Computational Methods for Effective Resource Allocation During Epidemics

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Introduction

History has shown that the results of ineffective preparation for combating public health emergencies such as an Influenza pandemic can be catastrophic; therefore, it is imperative to have practical methods of allocating and distributing limited hospital resources for control and treatment. The purpose of this project was to develop an optimization framework for the stockpiling problem and summarize the results to aid policymakers. I implemented this framework to optimize ventilator allocation during an influenza epidemic.

Optimization Framework

- Simulation Model: Create national level model that predicts the number of people infected with influenza in a county at a specific scenario and time. Scenarios are made up of three components:
  - Seeding: When, where, and how many infections are seeded based on one of the historical seasons (eg. 2005-06)
  - Vaccination season: Vaccine availability schedule based on one of the historical seasons (eg. 2009-10)
  - Efficacy: the chance the vaccine, when applied, gives protection for an individual. (eg. 4)
- Optimizer: Algorithm that calculates where ventilators are needed the most. Objective is to minimize deficits for ventilators. Four variables affect how much deficits there will be in a simulation:
  - Local fraction: Fraction of the local stockpile of ventilators that a county can share with another county (eg. 0.85 or 85%).
  - Total budget: Amount of ventilators available at the central stockpile (eg.13,000).
  - Threshold: Fraction of the initial allocation of ventilators that a county can share with another county(eg. 0.1 or 10%).
  - Delta: Time it takes for shared ventilator to return to its original owner (eg. 2 days).
- Analysis: Visualize results obtained from optimizer and observe how different parameters affect outcomes.

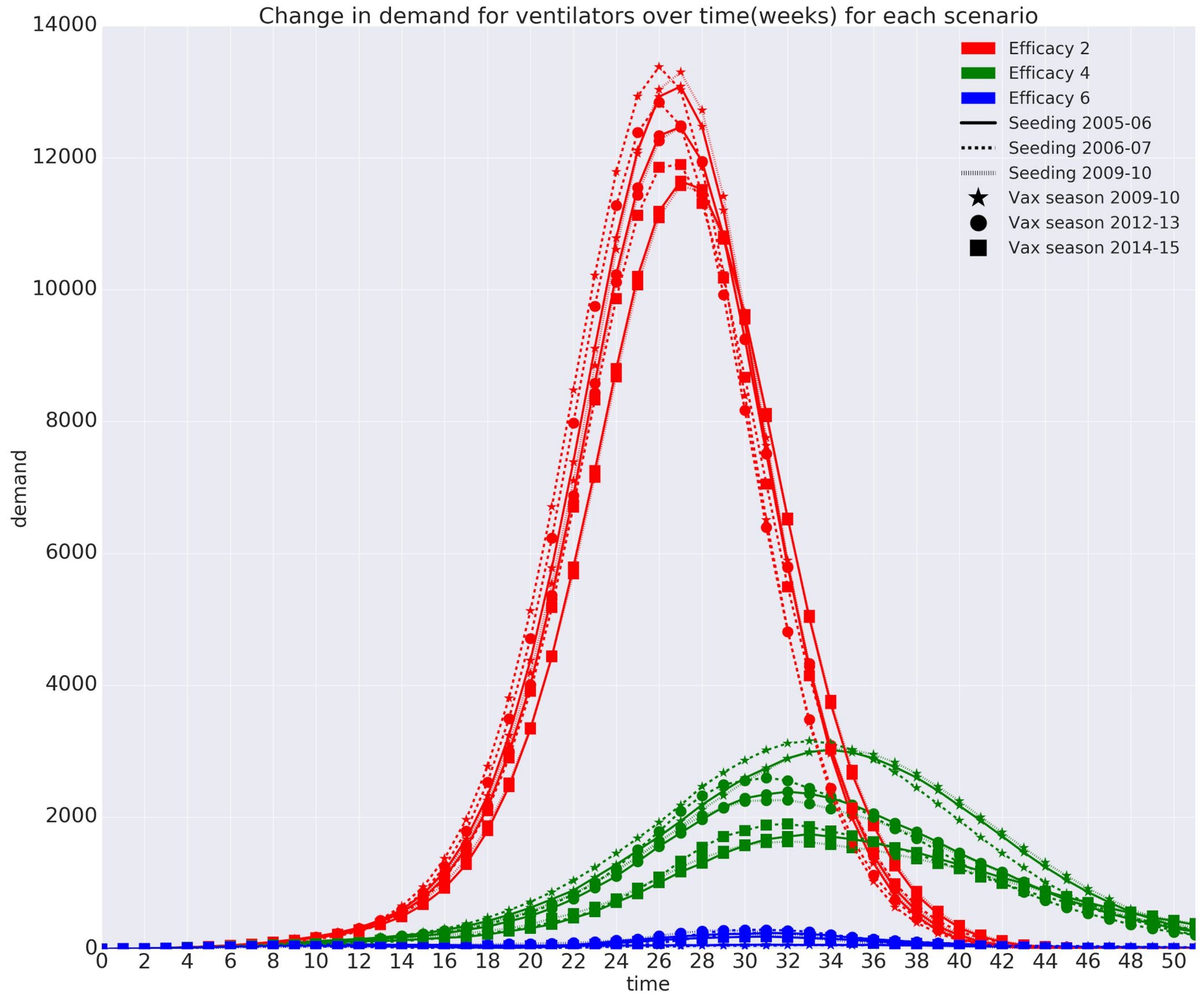
Questions?

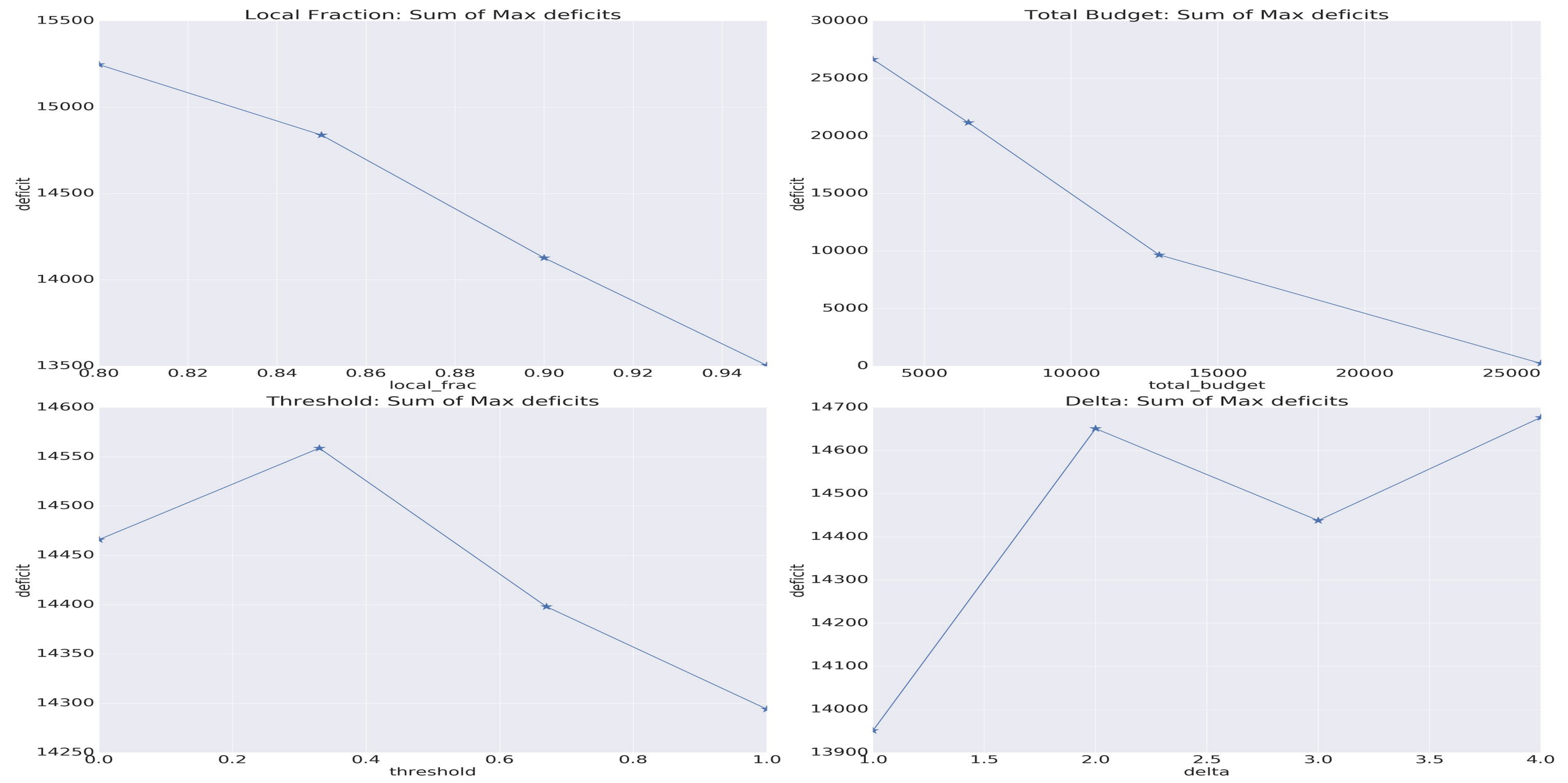
1. How will different combinations of scenario components (eg. seeding 2005-06, vaccination season 2009-10, efficacy 4) affect what the demand for ventilators would be throughout the United States over a course of 52 weeks?
2. Which of the four variables (local fraction, total budget, threshold, and delta) has the biggest impact on how much deficits there are for ventilators?

Methods

- Scenario Analysis:
  - Have three different arguments for each of the three components of a scenario. Run simulations on every possible combination of different components. Total number of simulations ran is 27.
  - For each simulation, plot how the demand for ventilators change over time (in weeks). Have the color of the plot correspond to the efficacy, the line style correspond to the seeding season, and line marker correspond to vaccination season.
- Variable Analysis:
  - Have four different arguments for each of the four variables. On a supercomputing cluster, run simulations on every possible combination of variables. Total number of simulations ran is 256.
  - For each simulation, find the highest amount of deficit across all counties, scenarios, and time. Then, add up all the max deficits for each argument (eg. Find the sum of the max deficits for all simulations where the total budget is 26,000 ventilators).
  - Plot the change in the sum of max deficits for each variable.

Results





Discussion

- Scenario Analysis:
  - When a scenario's efficacy is 2, the peak demand for ventilators is about 11,800-13,500. When a scenario's efficacy is 4, the peak demand is about 1,800 - 3,000. When a scenario's efficacy is 6, the peak demand is less than 500.
  - The simulations split into three groups, seemingly by their efficacy.
- Variable Analysis:
  - The difference between the minimum argument and the maximum argument for local fraction, threshold, and delta is less than 2,000 deficits.
  - For the total budget, the difference between the minimum argument and the maximum argument is about 26,000. Going from 26,000 deficits to 0 deficits!

Conclusions

1. The efficacy of a vaccine is a driving factor for the demand for ventilators in an influenza epidemic. Also, the 2009-2010 vaccination season was a rather poor year because for scenarios where it is the vax season, the demand for ventilators is higher than the other two vax seasons.
2. The total budget of ventilators (and to a lesser extent, the amount of ventilators a hospital can share in relation to their local stockpile) is a major factor in the amount of deficits that occur in an influenza epidemic.

References

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