# Robust territorial pandemic healthcare response planning

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#### 1 Introduction

The COVID-19 pandemic has exposed the lack of preparedness within healthcare systems to effectively respond to public health emergencies. A multitude of studies have investigated the challenges of capacity management during a pandemic crisis, such as [2, 3, 5]. Other studies used robust optimization techniques to handle the inherit demand uncertainty challenges related to this problem such as [4, 6, 7]. Our study proposes a territorial pandemic healthcare response planning approach for best matching a COVID-19 patient care network and capacity to the pandemic evolution in a specified territory over a given time horizon. More specifically, the healthcare demand for COVID-19 patients evolves both temporally and spatially. Each patient requires a bed for a random length of stay in one of the COVID-19 hospitals. For our model, the uncertainty regards the patient demand rate and is tackled using budget uncertainty to formulate the robust optimization model.

#### 2 Problem statement

Given a territory comprised of a set of demand zones Z and a set of healthcare facilities H, the decision problem consists of selects the set of facilities to open/close as well as their capacity level at each time period t of a time horizon T. At each time period t, patient arrival at a demand zone z is assumed to follow a Poisson distribution of parameter  $\lambda_{zt}$ . Each patient is either rejected (assigned to a facility outside of the territory) or assigned to an open facility, in which they will remain for a random number of periods called the length of stay (LoS), assumed to be independent and identically distributed (i.i.d). Capacity of facility h is defined as a number of fully equipped hospital beds and can be selected from a set I of capacity levels. A facility can be closed once its occupancy level reaches a lower threshold, in which case the remaining patients are discharged earlier. Moreover, The capacity constraint of each facility is described by some given least chance probability to not exceed the capacity in each period. Assignment decisions are made independently from the arrival scenario, following a routing probability that depends on the demand zone, time period and occupancy level of the facilities. Cost parameters include fixed opening costs, maintenance costs, capacity modification costs, patient assignment costs, rejection costs, and early discharge costs.

### 3 Solution methodology

In order to deal with the arrival rate uncertainty, we refer to robust optimization (RO) techniques introduced in [1], wherein uncertain parameters are assumed to vary within a certain range referred to as **the uncertainty set**. Let  $\bar{\lambda}_t$  be the nominal arrival rate at period t, and  $\bar{\sigma}_t(>0)$  is the maximum deviation of the actual arrival rate  $\lambda_t$  from  $\bar{\lambda}_t$ . We assume the total deviations within the study period are less than the budget B(> 0). In order to have some sort of correlation between periods, the deviation at the previous period bounds the deviation at period t. Starting from a previous stochastic model, A Robust decision model aiming to minimize the worst-case scenario is build taking into account these constraints.

### 4 Preliminary results

Table (1) presents the percentage increase in costs achieved by the robust model as compared to the stochastic model, considering diverse scenarios of pandemic wave, deviation, and budget configurations (expressed as a percentage of the total maximum deviation). The table emphasizes the trade-off between the level of robustness and the associated solution cost, offering decision-makers valuable insights for determining the optimal policy in light of the model's behavior across different parameter variations.

| Scenarios               | 1                   | 2    | 3    | 4    |
|-------------------------|---------------------|------|------|------|
| $\sum_t \bar{\sigma_t}$ | 66                  | 86   | 219  | 220  |
| В                       | % Cost augmentation |      |      |      |
| 20%                     | 3.4                 | 4.3  | 11.7 | 12.7 |
| 40%                     | 6.7                 | 8.6  | 23.9 | 25.7 |
| 60%                     | 9.8                 | 12.5 | 35.4 | 37.6 |
| 80%                     | 11.2                | 15.4 | 42.7 | 45.2 |
| 100%                    | 11.4                | 16.1 | 44.6 | 47.8 |

TAB. 1: Percentage of Cost augmentation of the robust model compared to the stochastic model for different values of the budget.

## 5 Conclusion and perspectives

This work aims to develop a Robust optimizations model to face the uncertainty regarding patient arrival rates. Initial results illustrate the impact of budget level on the solution outcome. Additional experimentation is in the works in order to further analyze the performance of the robust model.

## References

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