

A Comparison of Targeted Layered Containment Strategies for a Flu Pandemic in Three US Cities

(Extended Abstract)

Shuyu Chu, Samarth Swarup, Jiangzhuo Chen, Achla Marathe
Network Dynamics and Simulation Science Laboratory, Biocomplexity Institute of Virginia Tech
1015 Life Science Circle
Blacksburg, VA, USA 24061-0477
{cshuyu,swarup,chenj,amarathe}@vt.edu

ABSTRACT

We study strategies for targeted layered containment of an influenza pandemic in three US cities: Miami, Seattle, and Chicago. Differences in demographic, geographic, and other structures lead to differences in the social interaction networks in the three cities. This has consequences for how the containment strategies should be applied to mitigate the spread. We use large-scale simulations to study these containment strategies and show differences in outcomes across the three cities.

Keywords

computational epidemiology; influenza; synthetic information; multi-agent simulation

1. INTRODUCTION

Pandemic influenza outbreaks occur every few decades, where a novel variant of the virus can sweep across the globe in a short period of time. Besides, the usual seasonal vaccines do not offer protection against pandemic viruses due to low or no immunity to the novel pandemic strain. To plan for the H1N1 swine flu, the US Department of Health and Human Services designed a targeted layered containment strategy. This strategy was simulated for the city of Chicago by Halloran et al. [6]. However, the general assumption that Chicago is representative of many populations is not valid [7]. The demographic and geographic differences between cities will cause differences in their social contact networks, and hence differences in epidemic characteristics and the performance of interventions. Further, the ordering of the interventions has not been studied. In this work, we do detailed simulations of influenza outbreaks for Chicago, Miami, and Seattle. We compare the targeted layered containment strategy across these cities and show that there are significant differences in outcomes between them.

2. METHODOLOGY AND EXPERIMENTS

We use synthetic social contact networks of Miami, Seattle and Chicago [1, 4, 5, 3] to study the spread of pandemic

influenza. The simulations are run using EpiFast, a fast agent-based epidemic simulation tool [2]. An SEIR model is used to represent the disease progression within each host.

2.1 Interventions

We take one of the scenarios from [6] which includes a series of interventions and particular configurations of parameters. All interventions are triggered when 1% of the population is infected. For each city, six interventions have been considered: (i) antiviral treatment (AV): applied to all diagnosed individuals with 1 day delay, for a duration of 5 days; antiviral efficacy is 60%; (ii) home isolation of cases (SHO): 60% of the diagnosed stay home for 10 days; (iii) close schools (CS): 30% of the schools are closed in the city for the entire flu season; (iv) sick leave (SL): 50% of symptomatic workers stay home when infected; applied with 1 day delay; (v) stagger work (SW): Workers split into 2 shifts to reduce work place contacts into half; compliance is at 50%; (vi) Generic social distancing (GSD): All non-essential activities are stopped; compliance is at 50%.

3. RESULTS AND ANALYSIS

We run simulations for each of the interventions discussed above for each city and measure the drop in cumulative infection rate from base case (when there was no intervention) to assess its performance. Cumulative infection rate is also called the attack rate.

The effectiveness of individual interventions are then used to build a priority order for adding interventions sequentially. The most effective intervention is applied first, then the second most effective intervention is added on and so on. Two other priority orders are also considered, one based on the number of individuals intervened and the other based on the ease of implementation of interventions.

3.1 Effect of each intervention by city

Effect of each intervention is individually measured in the three cities. In Miami, stay home and antiviral strategies result in the biggest drop in the attack rate. The next most effective intervention is generic social distancing, followed by sick-leave and stagger-work strategies. The least effective strategy is close-schools.

The reason close-schools, sick-leave, and stagger work strategies are not as effective is because they only intervene on the population which attends school or goes to work. In contrast, generic social distancing is applied across the pop-

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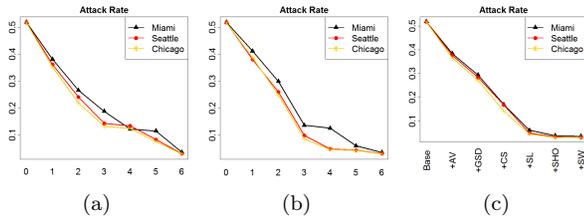


Figure 1: Attack rates when applying multiple interventions in three ways. ‘0’ corresponds to the base case, and ‘1’ to ‘6’ correspond to the six interventions.

ulation. Antiviral and stay-home perform well because they are targeted only at diagnosed individuals.

In case of Seattle and Chicago, stay-home and antiviral strategies performed the best too. Stay-home strategy performs better in Seattle and Chicago compared to Miami because Miami has a larger ‘senior’ or retired population which tends to be more at home on a typical day, thereby dampening the effect of intervention. Next most effective strategies are sick-leave and stagger-work followed by generic social distancing.

To check if the differences in attack rates are significant across interventions, we used t-test for all combinations and all cities and the p-values are significant at 1% level.

3.2 Prioritize by level of effectiveness

Results in section 3.1 show that each intervention by itself is not enough to control the pandemic. Thus pandemic planning requires applying multiple interventions (“layering”). We first build a priority order based on the performance of each intervention for each city. The most effective intervention is applied first, followed by the next most effective one and so on. Thus the intervention order for Miami is SHO (1), AV (2), GSD (3), SL (4), SW (5) and CS (6), whereas for Seattle and Chicago it is SHO (1), AV (2), SL (3), SW (4), GSD (5), CS (6). The results are shown in Figure 1a. As more interventions are layered on, the attack rate continues to drop. When all interventions are applied the attack rate drops to almost 3% in all the cities. However even when the best five interventions are applied in each city, attack rate stays at 8% or higher which is unacceptable.

3.3 Prioritize by number intervened

To improve the intervention performance, we consider the number of people who are intervened under each strategy and build a priority order based on that. The intervention which impacts the smallest percentage of the population is applied first, followed by the next smallest and so on. Hence the priority order for Miami is SL (1), CS (2), SHO (3), SW (4), AV (5), and GSD (6). Seattle and Chicago follow the same order, SL (1), CS (2), SHO (3), AV (4), SW (5), and GSD (6). The results of this priority order are shown in Figure 1b.

Note that the first three priorities are the same for all cities although the contribution of stay-home intervention is much smaller in Miami compared to the other cities. This is because Miami has more ‘seniors’. Also Miami has fewer work activities for the same reason, so stagger-work results in fewer number of intervened, bringing it up in the priority order.

Impact of stagger-work in dropping the attack rate is fairly

small in all cities. This is likely due to the fact that stagger-work only impacts the subpopulation of workers and only half their contacts.

3.4 Prioritize by the ease of implementation

Next we consider a new priority order, the ease of implementation of the intervention, and give the highest priority to the strategy that is the easiest and most practical to apply. Under this consideration, the priority order for all three cities is selected to be: AV, GSD, CS, SL, SHO and SW.

The reasons for choosing this priority order are as follows. Giving antiviral treatment to the sick individuals is the most practical and natural course of action. Social distancing, on the other hand, requires wide spread public support and voluntary compliance. Thus one of the easiest public health directive for social distancing is to cut down all non-essential activities (GSD). The next easiest and effective social distancing measure is CS because schools are high-density locations which facilitate transmission of disease.

A liberal sick leave policy is slightly harder to apply since the private sector needs to comply with this intervention and allow time off to their employees. SHO strategy isolates people at home and requires them to end all external activities, which can be hard to implement. Stagger work schedule is the hardest since it requires work places to run two shifts to reduce the workers’ contacts into half.

Figure 1c shows the attack rates for each additional intervention under this priority order. In Miami, when both AV and GSD are applied, the total attack rate drops by additional 9.03% compared to the case when only antiviral is applied. Similarly, adding CS intervention drops the attack rate further in Miami. The t-test shows that all differences are significant at 1% level except the addition of SW.

For Seattle and Chicago, this priority order performs better than any other priority order. Under this ordering, applying just 4 of the 6 strategies drops the attack rate to 5-6% in all cities, which is much better than the attack rate under any other priority order. For Miami, the ease of implementation based ordering works the best too but it takes 4 layers of interventions to bring down the attack rate to 6%.

4. SUMMARY AND CONCLUSIONS

In this work we have introduced the problem of sequencing interventions through targeted layered containment of pandemic influenza. We find that the optimal sequence of interventions depend upon the composition and the characteristics of the city. Surprisingly, it turns out that ease of implementation is a good heuristic for ordering the interventions. Finding the optimal ordering is still an open question. New methods for analysis may be needed to rigorously identify the redundancies between interventions and reduce the computational complexity of finding the optimal sequence of interventions.

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