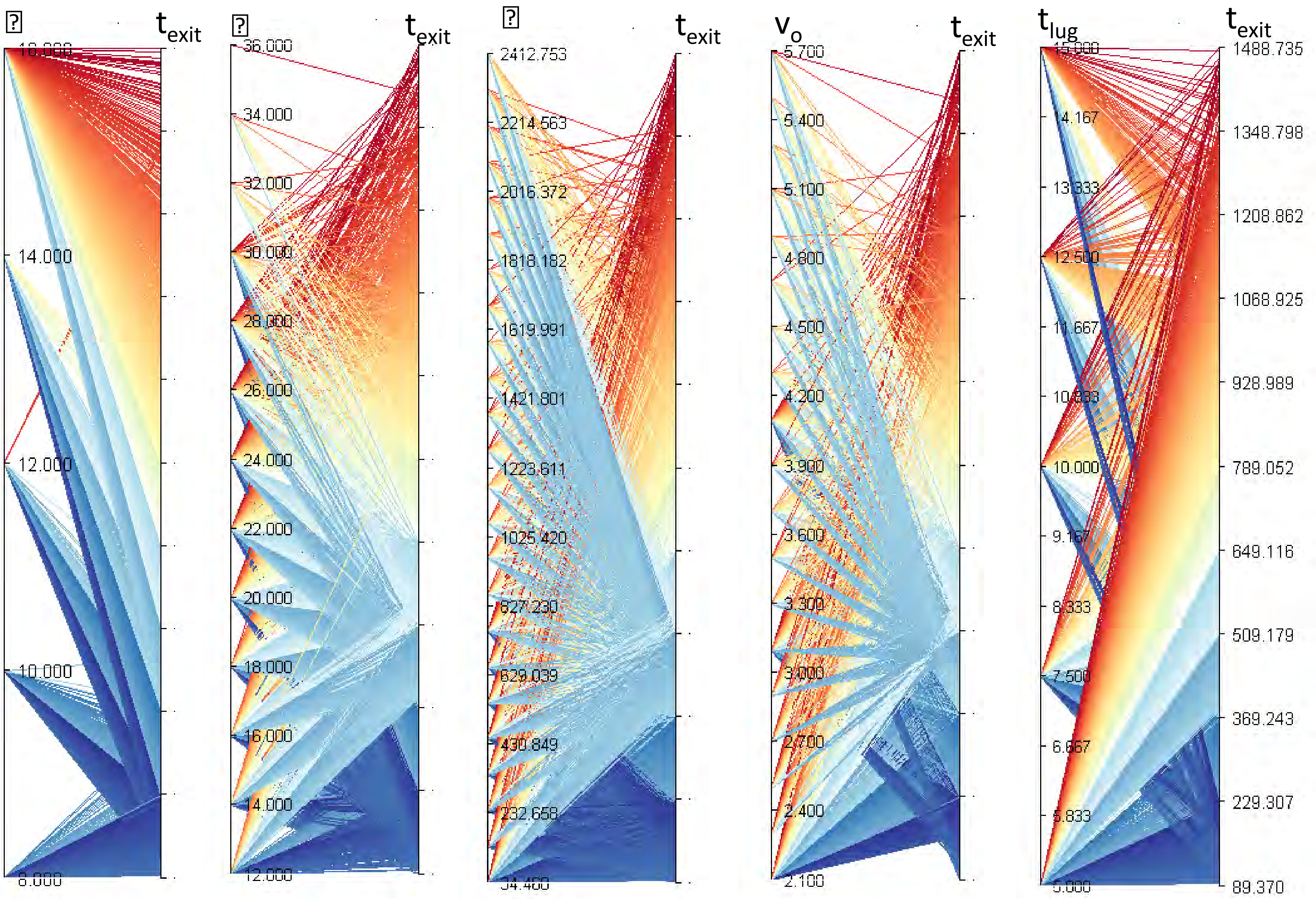
Parameter Estimation

First pass
Parameter estimation
On Bluewaters
Total simulations ~300,000

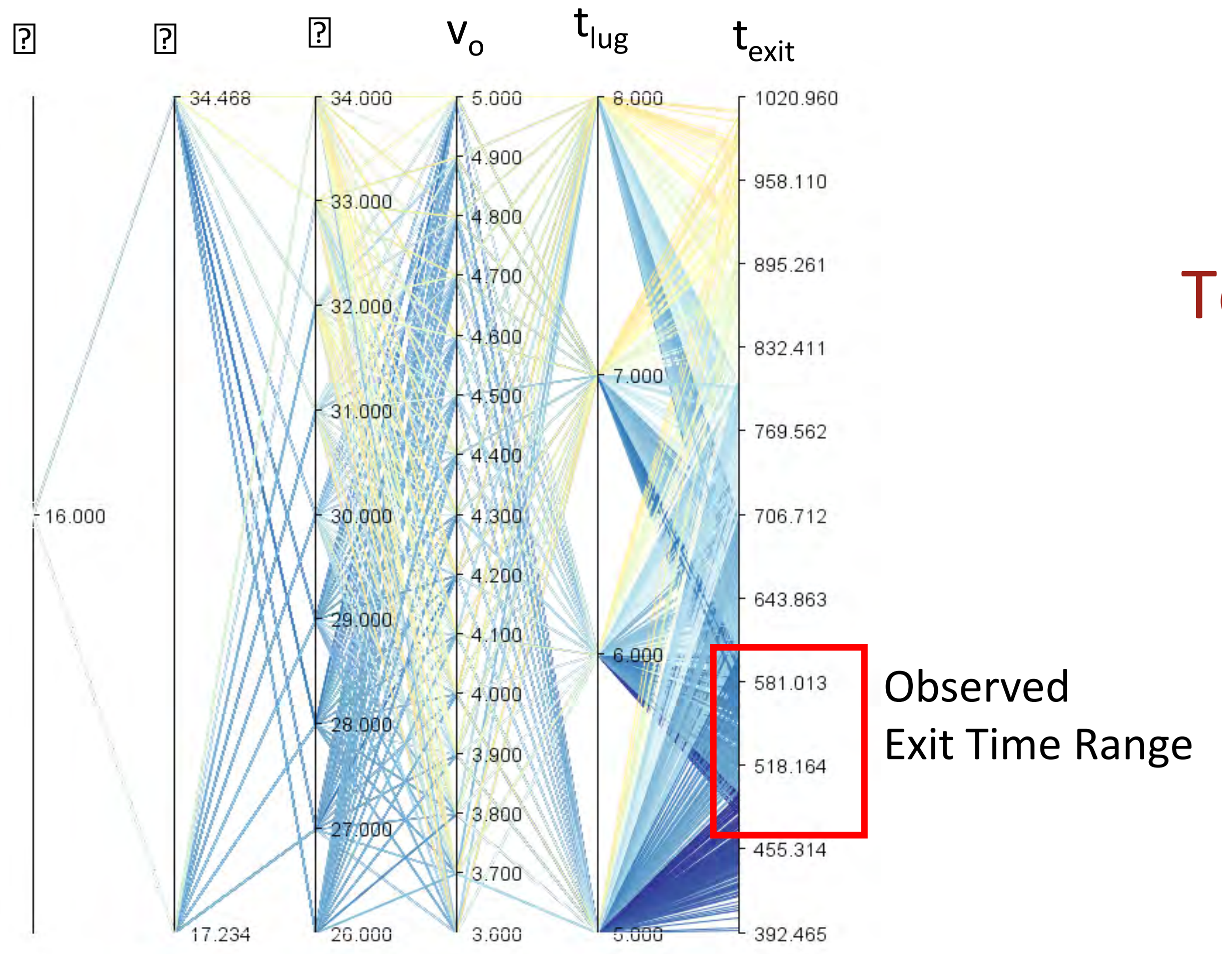
$$\bar{v}_o^i(t).\hat{e}_1 = (v_A + \gamma_i v_B)\left(1 - \frac{\delta}{\bar{r}_i\hat{e}_1 - \bar{r}_k\hat{e}_1}\right)$$

$$\bar{f}_i = \frac{m_i}{\tau}\left(\bar{v}_o^i(t) - \bar{v}^i(t)\right) + \sum_{j\neq i} \bar{f}_{ij}(t)$$

$$\bar{f}_{ij} = \frac{d}{d\bar{r}_{ij}}\left(\sigma.\left(\frac{\varepsilon}{r_{ij}}\right)^{12}\right)$$



Parameter Estimation



Second pass

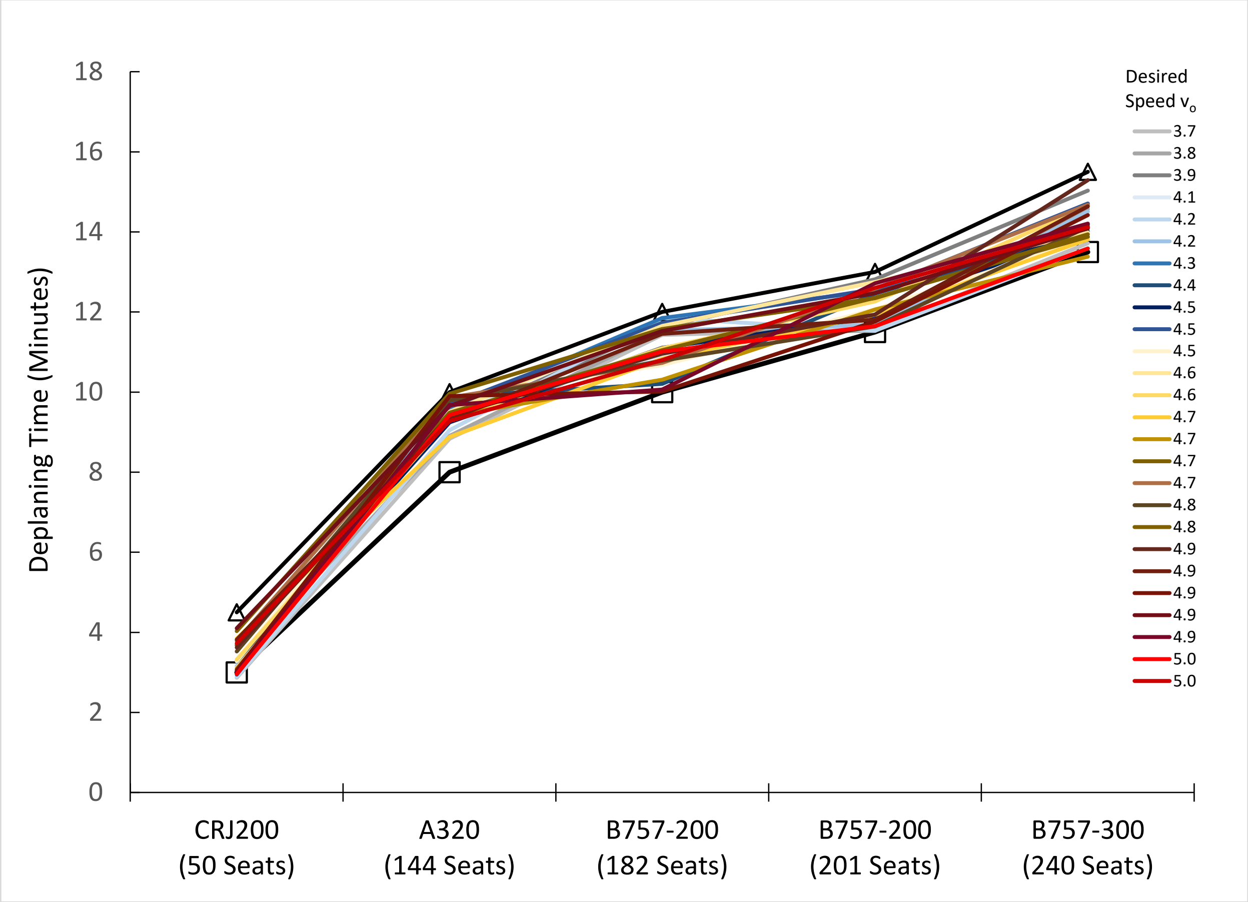
Parameter estimation

Total simulations ~300,000

Namilae et al, Physica A, in-print (2016)

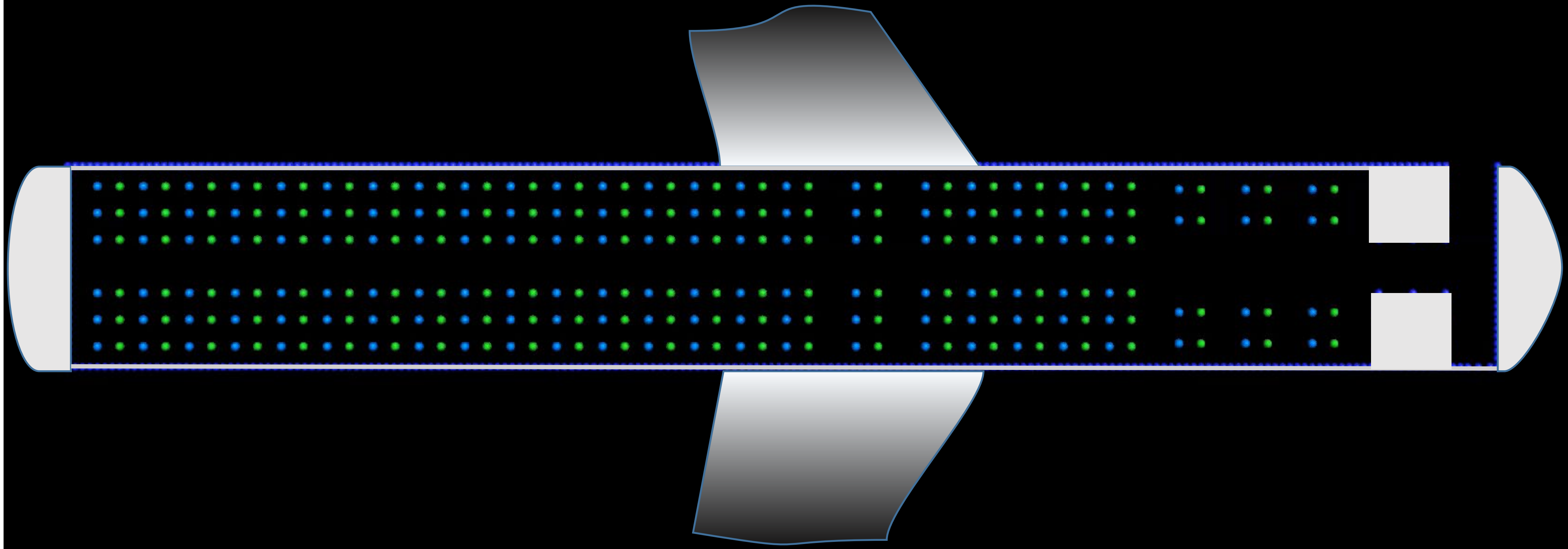
Physical aspects like front to back deplaning considered fro validating parameters

Model Validation



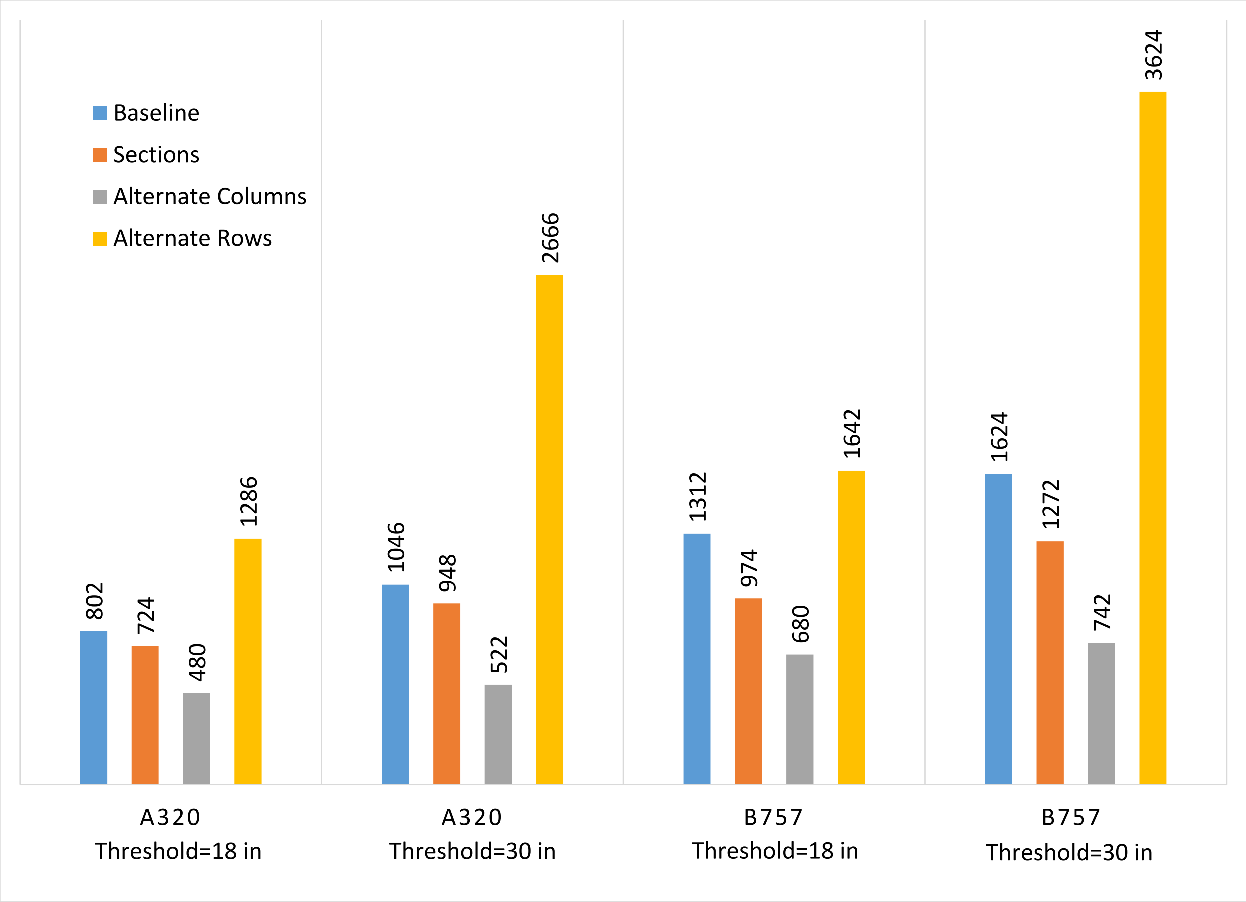
Different parameter combinations predict observed data for 5 airplanes

A320 144 Seats Egress

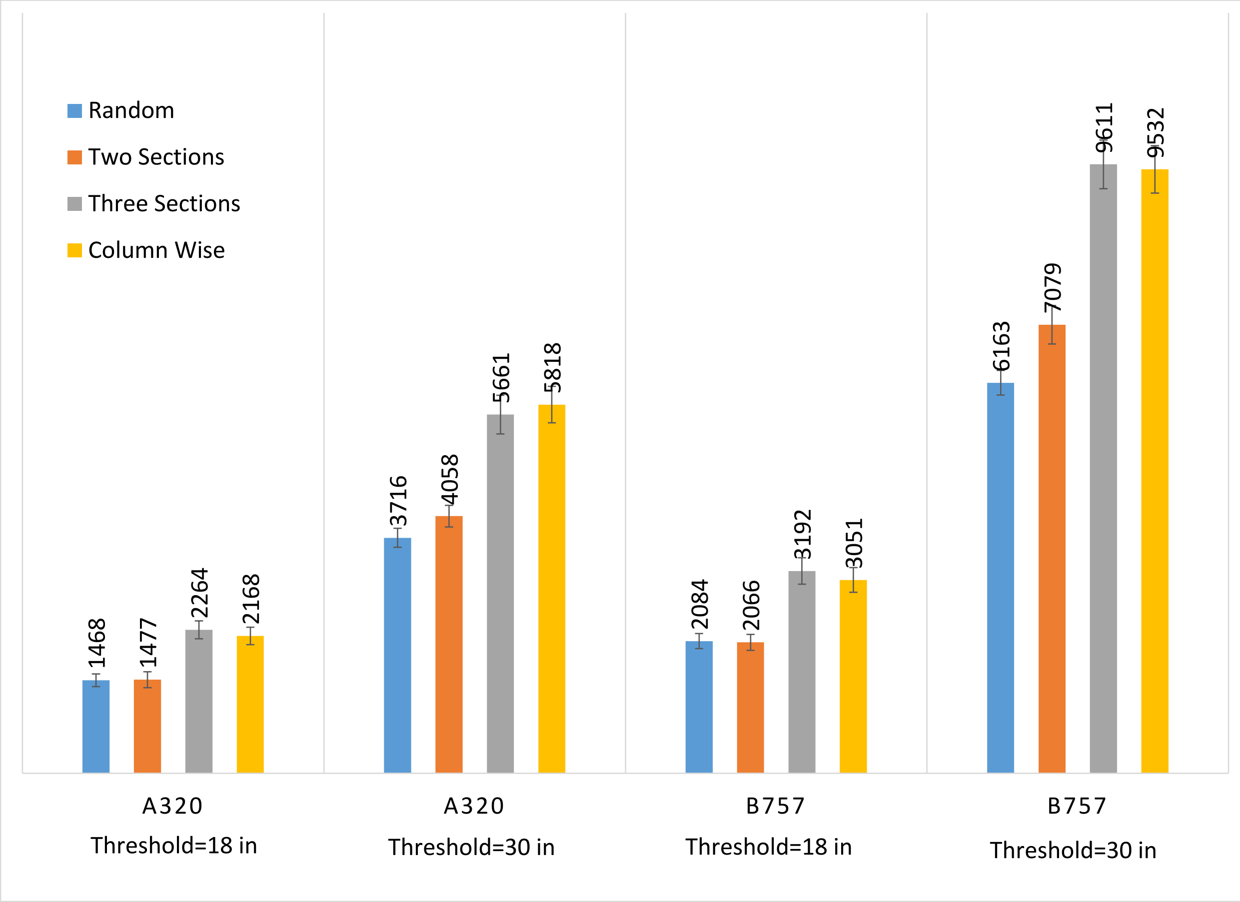


Results

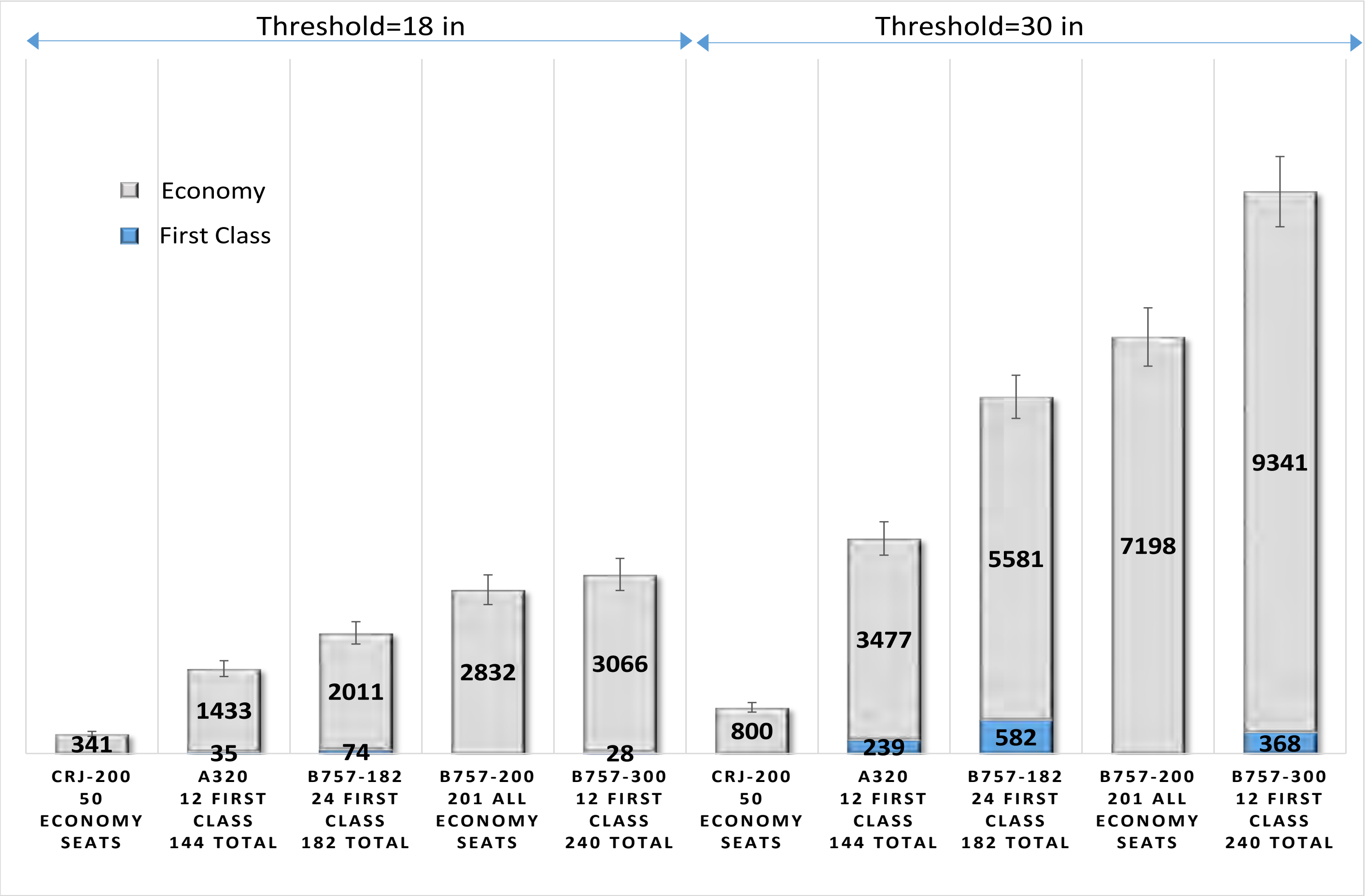
Boarding and Deplaning strategies



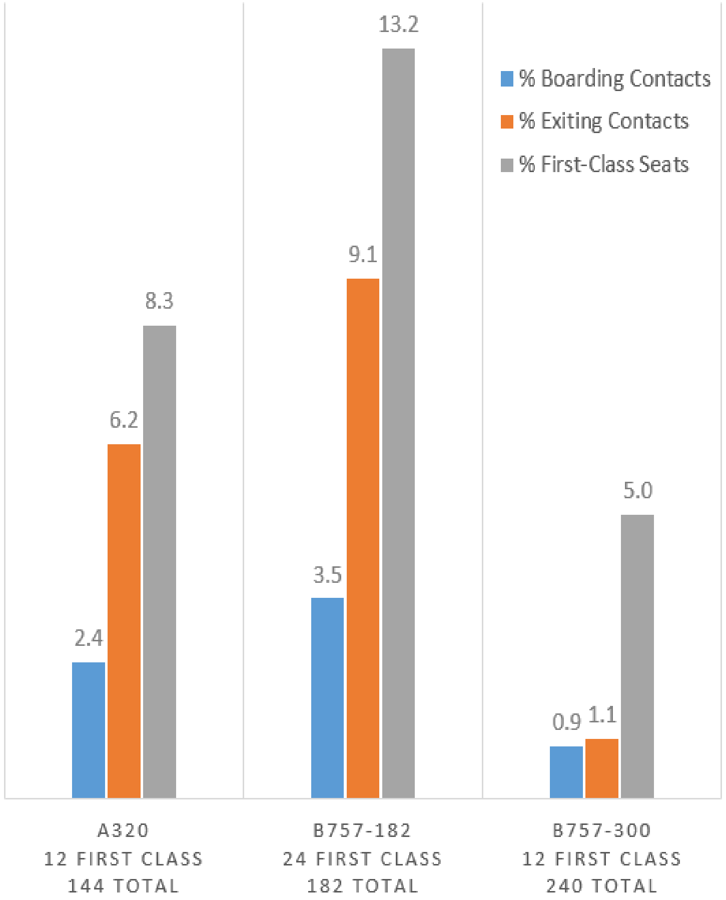
Number of contacts for different deplaning strategies in 144 seat Airbus A320 and 182 seat Boeing 757-200 seating configurations.



Number of contacts for different boarding strategies in 144 sea Airbus A320 and 182 seat Boeing 757-200 seating configurations. The bars represent standard deviation.



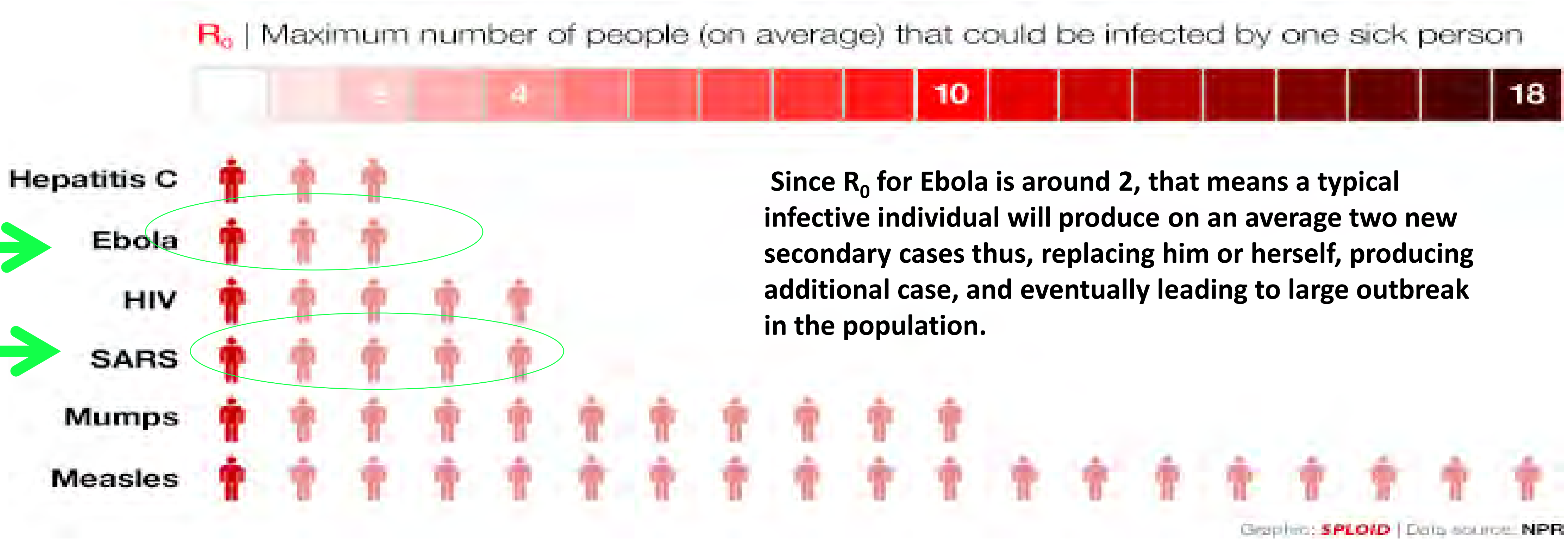
Number of human-human contacts during boarding for the five airplanes during deplaning for contact threshold of 18 inches and 30 inches. The bars represent standard deviation.



Percentage of first class seats vs contacts during boarding and deplaning for contact threshold of 18 inches.

Combining Models:
Pedestrian model & Susceptible- Infected (SI) model

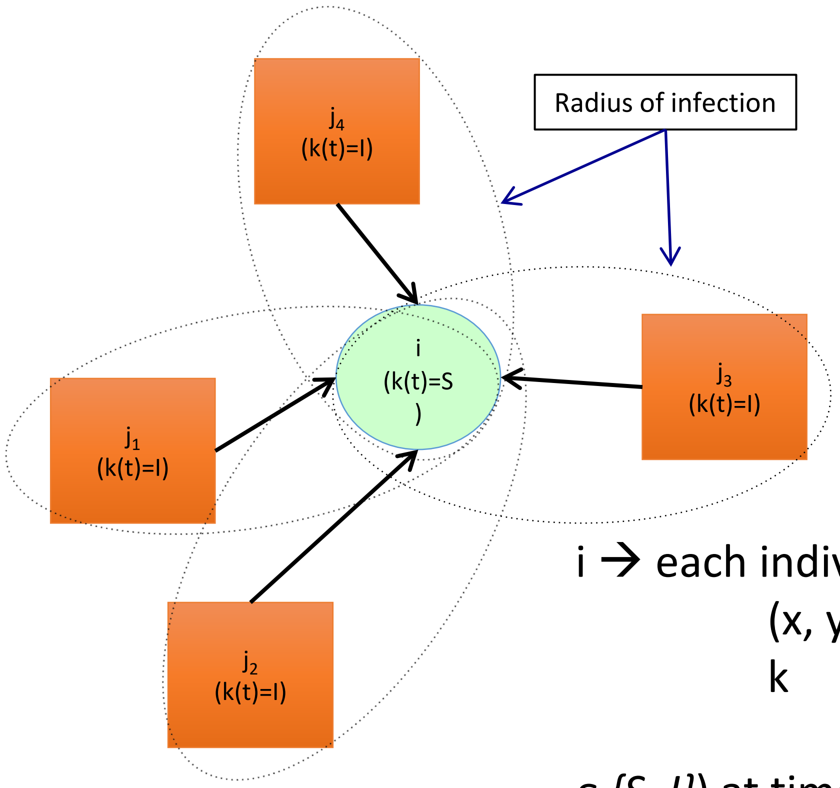
Spreading Rate of Diseases

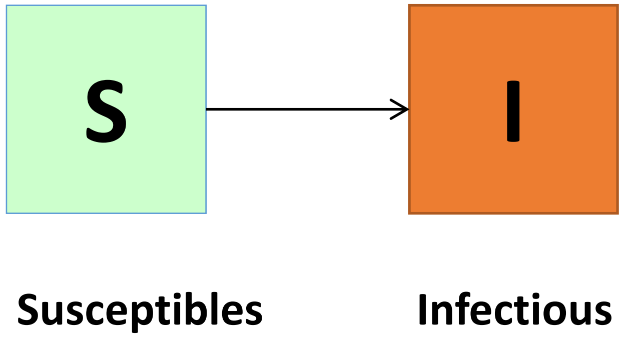


Since R_0 for Ebola is around 2, that means a typical infective individual will produce on an average two new secondary cases thus, replacing him or herself, producing additional case, and eventually leading to large outbreak in the population.

http://sploid.gizmodo.com/ebola-spreading-rate-compared-to-other-diseases-visuali-1642364575

Infection Transmission Model





i → each individual will consists of [x, y, k] components at each time where,

(x, y) → position of the individual i at time t

k → represents the individual's infection status (*Susceptible, Infectious; i.e., k ε {S, I}*) at time t

$$p_{ij} = \begin{cases} f(r, y, \tau) & \text{if i is in vicinity of j whose} \\ & \quad \text{"infectious radius" is r,} \\ & \quad \text{"infectivity level" is y,} \\ & \quad \text{"exposing for" } \tau \text{ time units} \\ 0 & \text{otherwise} \end{cases}$$

P_{ij} → probability of susceptible individual i to receive infection successfully from infectious individual j

Infection Transmission Model

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- Given the pedestrian trajectories from pedestrian model- we obtain contacts between people.

$$\text{P(contact and infection)} = \text{P (infection/contact) . P (contact)} = P_c \cdot \frac{m}{N}$$

- Number of susceptible

$$\text{S(t)} = \text{N} - \sum_{c=1}^{d} i_c^0 = \text{N} - \text{I(t)}$$

- The number infected is binomially distributed (for demographic stochasticity) with parameters
    - n= S(t-1), the number of susceptibles at time t, and p = $P_c \cdot \frac{m}{N}$
- Approximating the Binomial as Poisson. Number infected at time t

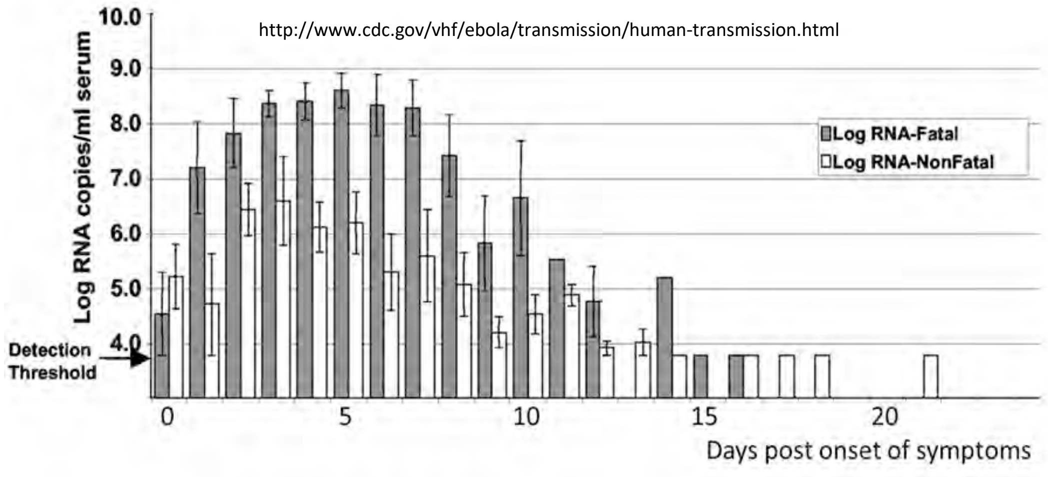
$$I(t) \sim Poisson\left(\sum_{c=1}^{d}\left(p_c \sum_{i=1}^{i_c^0}\left(\frac{m_i(t-1)s_{r_i}(t-1)}{N}\right)\right)\right)$$

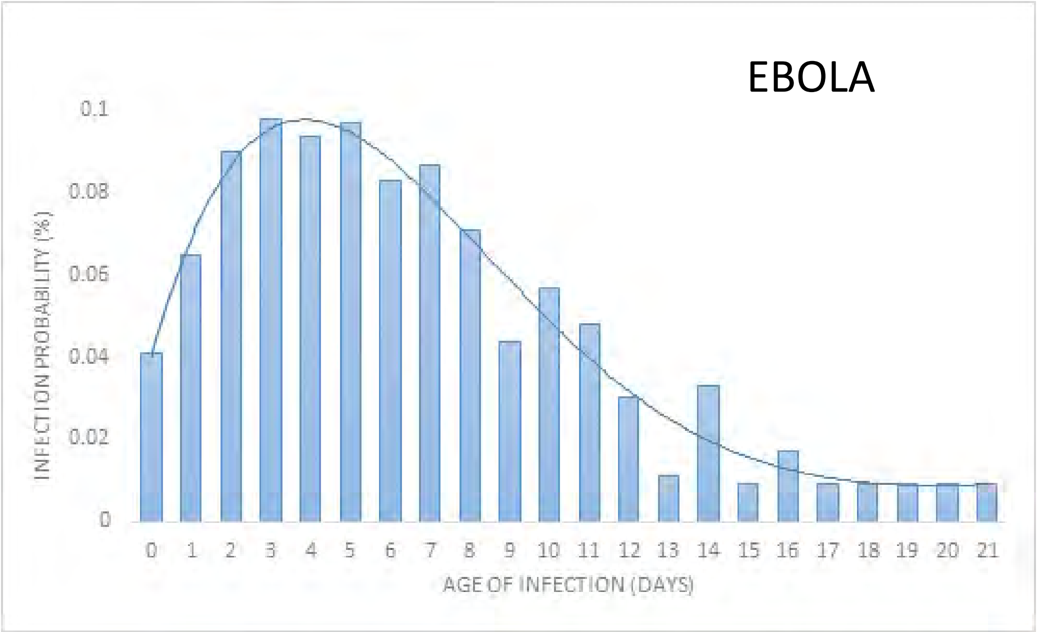
- **Location of Infected person is unknown and varied.**
- **Parametric variations to quantify uncertainty and risk**

Data for Infection Model – Infection probability

$$i(t) \sim Poisson\left(m\frac{S(t-1)}{N}\sum_{c=1}^{d} p_c i_c^0\right)$$

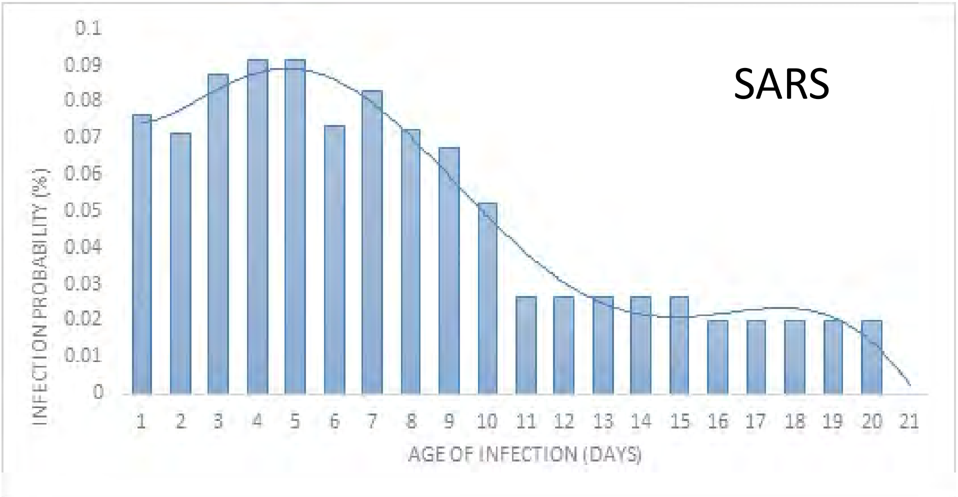
Data source: Centers for Disease Control and Prevention





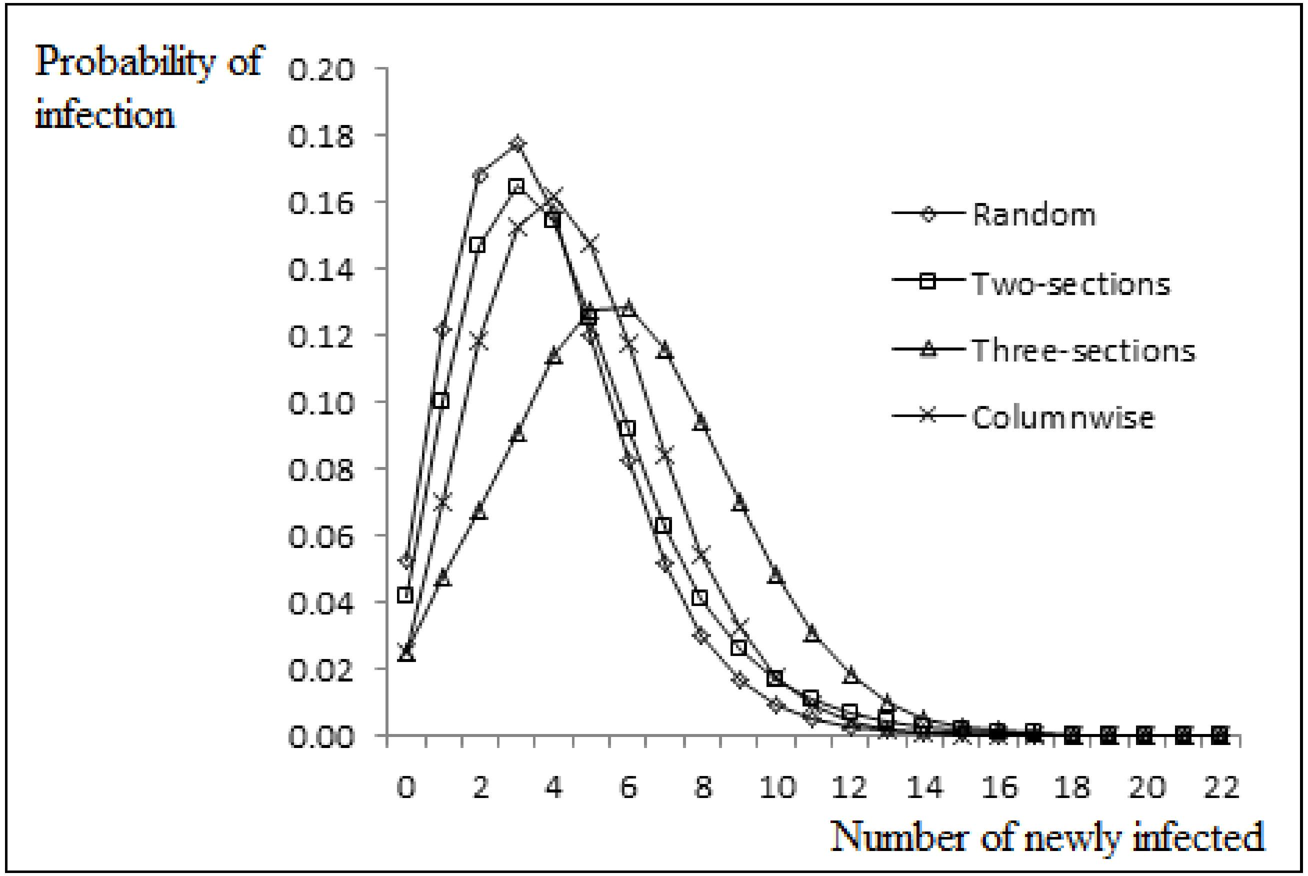
- ❑ Virus content in blood is used to create infectivity probability plot

- ❑ Difference between diseases like SARS and Ebola primarily dependent on contact definition (e.g. distance, time etc)



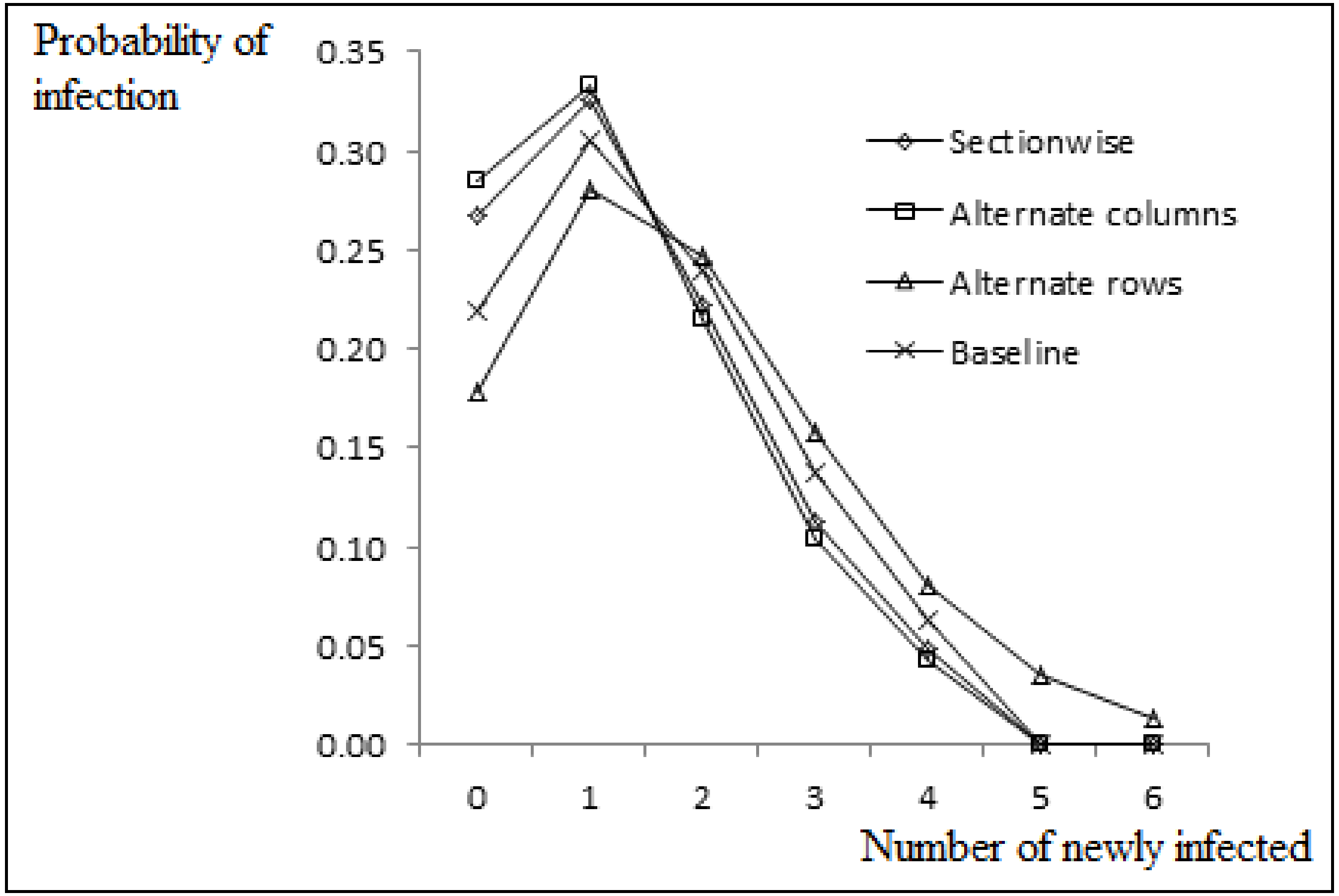
Results – Boarding Strategies

- Similar pattern for 144 seat A320 seating configuration & 182 seat Boeing 757
- There is clear difference between different boarding strategies.
- Strategies that lead to arbitrary movement along the cabin preventing clustering reduces infection transmission.



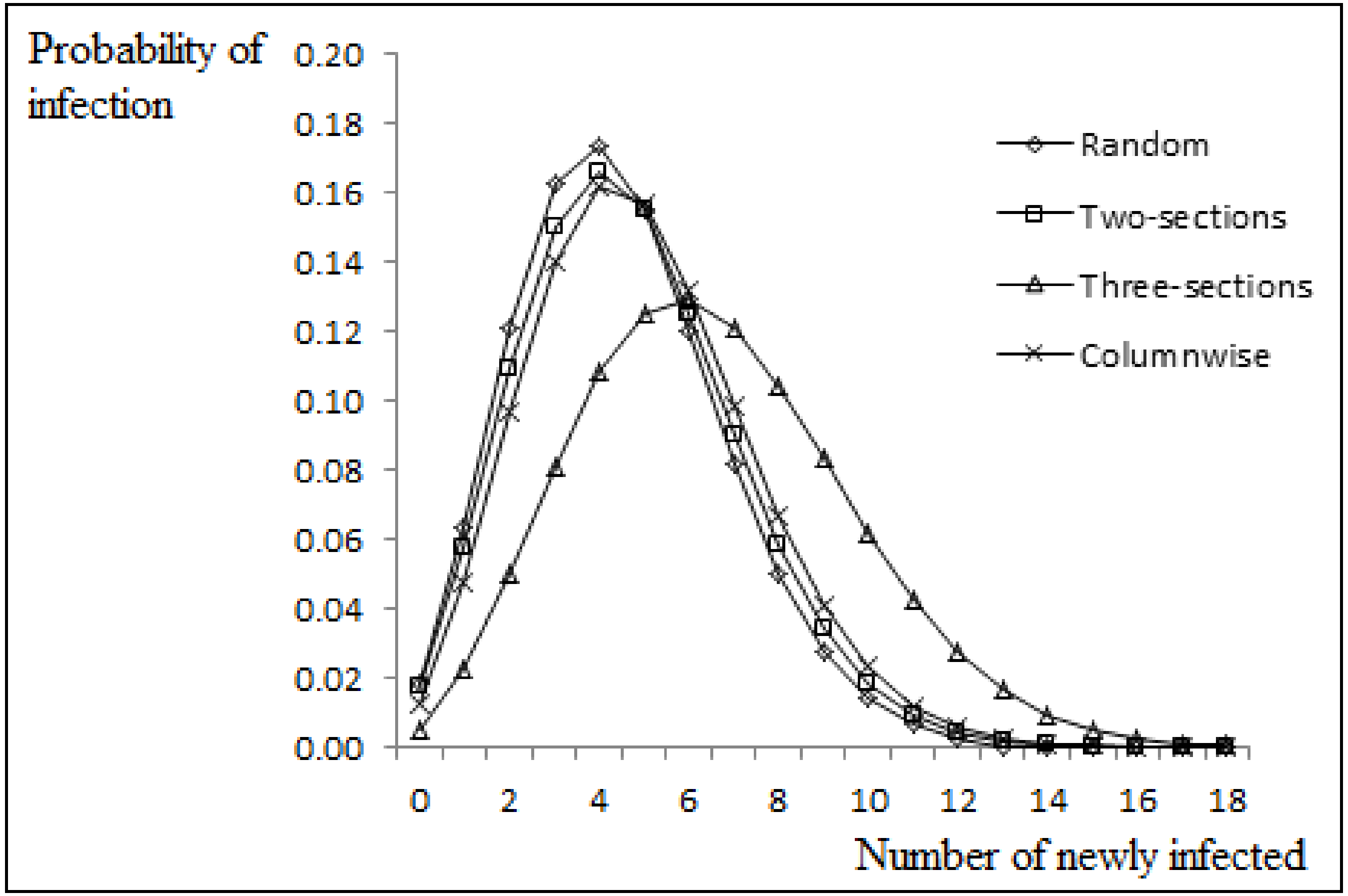
Boeing 757-200 for different boarding patterns for a single imported infective at the 9^{th} day of infection (probability of infection = 0.06), critical radius of infection 1.2 m.

Results – Deplaning Strategies



Boeing 757-200 for different exiting patterns for a single imported infective at the 9^{th} day of infection (probability of infection = 0.06), critical non-successive contact number of 3 and critical radius of infection 48 feet. The contacts of egressing passengers outside the airplane are not taken into account.

Results – Complete passenger movement



Boeing 757-200 combined baseline egress and different boarding patterns for a single imported infective at the 9^{th} day of infection (probability of infection = 0.06), critical radius of infection 48 in.

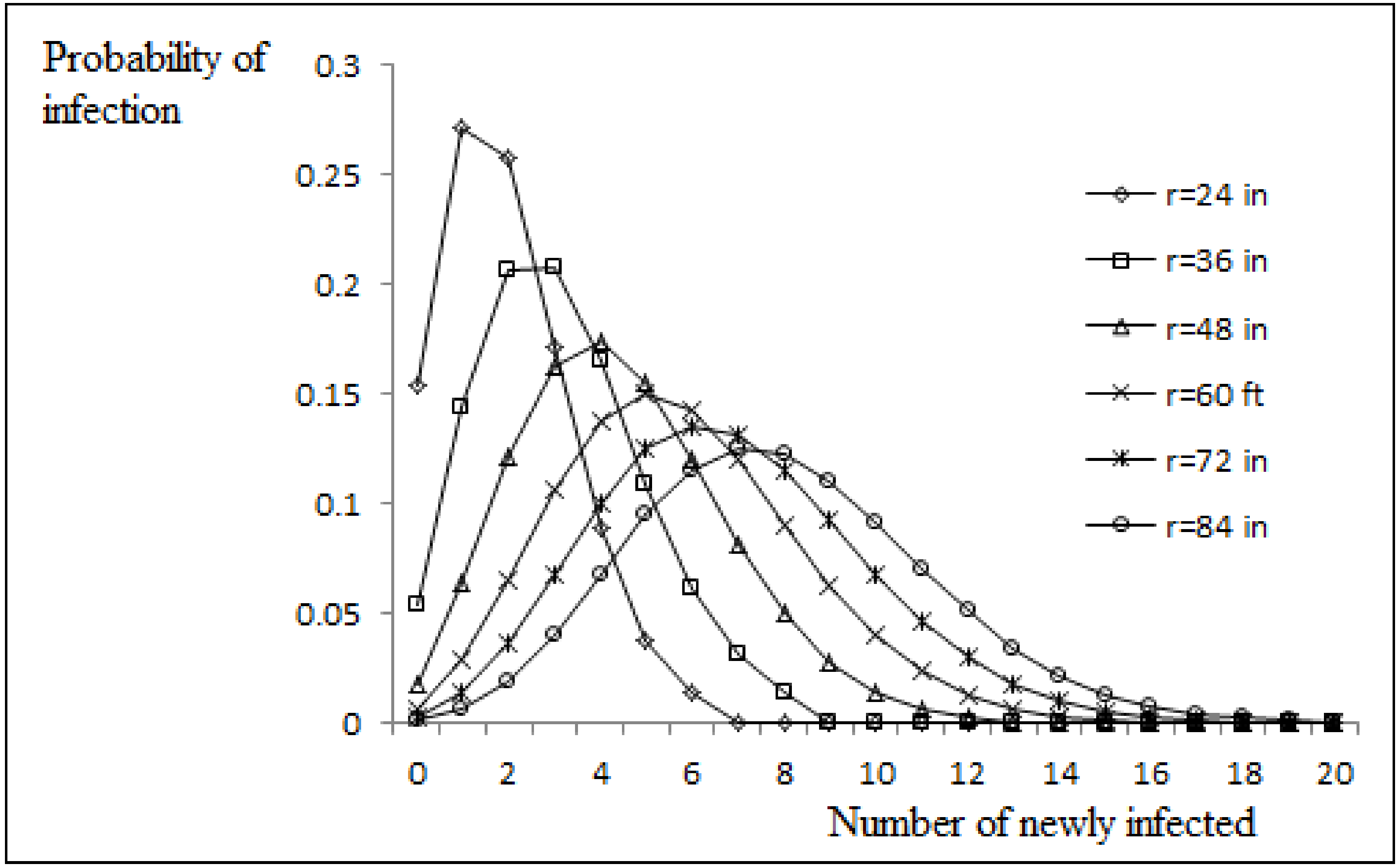
Parameter variation – Infection radius

- Critical model parameter - contact radius defined as minimum distance to define a contact

- Particles travel depending on (1) size and (2) fluid mechanics in expiratory events (e.g. coughing)

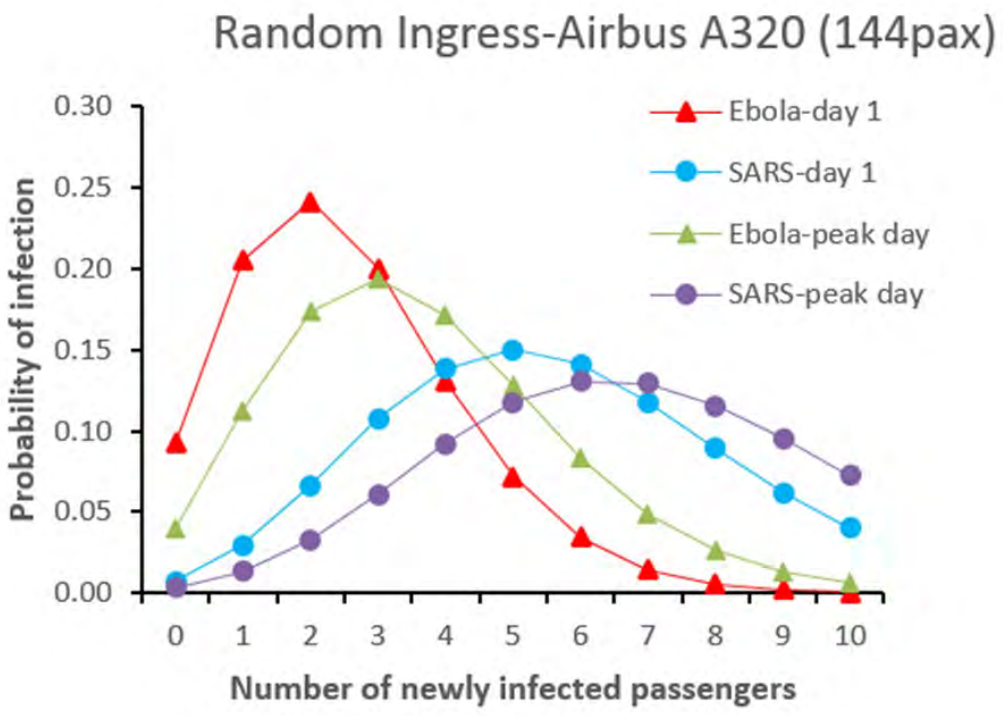
- Particle size 0,.1 to 10 micrometers. Distance travelled up to 2m

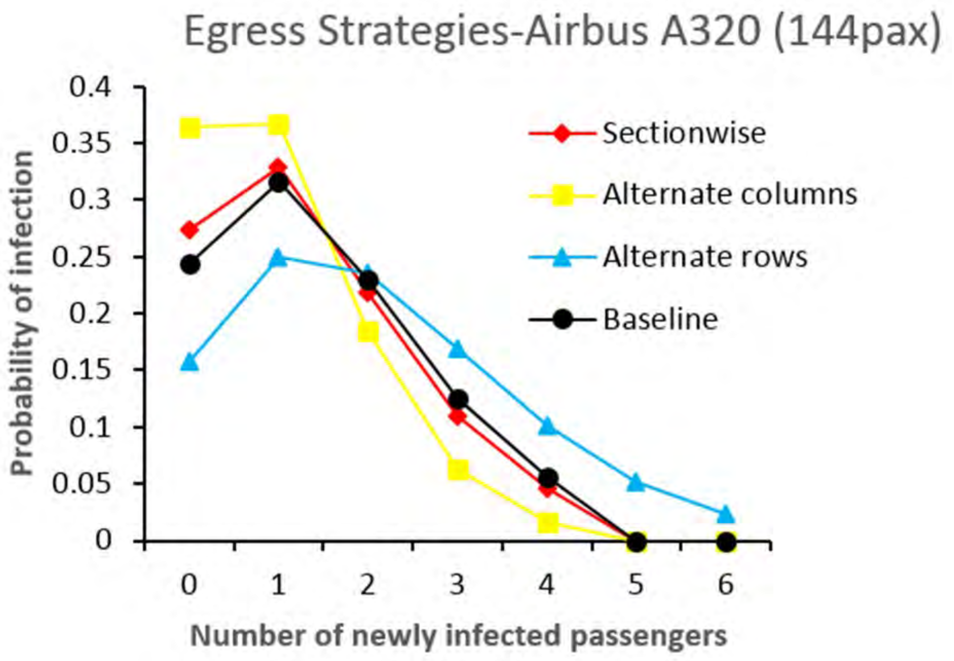
- Mechanism of infection –
  - long distance -transmitted by small particles like aerosols (SARS, H1N1)
  - Short distance – transmitted by coarse droplets e.g. Ebola.



Boeing 757-200 combined for a single imported infective at the 9^{th} day of infection (probability of infection = 0.06), different critical radii of infection.

Long vs short contact radius SARS vs Ebola

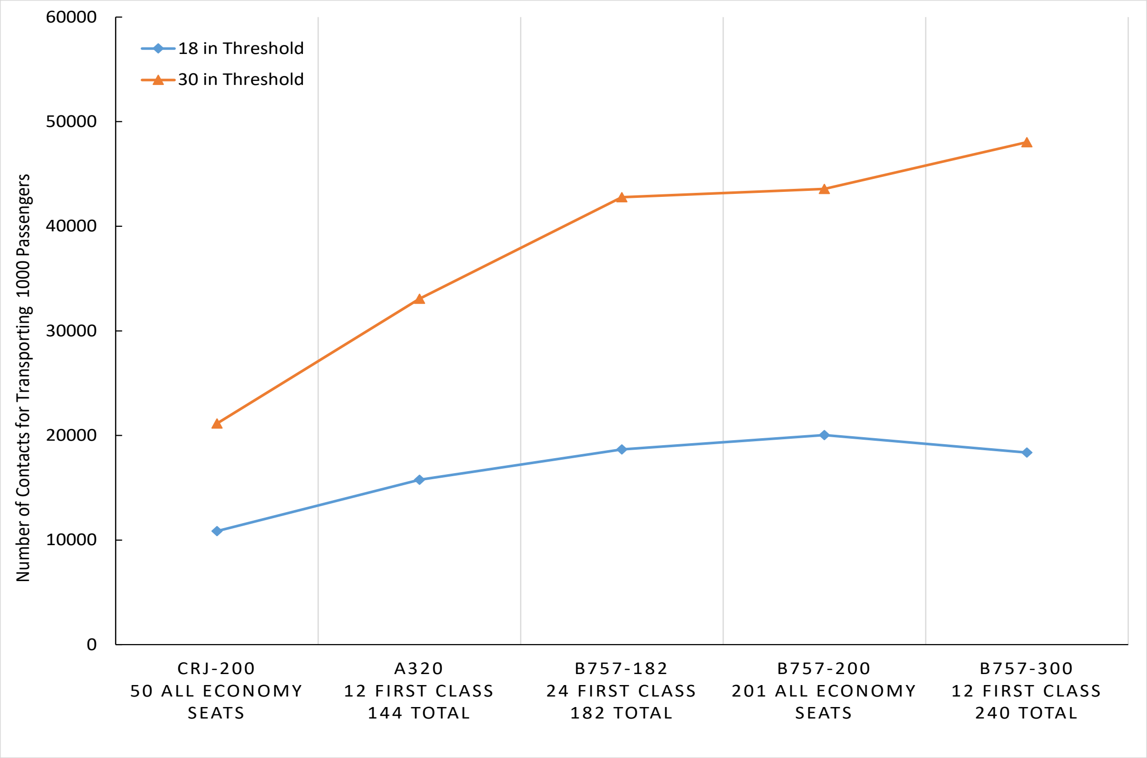




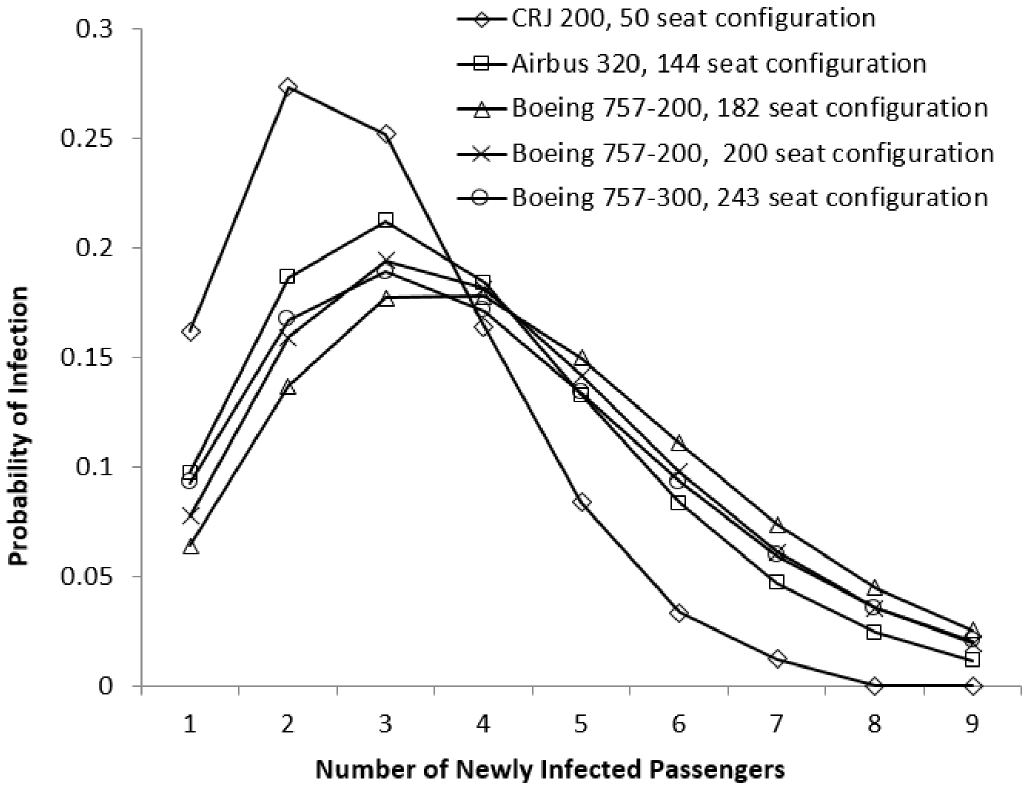
- ❑ Infection radius for Ebola 1.2 m and for SARS 2.1 m
- ❑ SARS more contacts and infection. SARS was transmitted on airplanes *
- ❑ Model includes airport gate.

*Mangili, A. and Gendreau, M.A., 2005. Transmission of infectious diseases during commercial air travel. *The Lancet*, *365*(9463), pp.989-996.

Airplane Size



Number of contacts for transporting 1000 passengers in different airplanes boarding and deplaning by default methods.

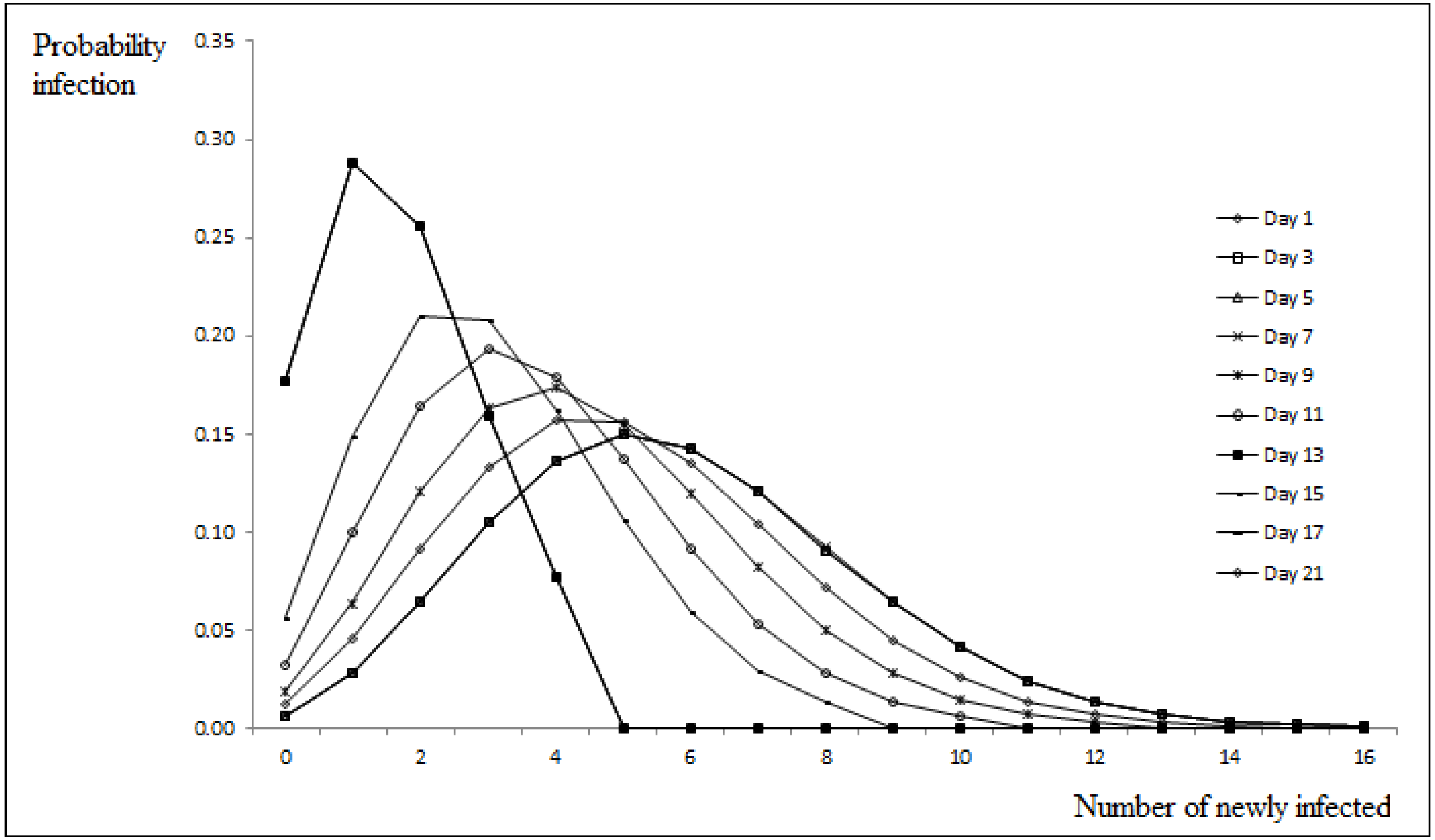


Infection distribution profile for random boarding strategy varying the airplane size.

- ❑ Smaller airplanes result in lower number of

- ❑ The smaller size of the susceptible population, lower number of susceptibles within a given contact radius and the reduced time of in-plane movement are some of the factors that benefit smaller airplanes.

Parameter variation – Infectivity



Boeing 757-200 combined baseline egress and random ingress for a single imported infective at different days of infection (probability of infection ranges from 0.00 to 0.08), critical radius of infection 48 feet.

Summary

- Pedestrian movement model based on social force model formulated and applied to evaluate contacts in airplane setting

- Pedestrian movement model combined with stochastic Susceptible – Infected model for Ebola and SARS

- Airplane movement patterns evaluated for disease propagation
  - Boarding in 2 sections with randomized within sections is the most effective strategy to reduce infections
  - Boarding has higher effect than deplaning.
  - Smaller airplanes are better

- Acknowledgements: NSF Rapid and PRAC grants & ERAU internal funding

Extensive News coverage of our Research

- Covered in over 75 news outlets in four continents

Come flu with me

The way airlines board planes affects how easily bugs are spread among passengers

The way we board planes could actually be spreading diseases

Can flying make you sick? Plane rides are one of the fastest ways for infectious diseases to spread

Publications

- S. Namilae, P Derjany, A Mubayi, M Scotch and A Srinivasan, Multiscale Model For Infection Dynamics During Air Travel, Physical review E, 002300 (2017)
- S. Namilae, A Srinivasan, A Mubayi, M Scotch and R Pahle, Self-propelled pedestrian dynamics model: Application to passenger movement and infection propagation in airplanes, Physica A 465 (2017) 248–260
- S. Namilae, A Srinivasan, A Mubayi, M Scotch and R Pahle, Self-Propelled Pedestrian Dynamics Model for Studying Infectious Disease Propagation during Air-Travel, Journal of Transport & Health (2016) 3 (2), S40
- P Derjany, S Namilae, A Mubayi and A Srinivasan, Computational Model for Pedestrian Movement and Infectious Diseases Spread During Air Travel, AIAA Scitech (2018)
- S. Namilae, Multiscale Model for Pedestrian and Infection Dynamics During Air Travel, International Conference for Risk Analysis 2017 Chicago (Invited Presentation)
- P Derjany, S Namilae, A Mubayi M Scotch and A Srinivasan, Molecular Dynamics Like Numerical Approach for Studying Infection Propagation, International conference of composites Engineering ICCE (2017)
- P Derjany, S Namilae, A Mubayi M Scotch and A Srinivasan, Multiscale pedestrian movement - infection dynamics model for transportation hubs, Transportation Research Forum, Chicago (2017)