VIRAL INFECTION PROPAGATION THROUGH AIR TRAVEL

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OUTLINE

- Introduction
- Prior Results
- Recent Infection Propagation Results
- Conclusions

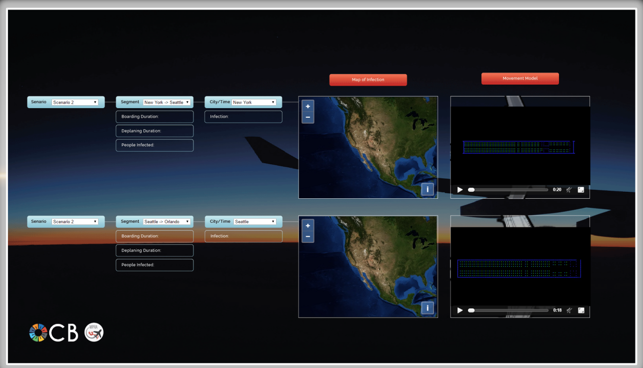
INTRODUCTION

MOTIVATION

- Air travel is an important factor in the spread of infections
- There had been calls to ban flights from Ebola infected areas
  - This can have large human and economic impact
  - Fine-tuned policy prescriptions can be as effective
    - Reassures the public that action is being taken
    - Avoids negative human and economic impacts

PROJECT GOALS

- Develop models and decision support tools to help analyze impact of policy decisions on spread of diseases through air-travel
  - Will provide insight to decision makers on consequences of policy or procedural choices
  - Original work focused on Ebola
    - Current work includes other diseases

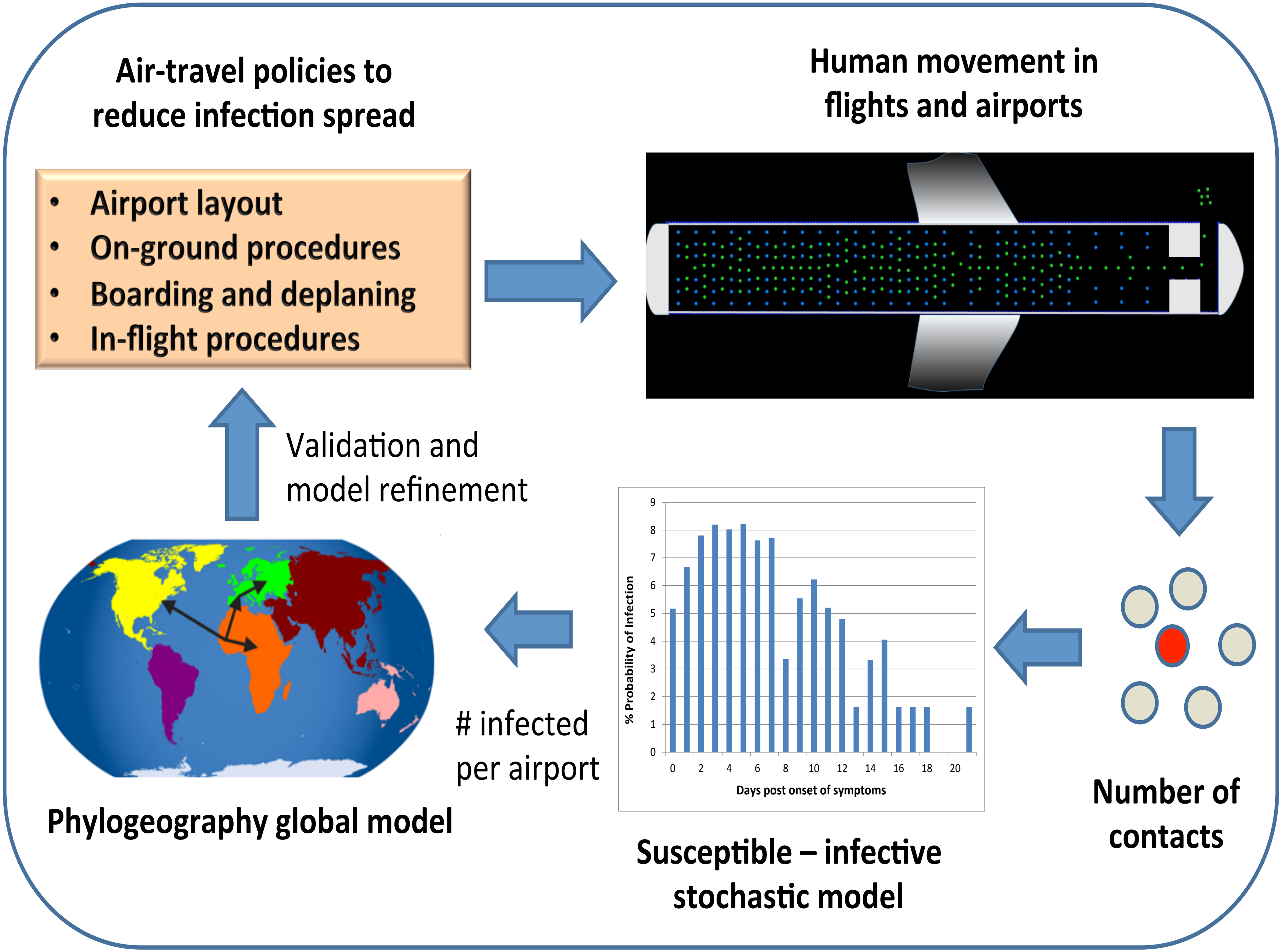


CURRENT MODELS

- Typically focused on scientific understanding, rather than policy analysis
  - Predictions are difficulty due to inherent uncertainties
- Usually at an aggregate level, which makes evaluation of impact of new policies difficult
- Inaccurate predictions on Ebola
  - Predicted millions infected by early 2015 and hundreds of thousands dead

OUR MODELING APPROACH

- Use fine-scale model of human movement in planes to determine response to policies
- Link with phylogeography model to examine global consequences
- Parameterize sources of uncertainty
  - Parameter sweep over this space to identify vulnerability
- Validate with similar diseases


Air-travel policies to reduce infection spread
Airport layout
On-ground procedures
Boarding and deplaning
In-flight procedures
Human movement in flights and airports
Validation and model refinement
infected per airport
Phylogeography global model
% Probability of Infection
Days post onset of symptoms
Susceptible – infective stochastic model
Number of contacts

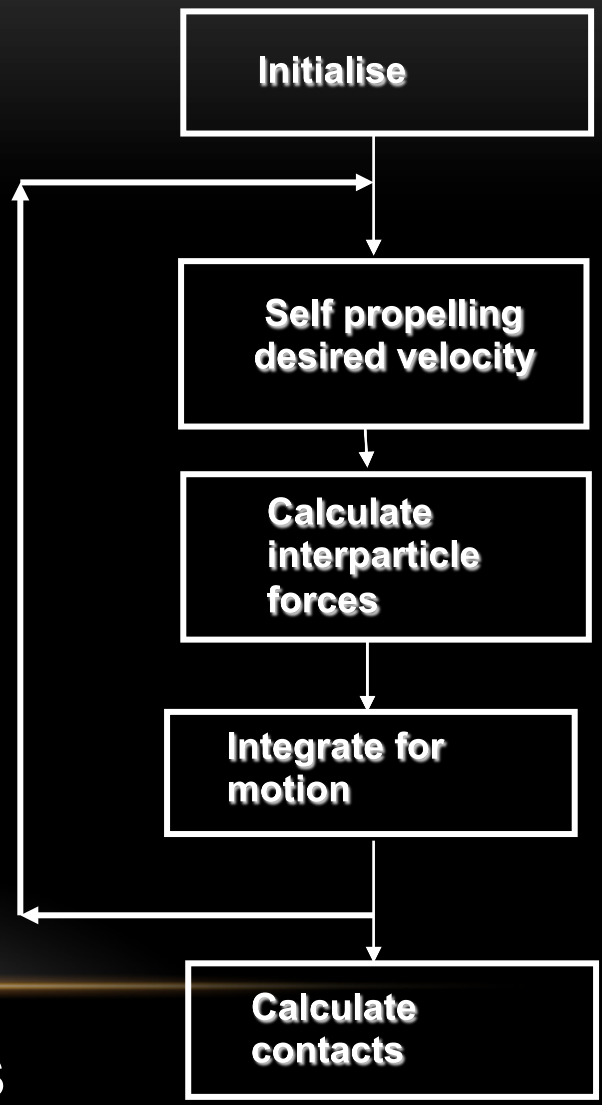
QUESTIONS TO BE ANSWERED

- How high a risk does air-travel pose in spreading a disease outside its source countries?
- Can simple policies reduce infection risk without causing major disruptions?
    - Change plane type
    - Change boarding and disembarkation procedures
    - Change seating arrangements
    - Airport layout and procedures

PRIOR RESULTS

SELF PROPELLED ENTITY DYNAMICS MODEL

- Social dynamics is based on the idea of Molecular Dynamics, with each entity treated as a particle
  - Individuals experience self propulsion that induces them to move toward their desired goal
  - They experience repulsive forces from other persons and surfaces
- We add human behavioral characteristics to social dynamics

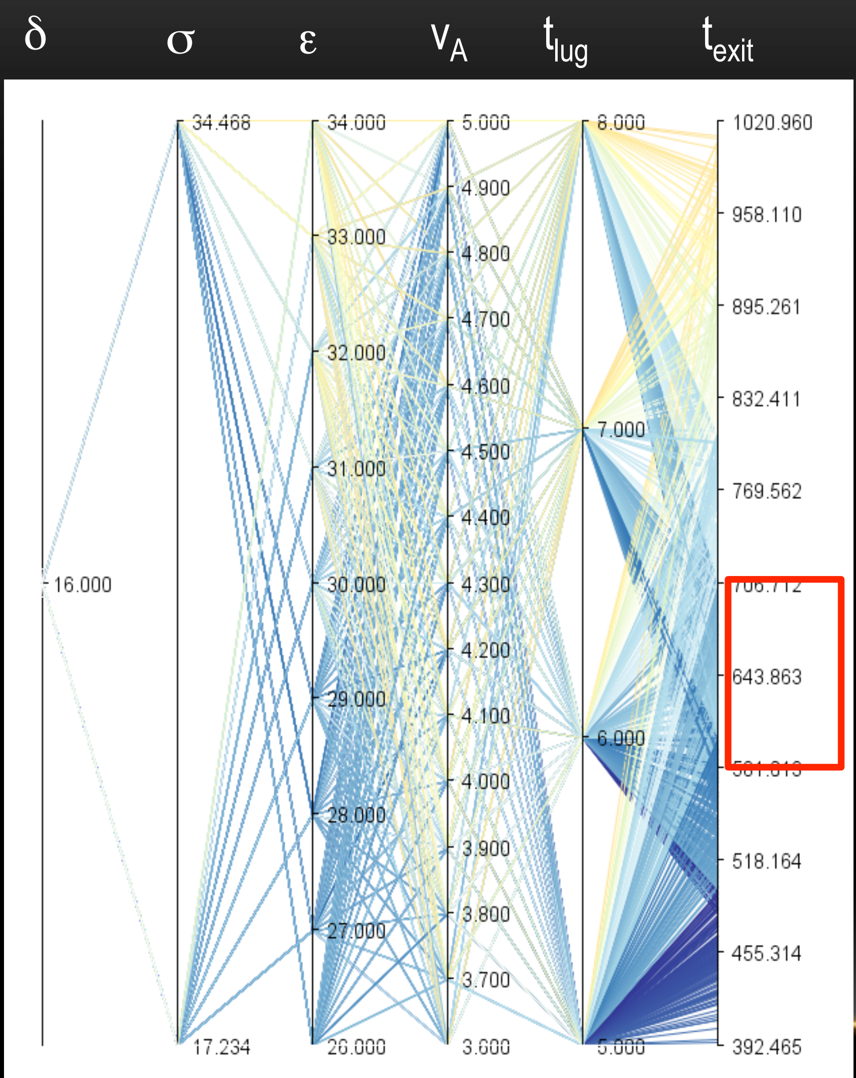


EXAMPLE OF UNCERTAINTY: PEDESTRIAN SPEED

		Manner of movement (pace)				
	Age	Slow	Ordinary	Fast	Running	Sprinting
Female	21–30	0.7–1.4	1.1–1.6	1.5–2.0	2.0–3.6	3.6–5.2
	31–40	0.8–1.3	1.1–1.5	1.5–2.1	2.0–3.7	3.9–4.5
	41–50	0.7–1.3	1.1–1.6	1.5–2.0	2.4–3.0	3.0–4.2
	51–60	0.7–1.1	1.1–1.6	1.6–2.1	2.0–3.6	2.9–4.3
Male	21–30	0.8–1.4	1.3–1.6	1.8–2.2	2.6–4.6	4.3–6.6
	31–40	1.0–1.4	1.2–1.8	1.8–2.5	2.8–4.6	4.8–6.9
	41–50	0.8–1.3	1.2–1.6	1.8–2.3	3.0–4.2	4.3–6.9
	51–60	1.0–1.3	1.3–1.6	1.8–2.1	2.6–4.2	5.0–5.7

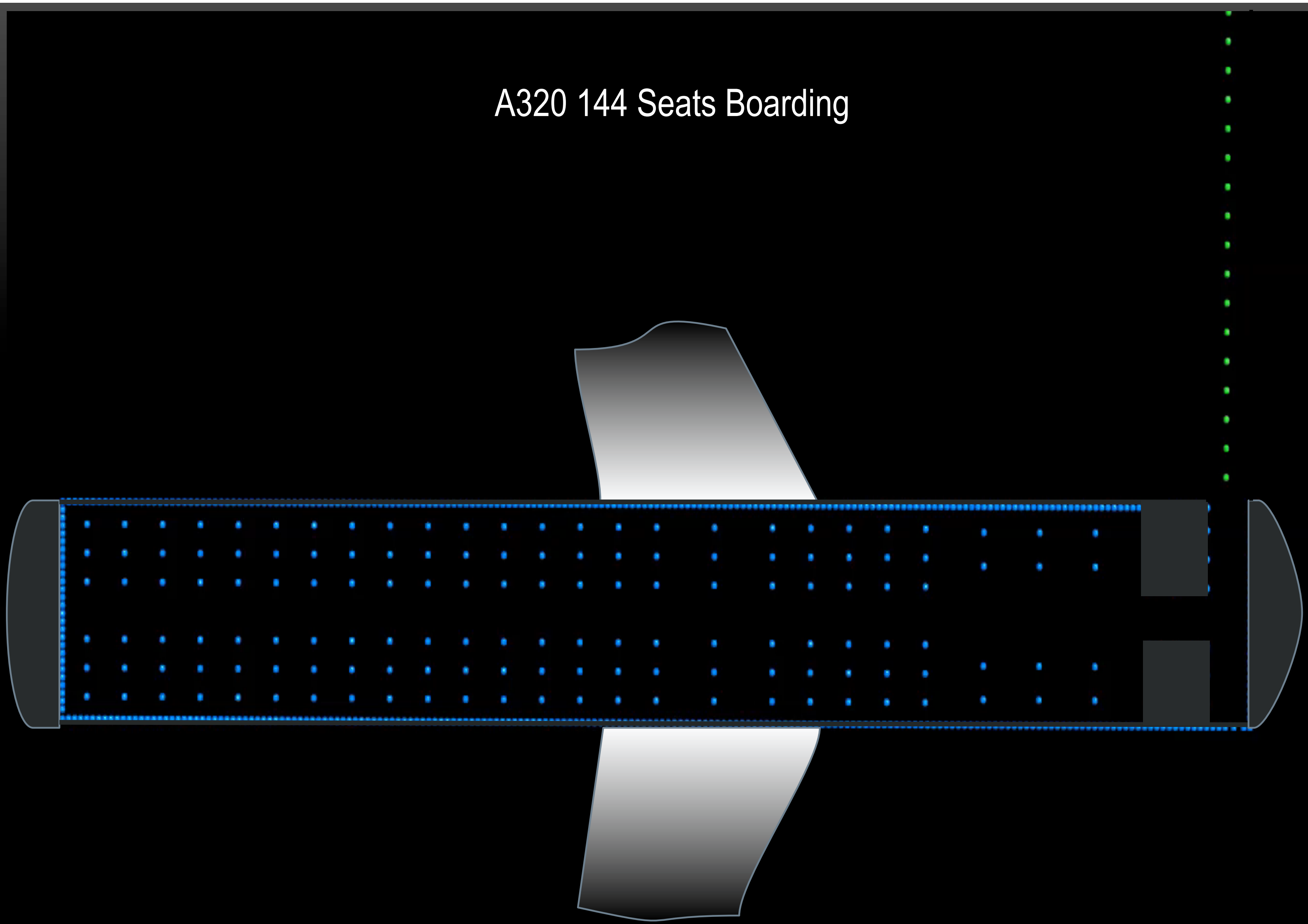
From: Pedestrian speeds and accelerations, Jakub Zębala, Piotr Ciępka, Adam Reza, Problems of Forensic Science 91, (2012)

PARAMETER COMBINATIONS

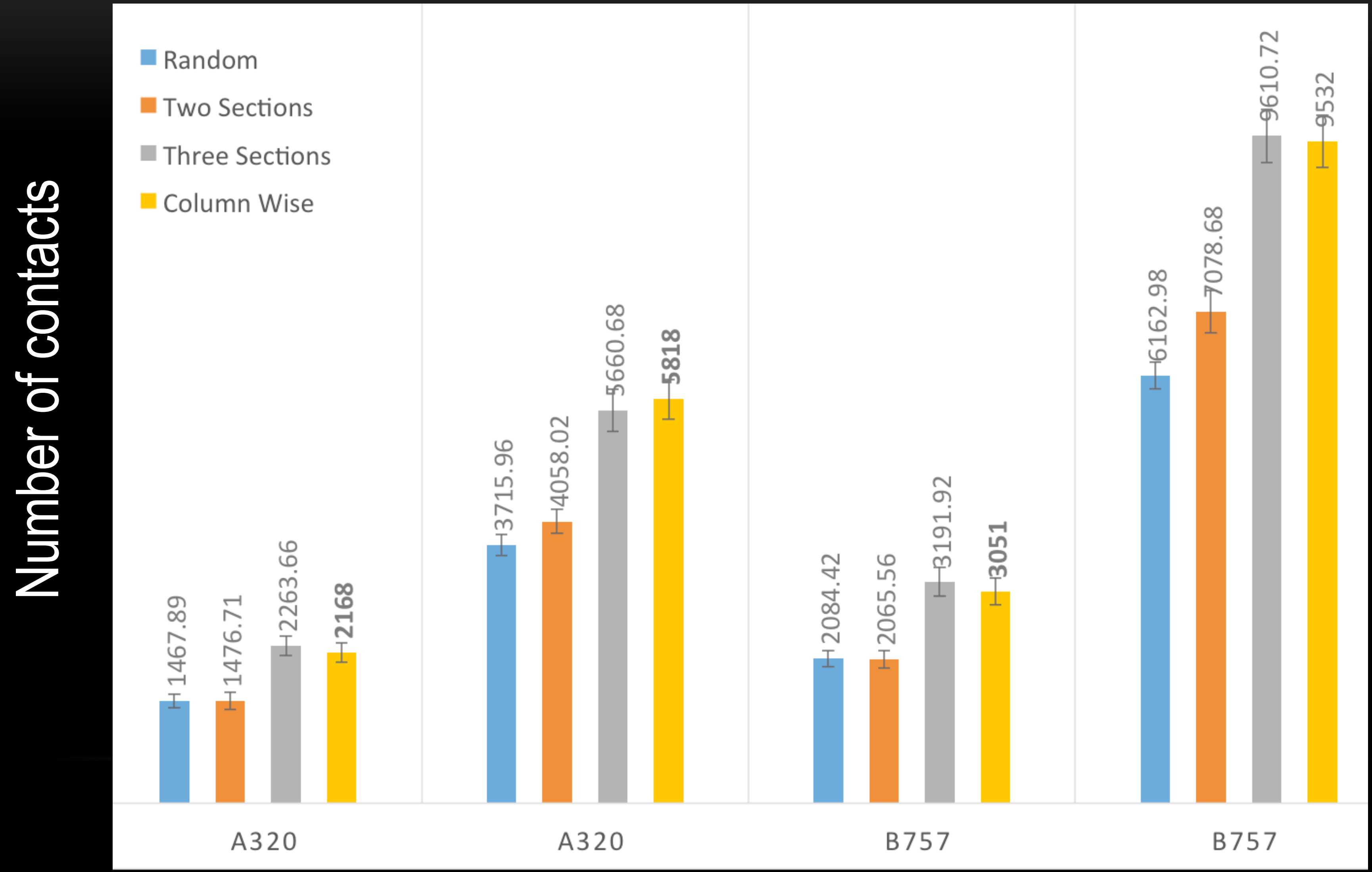


- Choose parameter combinations that reflect real behavior
- Select a variety of distinct scenarios

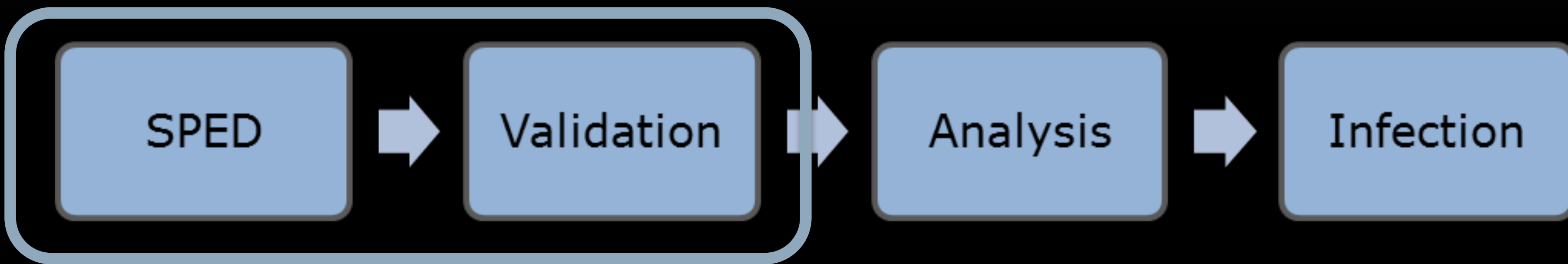
A320 144 Seats Boarding



BOARDING STRATEGIES

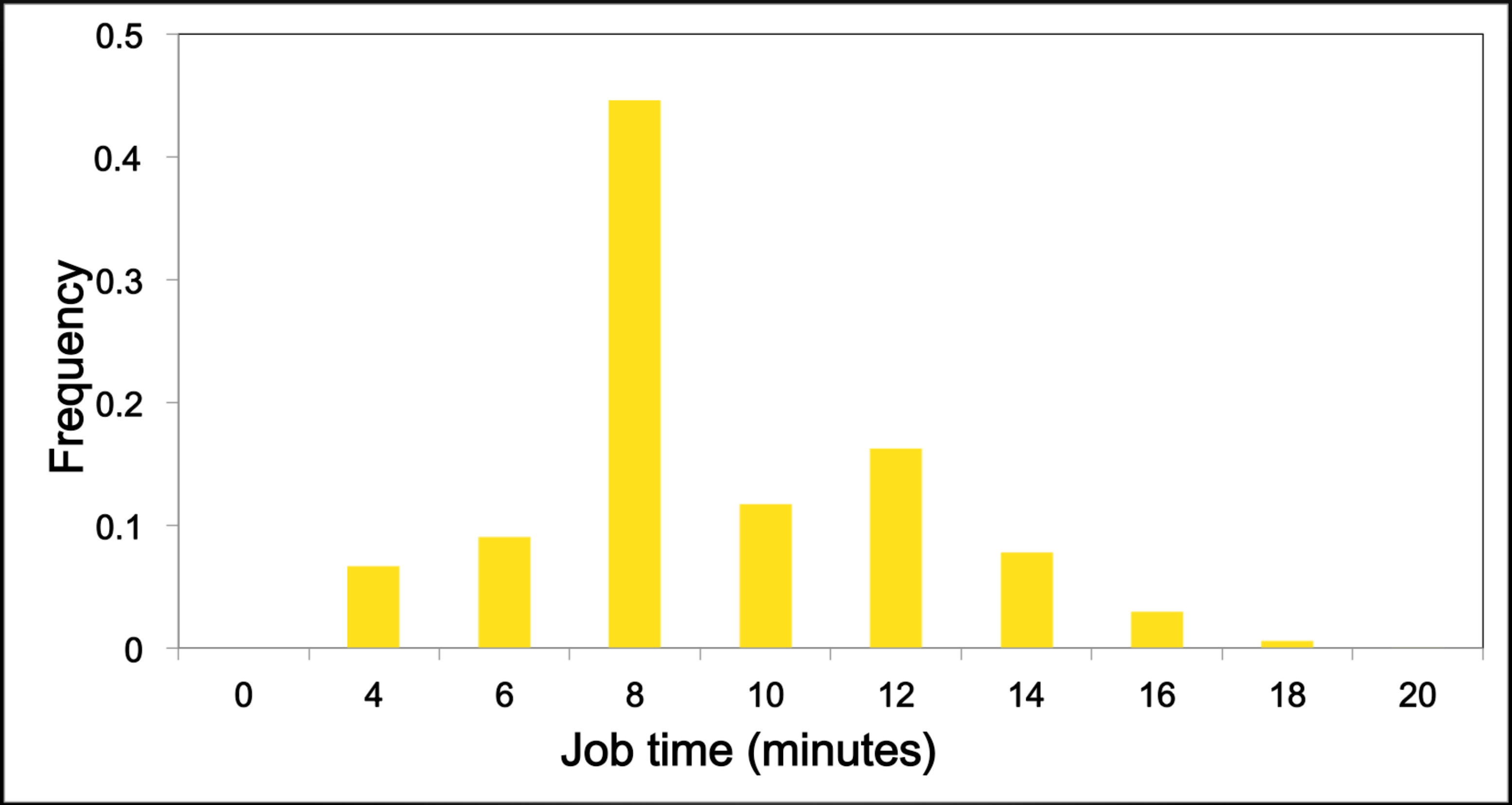


WORKFLOW AND OTHER OPTIMIZATIONS



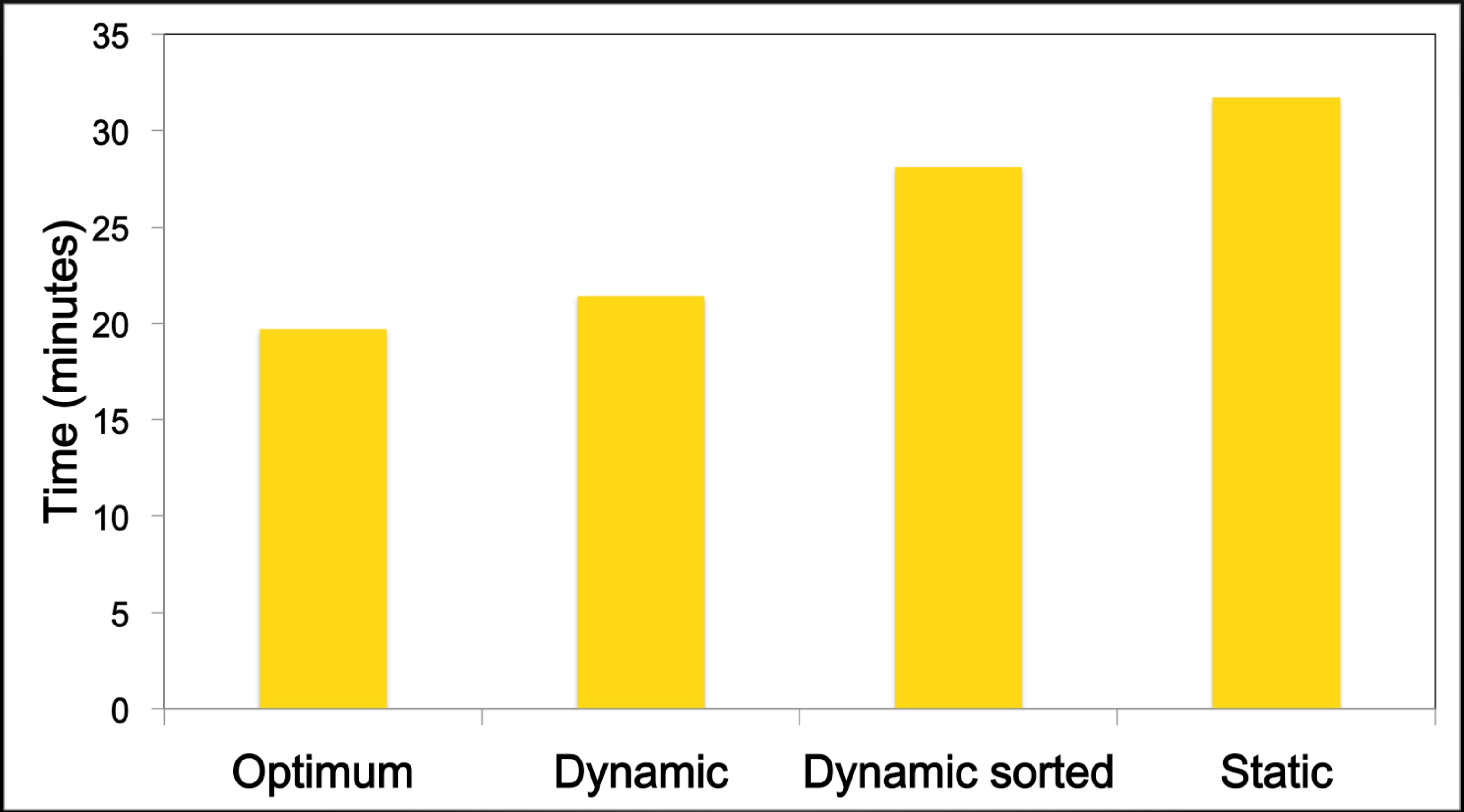
- Include some validation with the simulation
- Basic sequential optimization
- The above two improve performance by an order of magnitude on 1331 cores

CODE PERFORMANCE AFTER IO OPTIMIZATION



IO optimization on 68921 cores of Blue Waters led to factor 2 decrease in wall clock time

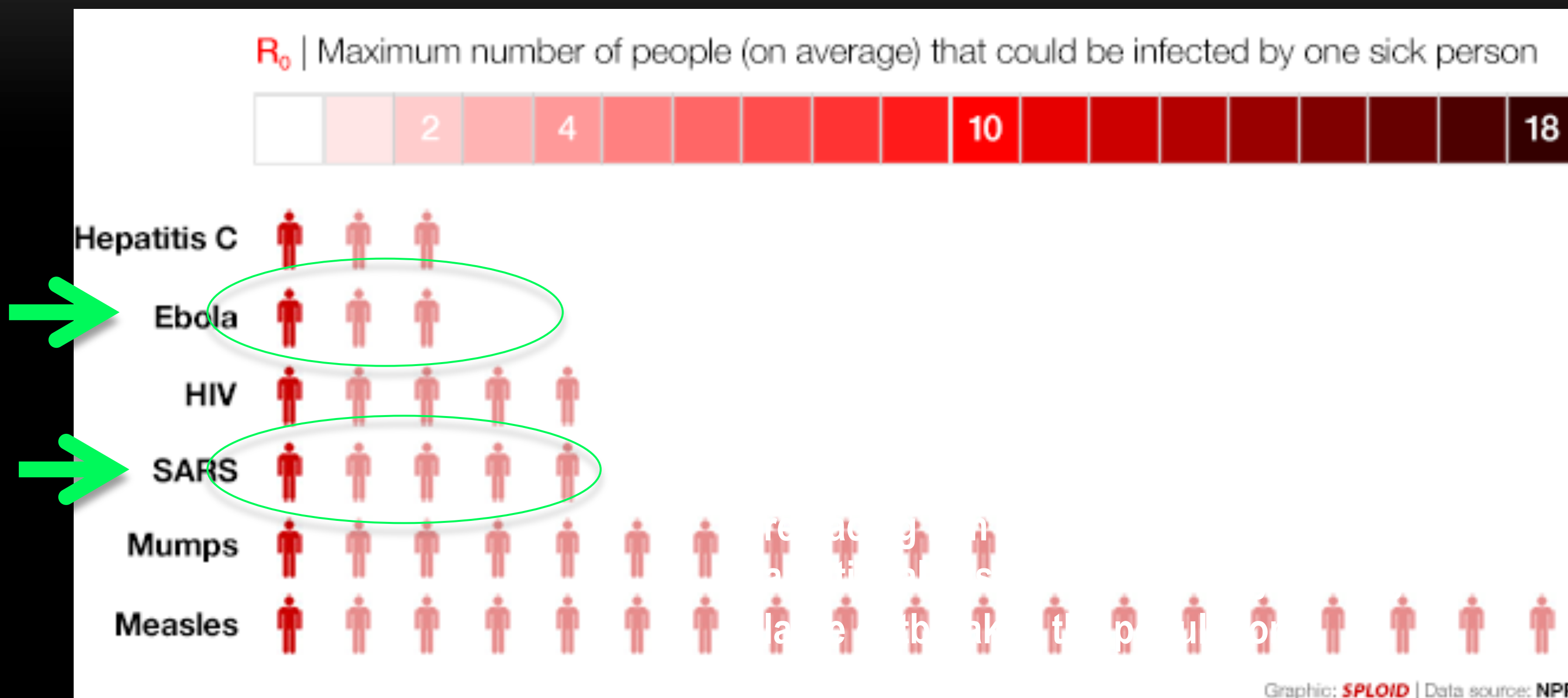
PERFORMANCE WITH LOAD BALANCING



- Time with 68921 parameters using 39655 cores

RECENT INFECTION PROPAGATION RESULTS

INFECTION TRANSMISSION

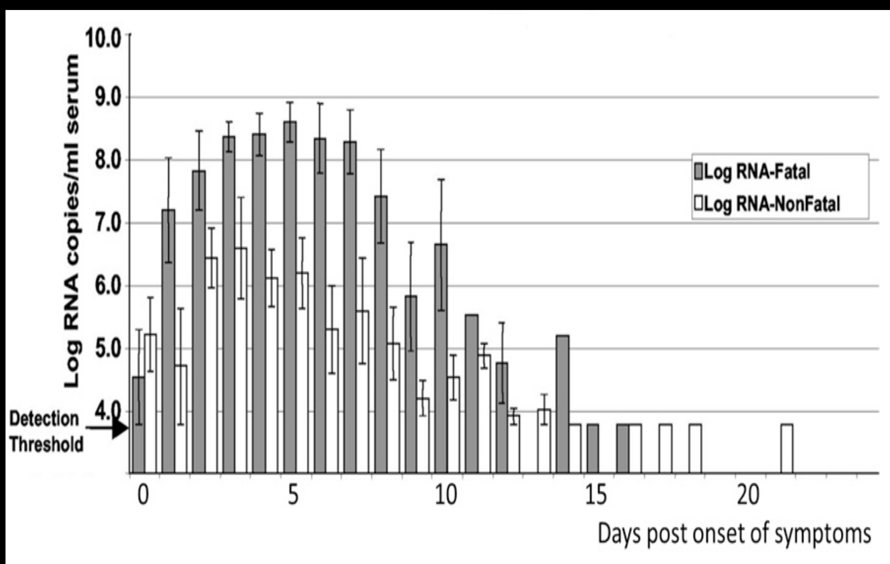


http://sploid.gizmodo.com/ebola-spreading-rate-compared-to-other-diseases-visuali-1642364575

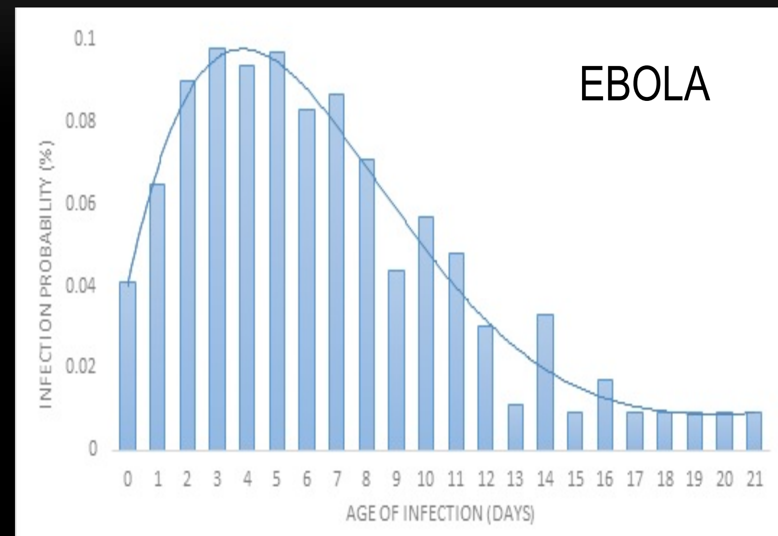
- Probability of infection transmission modeled as a function of distance to infected person, exposure time, and infectivity

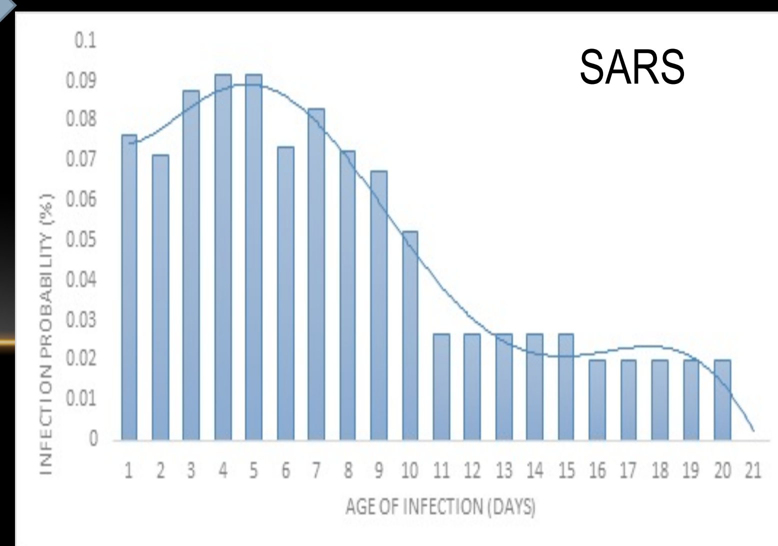
DETERMINING INFECTION PROBABILITY

- Blood virus content used to estimate infectivity probability



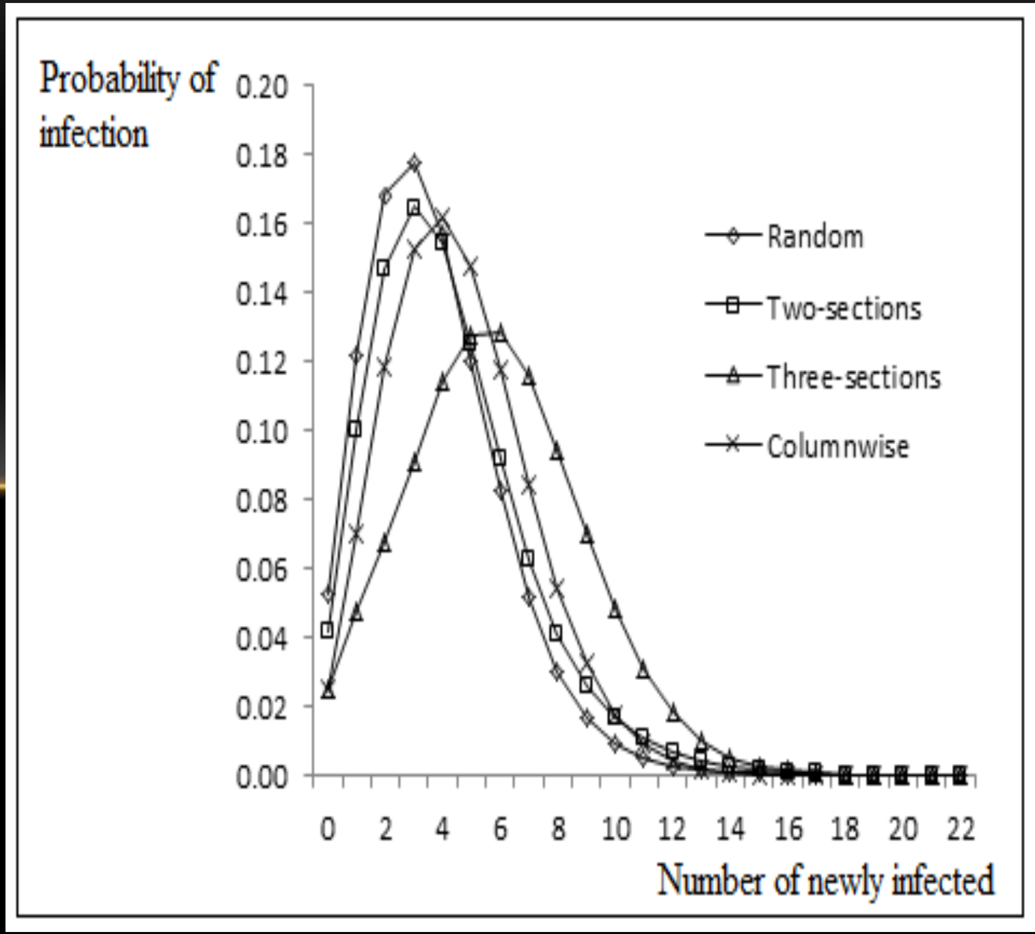
Data source: Centers for Disease Control and Prevention





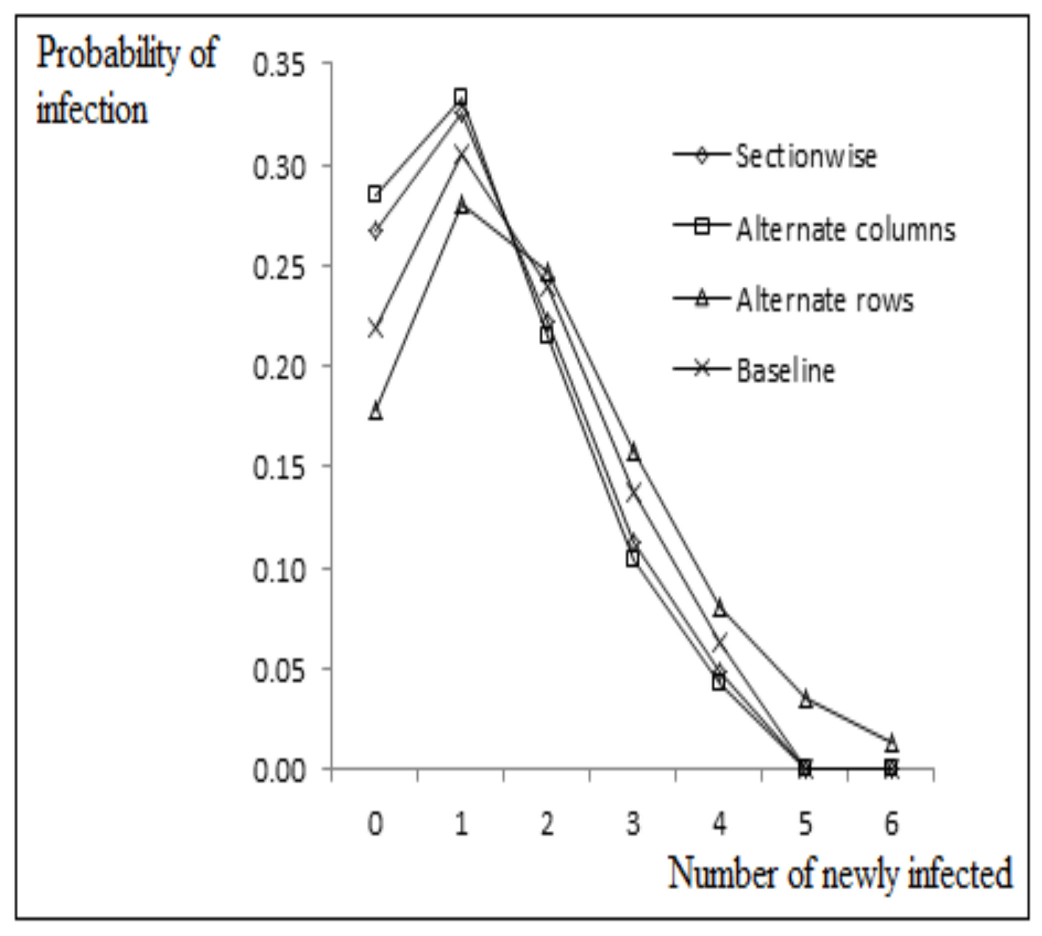
IMPACT OF BOARDING STRATEGIES

- Boarding Boeing 757-200
  - One passenger at the first day of infection
  - Infection probability = 0.06
  - Contact radius = 1.2 m
- Strategies that prevent clustering in the cabin reduce infection likelihood



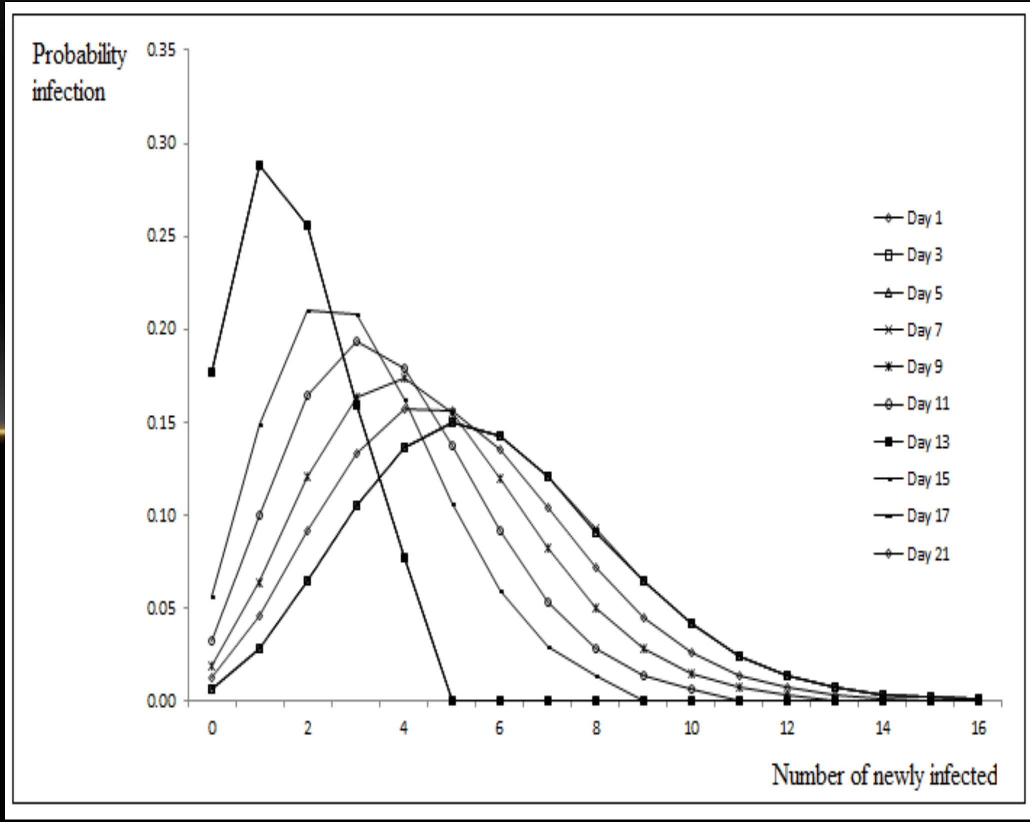
IMPACT OF DEPLANING STRATEGIES

- Deplaning Boeing 757-200
  - One passenger at the first day of infection
  - Infection probability = 0.06
  - Contact radius = 1.2 m
- Less important than boarding in infection spread



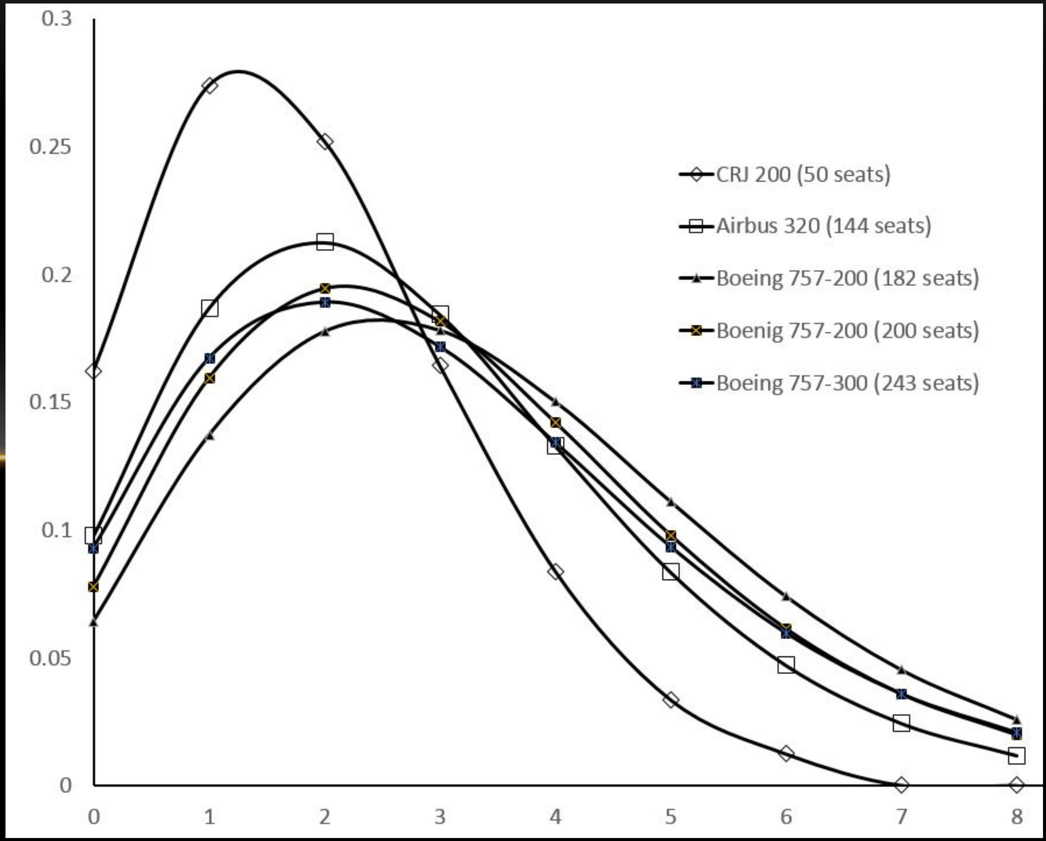
IMPACT OF INFECTIVITY

- Boarding + deplaning Boeing 757-200
  - One infected passenger
  - Infection probability varies in (0, 0.6]
  - Contact radius = 1.2 m



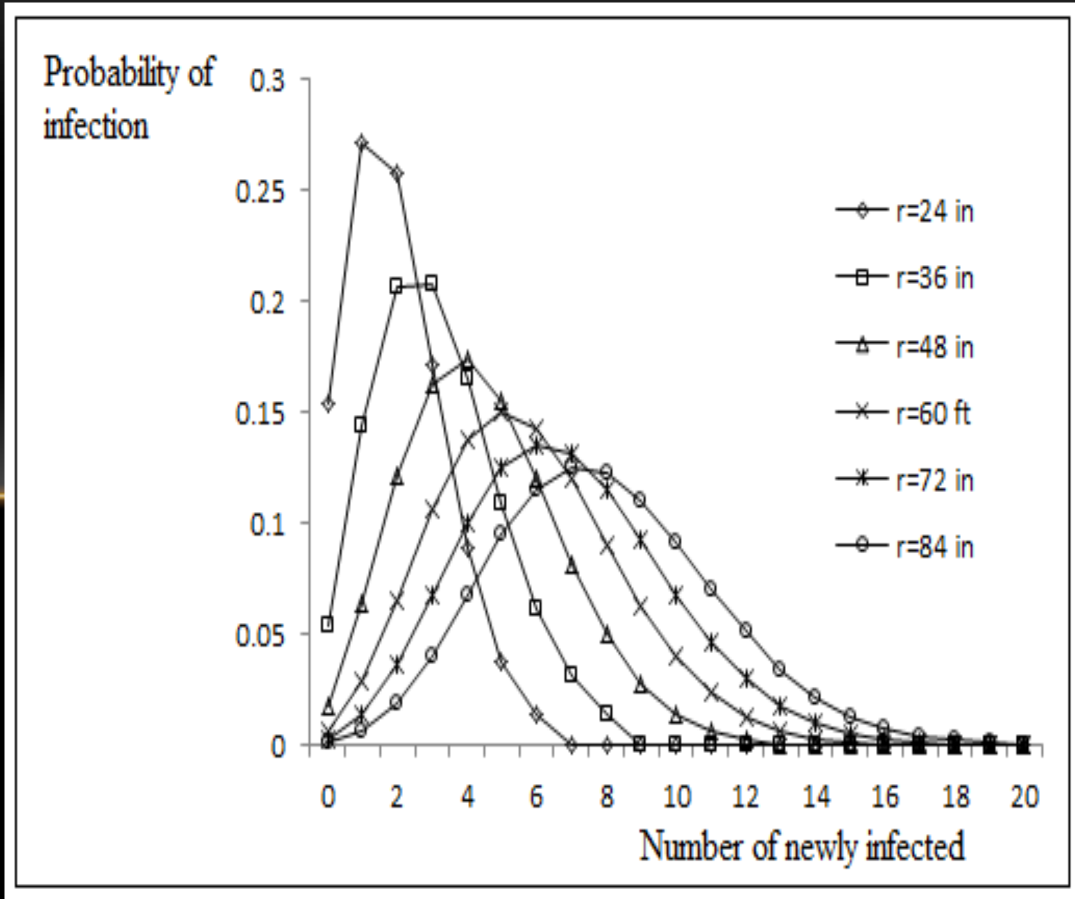
IMPACT OF PLANE SIZE

- Boarding Boeing 757-200
  - One passenger at the first day of infection
  - Infection probability = 0.06
  - Contact radius = 1.2 m



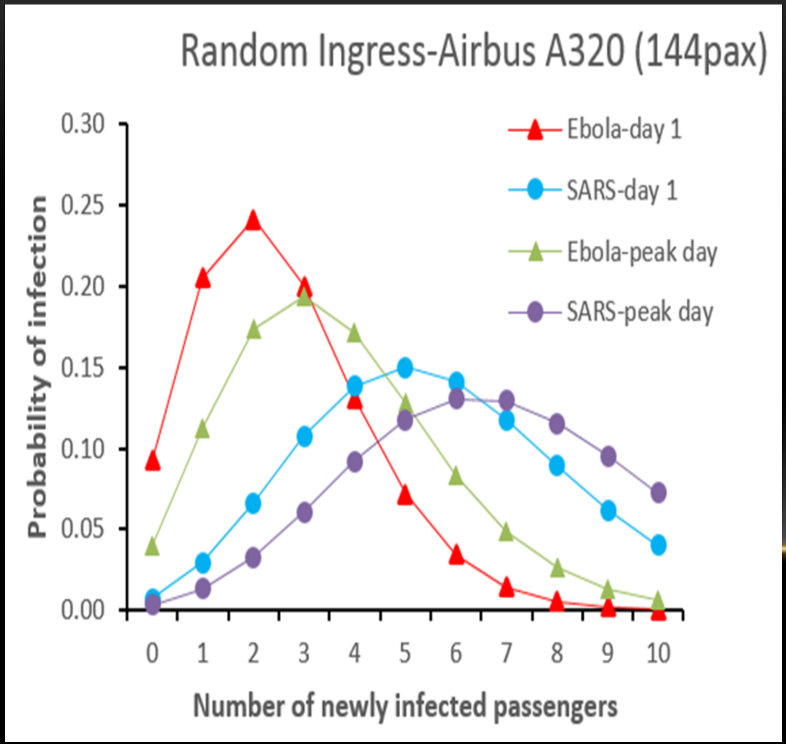
IMPACT OF CONTACT RADIUS

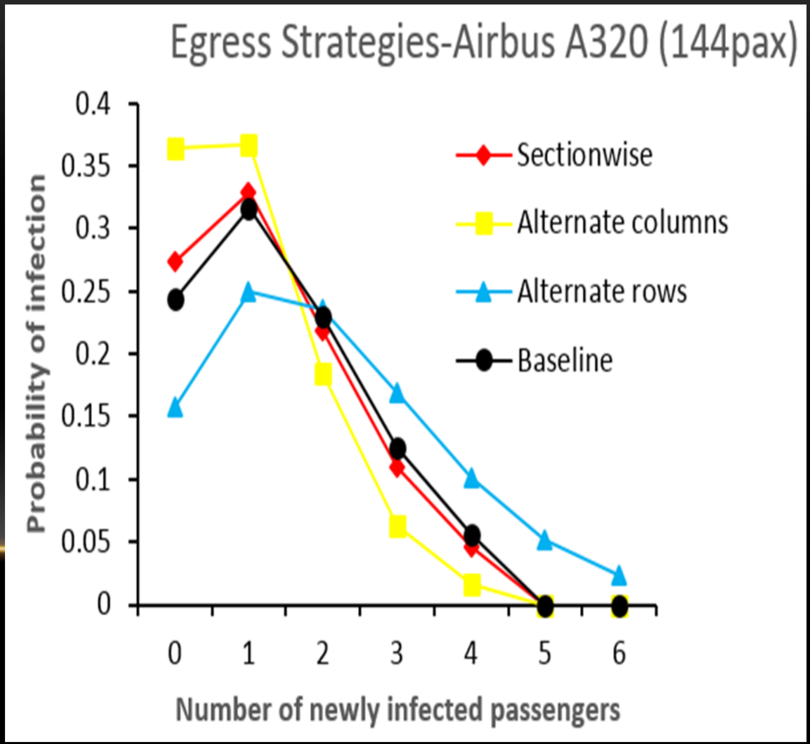
- Boarding + deplaning Boeing 757-200
  - One passenger at the first day of infection
  - Infection probability = 0.06
- Particle size 0.1-10μm
  - Distance traveled up to 2 m



- Long Distance: Small particles (aerosols) – SARS, H1N1
- Short distance: Coarse droplets – Ebola

LONG VS SHORT CONTACT RADIUS





- Infection contact radius
  - Ebola: 1.2 m
  - SARS: 2.1 m
- Model includes airport gates

CONCLUSIONS

SUMMARY OF COMPUTATIONAL OPTIMIZATIONS

- Factor 10 improvement in performance through optimization
- Dynamic load balancing increases efficiency from ~50% to ~90%
  - Post-priori bound shows it is within 10% of optimum in time taken for the number of cores used
- Better run time prediction will permit more efficient parallelization
  - Can reduce cores used further
  - Almost optimum static load balancing

SUMMARY OF APPLICATION RESULTS

- Identified procedures that can lead to significant decrease in contacts
  - Random boarding leads to lower risk of infection spread
  - Boarding has a higher impact than deplaning
  - Smaller planes are better than larger ones

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FUTURE DIRECTIONS

- Extend this approach
  - Other disease: Flu, measles, SARS, etc
  - Include infection spread in airports
- Improve computational efficiency
  - Better time prediction
  - More efficient parameter sweep
- Eventual goal is simulation time ~ 1 minute
  - Requires finer grained parallelization