2017 IEEE International Conference on Computational Science and Engineering (CSE) and IEEE International Conference on Embedded and Ubiquitous Computing (EUC)

# Optimizing Pharmacy-based Distribution of Pandemic Influenza Antiviral Drugs based on Large urban network

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***Abstract*—Antiviral drugs are taken as the primary measures to control influenza pandemics efficacious, especially in the early stage of pandemic influenza outbreak. To limit strain on hospitals, commercial pharmacies have been taken as antiviral drug-dispensing partners in some governments' pandemic response plans. Existing researches focus on site selection by optimizing the single objective of access to the target population. However there are still some other important social factors (such as social unbalance and spatial unbalance) should be considered. In this paper, we propose a network-perspective optimization model through the network-level, node-level and edge-level factors to assign a given amount of antiviral drugs to the dispensing pharmacies in a city. Taking Shanghai as a example, we shown the flexibility of the proposed multi-objective model, comparing with the traditional methods. For example, we found that there are 29 pharmacies needed with covering 81% districts by tradition single-objective method. In the contrast, only 12 pharmacies are needed with similar access ability but can still cover 75% districts. Or more pharmacies are assigned with covering 87% districts. This research can supply a initial exploration of pharmacy-based distribution of antiviral drugs for the studying construction of strategic national stockpile in some countries.**

## INTRODUCTION

In the early 21-th century, people has already suffered several global epidemic influenzas (such as pandemic H1N1 in 2009[1] and H7N9 in 2013[2]) with enormous life and property losses. However, the risk of future pandemic influenza outbreak are expected to increase in the coming decades[3], especially in cities due to the potential huge traffics [4], [5]. Once there is a influenza Pandemic, both antiviral drugs and vaccines are taken as the primary measures to control influenza pandemics efficacious[6], [7]. However, the developing and delivering vaccines for diseases may need several months[8], antiviral drugs are thus particularly critical and taken as the major pharmaceutical intervention in the early stage of pandemic influenza outbreak.

In preparation for coming influenza pandemics, the US governments have maintained a large Strategic National Stockpile (SNS) of antiviral drugs as a major component in their pandemic response plans [9]. To limit strain on hospitals and improve convenience, the commercial pharmacies have been taken as antiviral drug-dispensing partners in some state pandemic response plans (such as Virginia [10] and Louisiana [11]). The goal of this paper is to explore a optimization method to assign a given amount of antiviral drugs to the chosen location of dispensing points (such as pharmacies) within a city.

In the existing research of optimizing pharmacy-based distribution, there are a number of researches[12], [13], [14], studying the factors (such as traffic and consumption environment) that a consumer might consider when choosing a pharmacy to buy medicines. The pharmacy site selection problem can be considered as the traditional location problem in theory of combinatorial optimization. However, the site location selection becomes complex once we consider it from the drug assignment perspective. Specifically, with the existing pharmacies, the problem is how to assign the limited dose of drug into different pharmacies in order to benefit the society best. In the related existing mathematical models, they are mostly data driven to help government to choose pharmacies for antiviral drugs through 0-1 integer linear programming[15]. However, in the process of modeling, the single objective is to maximize the access of the target population to pharmacies. However, there are still some other social parts needed to be considered:

- The access is modeled mostly by the distance. How-

ever people's willingness to a health department is also depended on many other social factors( such as the reputation[16]).
- Although the social unbalance for small areas is considered[15], the single-objective modeling process can not reflect the balance between the multiple optimization objectives(access and social unbalance) .

To sum up, with maximizing the people's access to the pharmacies, there are at least three other objectives needed to be considered. The first is from the network perspective for the social unbalance. Each target areas should be assigned of antiviral drugs. The second is from the spatial unbalance perspective for any two chosen pharmacies. The chosen pharmacies should not be too close with each other. The last is from the node perspective for each chosen pharmacies. The volume of antiviral drug assigned for a pharmacy should be larger than a certain threshold, to avoid too many administrative work for trivial assignment.

Thus to assign optimized amount of antiviral drug for each pharmacy, we propose a network-based model by maximizing multiple objectives (access, social unbalance and spatial unbalance) . Here access is based on a willingness-to-travel model to reflect people's tendency to a pharmacy according to its distance and reputation. As for social unbalance, it is modeling with L12 norm to make even small areas have antiviral drugs supplied. Besides, to meet the spatial unbalance between any two pharmacies, the concept of network lasso[17] is introduced here to constraint the choices of pharmacies. Taking the city of Shanghai in 2015 as a example, we use this model to optimize the commercial pharmacy distribution network , given fixed amount of antiviral drugs. This research can supply a initial exploration of pharmacy-based distribution of antiviral drugs for the studying construction of strategic national stockpile in China's Twelfth Five-Year Plan[18].

## METHODS

### *Data*

*1) Subway:* To describe the population distribution of Shanghai, we use the travel smart card dataset (collected by Shanghai Public Transportation Card Co.Ltd) in Shanghai, China during 30 days in April 2015. This dataset involves 313 subway stations, 11 million individuals and 123 million events of trips. Once people travel through the subway stations by their smart card, when and where this event happen will be recorded automatically[19]. With these records, we mainly consider the volume of check-in passengers for each station to reveal the population distribution.

*2) Pharmacy :* To get the spatial information of pharmacies in Shanghai, we use the API of Baidu Map to get their names and spatial positions[20]. Specifically, there are around 5600 pharmacies, in which there are 2036 pharmacies marked by 11 famous brands (which have more than 50 pharmacies in Shanghai). As for their ratings of popular, they can be found in the website of Dianping, one of the China's leading O2O platforms for urban and lifestyle services[21].

### *Willingness-to-Travel Model*

We use the gravity model[22], [23], [24] to estimate the effect of distances on individuals' willingness to travel in Shanghai to get antiviral drugs from pharmacies. Besides, the influence of distances on people's willingness, pharmacies' own social profiles (such as reputation and scale) also show obvious effect[16]. Such the probability of people's willingness to the $i$-th pharmacy can be modeled as the following equation: $p(i) = \sum_j p_{ij} S_i R_i$ Here $p_{ij}$ is the effect of distances on willingness by gravity model. $S_i$ denotes the scale of the $i$-th pharmacy, as the number of drug stores in the brand which the $i$-th drug store belongs. $R_i$ denotes the reputation of the $i$-th drug store, as the rating of popular by individuals.

### *Optimization Model*

We mainly consider three items for the multi-objectiveness of access, social unbalance and sparsely spatial distribution.

1) The access is used to reflect people's tendency to a pharmacy according to its distance and popularity. For a pharmacy, the tendency is proportional to the number of people living around and the popularity (such as the scale and reputation) of this pharmacy. Specifically, let $\alpha$ be the access measure of $x_i$, with element $\alpha_i = \sum_j pop_j p_{ij} S_i R_i$ . Here $pop_j$ is the population for the $j$-th station, $S_i$ is the scale of the $i$-th drug store and $R_i$ denotes the reputation of the $i$-th pharmacy. Let $p_{ij} = \frac{1}{r_{ij}^2}$ , where $r_{ij}$ represents the distance between the $j$-th station and the $i$-th drug store.
2) As for the social unbalance, $l_{12}$ norm is commonly used as the exclusive Lasso for multi-view feature selection [25], which is suitable for us to balance the resources in different management areas. Thus no area is assigned without resources. The only difference between areas is the dose of drug distributed.
3) To meet the request of sparsely spatial distribution, a network-lasso penalty operator $D$ [17] is introduced here, which is used to describe the relationships between two nodes. In our case, the closer two chosen pharmacies are, the larger the penalty tends to be,

## RESULTS

During early 2016, there are 2036 pharmacies in Shanghai from 11 famous in 15 administrative districts. To be specific, the density distribution of logarithmic access follows the Gamma distribution, while the logarithmic distance follows the Normal distribution. These distributions tell us that the pharmacies with high or low access are in the minority, the same with the distances.

Next, we begin to evaluate the optimization model for the pharmacy-based distribution of antiviral drugs. Assuming there are $10^5$ dose of antiviral drugs for assignment, which is more than any single pharmacy's access, but not enough for the full coverage of all pharmacies. We estimate the spatial network of pharmacies shown in Fig. 1 by varying the influence of social unbalance and spatial unbalance, given fixed threshold for the minimum of pharmacies' drug for assignment.

With increasing influence of social unbalance (represented by $\lambda$), drugs tend to focus on several pharmacies with different districts, showing the social unbalance to some extent. In contrast, with the increasing spatial influence (denoted by $\mu$), the doses of drugs tend to focus on the pharmacy with highest access.

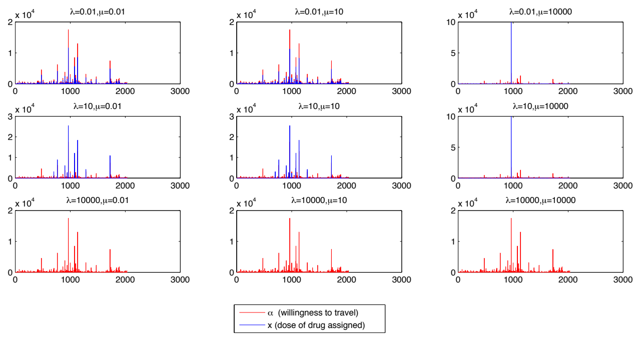


Fig. 1. Dynamics of pharmacies' access with varying lambda ($\lambda$) and mu ($\mu$) from 0.01 to 10000. When lambda and mu are small in sub-graph a, many pharmacies are chosen for drug assignment. As for the increasing mu and lambda, the drugs tend to focus on a single pharmacy or different pharmacies in dynamic districts.

## Discussion

Increasing governments take the pharmacies in their plans of the dispensing of antiviral drugs. Whether and how much this strategy can benefit the society is needed to study, especially for the constructing strategic national stockpile. In this paper, we study a optimization method to assign a given amount of antiviral drugs to pharmacies within a city. A network-based method is proposed by maximizing multiple objectives (access, social unbalance and spatial unbalance) . We can see how these objectives change with dynamic number of pharmacies chosen. The improvements of social and spatial unbalance are in the cost of access. In future, we may involve more areas, such as people's emotions [26], [27] and spatial distribution [28], into the optimizations.


## Acknowledgment

The authors are grateful for the support of National Social Science Foundation of China no. 16BGL180.


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