Healthcare response tool for a territorial hospital group during a pandemic

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1 Introduction

The ongoing COVID-19 pandemic has shown to be most difficult to handle due to how rapidly it has spread, resulting in a considerable amount of infected people in need of hospitalisation. It has unveiled a great deficit in hospital resources necessary to support the sudden surge in demand for hospital care, as well as the lack of robust patient management strategies essential to alleviate the pressure of high rate patient arrivals endured by healthcare facilities ([2, 3, 7]).

Several researchers studied the problems of capacity management and scarce-resource sharing since the COVID-19 outbreak such as [1, 4, 5, 6], where optimisation strategies and decision aiding tools have been developed to assist healthcare facilities. Herein, the main focus lies on COVID-19 patients, our goal is to develop a dynamic response tool capable of arming and disarming healthcare facilities in order to handle the surge in COVID patients. The novelty of this response tool is that throughout a time horizon, healthcare facilities are added, removed or have their capacities altered in a dynamic fashion following the progress of the pandemic.

2 Problem statement

Given a time horizon T, A set of healthcare facilities H covering a certain territory and a set of demand zones Z in that territory, the capacity planning and patient assignment problem is addressed under a number of assumptions. For each facility, a set of capacity levels I is defined, describing the number of beds to open for COVID-19 patients. Patients arrivals at each demand zone are assumed to follow a Poisson distribution, with a length of stay following a Log-normal distribution, thus giving the value of $D_{z,t}$, the demand at each zone z at each time period t. The goal is to provide an optimal strategy for the healthcare services. A solution is represented by a set of decisions determining : the periods of opening and closing COVID-19 units, the capacity levels of each facility at each time period and the proportion of patient demand assigned from demand zones to healthcare facilities at each time periods. The objective function is defined by the following criteria : CO_h, the cost of opening a COVID-19 unit in facility h, CM_h the maintenance cost of a capacity level, CA_h the capacity alteration cost and $CT_{z,h}$ the patient assignment cost from zone z to facility h (a dummy facility with infinite capacity is added to handle overcrowding).

3 Resolution methods

To tackle this problem, two mixed integer linear programmes have been developed, as well as a local search based approach to handle larger instances.

Model 1 : For this model, the decisions regarding patient allocation are considered permanent, meaning that once a patient is assigned to a certain facility, that decision is unchanged throughout the duration of his length of stay.

Model 2 : Here, contrary to the first model, decisions regarding patient allocation can be

revised at each time period. The expected value of the occupancy rate of each facility h at each time period t is then calculated according to the assumptions given by each model. Furthermore, a set of chance constraints on the capacity levels is added in order to account for overcapacity and guaranty, with a probability, a certain level of service.
Local search based approach : Given an initial solution in the form of a matrix where each row represents the capacities of a facility at each time period, each neighbouring solution is produced by re-optimising the capacity decisions one facility at a time using Model 1.

4 Numerical experiments

The decision models described in the previous section were implemented using C++ language and solved with Cplex solver. Performance tests were conducted using randomly generated instances. As for the proposed heuristic, performance results on small and medium size instances are shown in Table 1. Tests on large instances are being done at the moment, more detailed numerical results comparing the two models as well as the performance of the heuristic will be shown during the conference.

Size(T,Z,H)	Time allowed (s)	Solution gap (%)
Small	30	$[0, 1]$
Medium	100	$[1, 2]$

TAB. 1 – Performance results of the heuristic approach on small and medium size instances

5 Conclusion and perspectives

The two MIPs described in this work, although being exact approaches, show great difficulty in handling instances of large size (unreasonable solving time). However, The proposed heuristic is showing promising results, giving efficient solution in a reasonable solving time.
The next step will be to conduct experiments using real healthcare data and compare our strategies to the ones used in previous COVID-19 waves.

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