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Design and operation of healthcare facilities using batch-lines: the COVID-19 case in Qatar

Brenno C. Menezes[a*], Mohamed Sawaly[a,b], Mohammed Yaqot[a], Robert E. Franzoi[a], Jeffrey D. Kelly[c]

[a]*Division of Engineering Management and Decision Sciences, College of Science and Engineering, Hamad Bin Khalifa University, Qatar Foundation, Doha, Qatar*
[b]*Department of Supply Chain, Hamad Medical Corporation, Doha, Qatar*
[c]*Industrial Algorithms Ltd., 15 St. Andrews Road, Toronto M1P 4C3, Canada*
bmenezes@hbku.edu.qa

Abstract

In the wake of the COVID-19 pandemic, hospitals worldwide have been overwhelmed and deprived of valuable resources such as bed capacities, medical equipment, personal protection equipment (PPE) stocks, and personnel. These factors imposed unforeseen challenges in the healthcare treatment systems. Mitigating inefficiencies by learning from COVID-19 is necessary to be better prepared to save lives and conserve resources. The main goal of this study is the development of an optimized healthcare treatment network by using predicted epidemiology curves to determine influxes of patients and bed capacities in a hospital facility for both in-patient (IP) wards (oxygen outlets) and intensive care units (ICU). Our model considers flows of patients by distinguishing them in terms of medical severity for their optimal allocation in an existing or installed healthcare facility treated as batch-lines (batch-processes in lines) with time-varying yields of a number of patients per day of treatment. Considering the hospital's admission and discharge of patients from 2020's 1st wave of COVID-19 in Qatar, we determine the bed space availability at any given future date for a hospital facility. This enables the prescription of engineered solutions to increase the capacity, responsiveness, and preparedness of healthcare systems infrastructure and management.

Keywords: Healthcare systems, supply chain resilience, optimization, COVID-19.

1. Introduction

The rapid spread of COVID-19 cases demonstrated the challenges of containing a pandemic whilst providing adequate care (Murthy et al., 2020). Design and operational inefficiencies are among the biggest reasons healthcare systems fail to minimize death rates and spreads of pandemics. Given the inevitable occurrence of future pandemics, healthcare systems must predict the growth and spread of the virus, implement strategies to contain it, and prepare their facilities and resources accordingly.

Several works address predictions on epidemiology curves (Santosh, 2020; Jewell et al., 2020) and their respective effects on resources such as personal protective equipment (PPE) (Tosh et al., 2014). Stübinger and Schneider (2020) propose a forecast of the future COVID-19 spread by addressing identified lead-lag effects using dynamic time warping from batch process monitoring and analysis. Garbey et al. (2020) use data obtained from the French Government during COVID-19 in a computational model to anticipate the patient load of each care unit, and the amount of PPE required by these units, as well as other key parameters that measure the performance of a healthcare system. Goodarzian et al. (2021) introduce a sustainable-resilience healthcare network for handling COVID-19 pandemic using meta-heuristics for allocation of medicine, resources, and staff throughout the supply chain elements considering capacities and flows among warehouses, distribution centers, pharmacies, hospitals, etc.

The proposition of this work is to develop prescriptive analytics for the optimal healthcare treatment systems in the planning, scheduling, and coordination of the disease treatment networks. With the utilization of the epidemiology curves, decisions can be made to determine optimal bed capacities needed during the COVID-19 pandemic, enabling the design and operation for a resilient medical supply chain to the COVID-19 pandemic.

2. Problem statement

The epidemiology data obtained for this study provide a daily prediction of positive cases from February 1st to May 31st, 2021 in Qatar. From the total number of suspected cases, it is assumed that 1% ends up in to the national healthcare systems' triage facility. We develop a mixed-integer linear programming (MILP) model for 120 days as time-horizon with 1-day time-step, in which 30% of the suspected patients at the triage result in negative diagnostic, and the remaining 70% result in positive. Among the admitted in hospital, 70% of the patients went as an in-patient (IP) and 30% in an intensive care unit (ICU). The model considers actual distributions (in terms of medical severity) of approximately 7,800 patients admitted into a hospital from March 2020 for one year, including the daily inflows and outflows of patients among the facility networks. It also considers the hospital's capacity as 335 IP and 230 ICU beds, with initial occupancies of 30% for each. The field hospital to be opened has a capacity of 160 IP and 80 ICU beds.

For the design and operation optimization of healthcare treatment systems, the network in Figure 1 shows a flowsheet of existing and future facilities and connections constructed in the unit-operation-port-state superstructure (UOPSS) from Kelly (2005) built-in in the Industrial Modeling and Programming Language (IMPL) (Kelly and Menezes, 2019). The shapes are considered as: a) unit-operations m for sources and sinks (◇), tanks or inventories (Δ), batch-processes (□) and b) the connectivity involving arrows (→), inlet-port i (○) and outlet-port j. Unit-operations and arrows are modeled by binary y and continuous x variables and the ports as yields of patients.

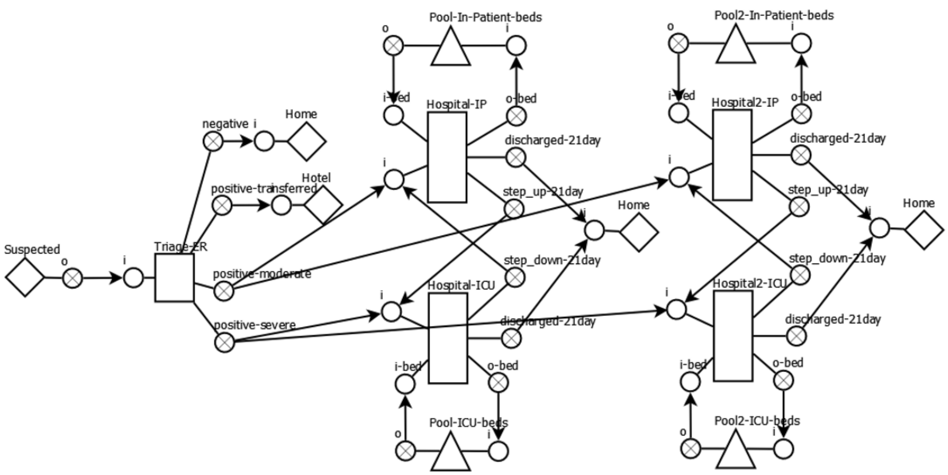

Figure 1. Base flowsheet of the healthcare system.

The model includes predicted yields of patient step-downs (from ICU to IP – meaning the patients' medical status improved), patient step-ups (from IP to ICU – meaning the patients' medical status deteriorated), patient admission yields, patient discharge yields, death yields, and transfer yields. The maximum batch-time is 21 days (which captures approximately 85 to 90% of hospitalized patients' lengths of stay), although there are time-varying yields from the actual distribution of patients in- and out-fluxes both IP and ICU wards from the observed cases. The 1- to 20-days yields and their connections are not represented in Figure 1 for simplicity.

3. Mathematical modeling

The objective function in Eq.(1) maximizes the pre-treatment of the suspected cases in the triage emergency room (ER), where $x_{j,i,t}$ represent number of cases for flows from the outlet port set j to inlet set i at time t. The variable $xh_{m,t}$ defines batch-processes' or hospital-units' holdups and pools of bed capacity in the model. All flows and holdups are governed by semi-continuous constraints of the shapes to themselves, such as $\bar{x}^L_{j,i,t}\, y_{j,i,t} \leq x_{j,i,t} \leq \bar{x}^U_{j,i,t}\, y_{j,i,t}\ \forall\ (j,i) \in JI, t$. The sets I and J represent in- and out-ports, respectively, while the set JI defines connecting patient flows between out- and in-ports. For the batch-processes (triage and hospitals), the holdup $xh_{m,t}$ is taken when they are starting up ($zu_{m,t}$=1) constrained by the respective bounds of the hospital facility capacities. The UOPSS formulation in Eq.(2) establishes that the holdup or inventory level bounds ($\overline{xh}^L_{m,t}$ and $\overline{xh}^U_{m,t}$) of the hospital facilities respect the sum of the flows arriving in and leaving from ports (in- and out-ports) whenever the respective startup variable $zsu_{m,t}$ is active. The sets M_{BATCH} include triage-ER, IP, and ICU facilities and M_{POOL} the IP/ICU bed's pools. In the indices in the summations from Eq.(1) to (5), the subsets of the I, J, and JI follow the flowsheet in Figure 1. For $x_{j,i,t}, xh_{m,t} \geq 0$; $y_{j,i,t}, y_{m,t} = \{0,1\}$; $zsu_{m,t} = (0,1)$:

$$Max\ Z = \sum_{t} \sum_{JI_{Suspected}} x_{j,i,t} \tag{1}$$

$$\overline{xh}^L_{m,t}\ zsu_{m,t} \leq \sum_{i \in I} x_{j,i,t} \leq \overline{xh}^U_{m,t}\ zsu_{m,t} \quad \forall\ (m,j) \in M_{BATCH}, t \tag{2}$$

$$\sum_{j \in J_{up}} x_{j,i,t} = xh_{m,t} \quad \forall\ (i,m) \in M_{BATCH}, t \tag{3}$$

$$x_{j,i \in I_{do}, t+delay} = \bar{r}_{j,t+delay}\ xh_{m,t} \quad \forall\ (m,j) \in M_{BATCH}, t \tag{4}$$

$$xh_{m,t} = xh_{m,t-1} + \sum_{j_{up} \in J} x_{j_{up},i,t} - \sum_{i_{do} \in I} x_{j,i_{do},t} \quad \forall\ (i,m,j) \in M_{POOL}, t \tag{5}$$

$$y_{m_{up},t} + y_{m,t} \geq 2 y_{j_{up},i,t} \quad \forall\ \left(m_{up}, j_{up}, i, m\right), t \tag{6}$$

$$\sum_{tt<t} zsu_{m',tt} + y_{m,t} \leq y_{j,i,t} \quad \forall\ (m', j, i, m), t \tag{7}$$

$$y_{m,t} - y_{m,t-1} - zsu_{m,t} + zsd_{m,t} = 0 \ \ \forall\ m \in M_{BATCH}, t \tag{8}$$

$$y_{m,t} + y_{m,t-1} - zsu_{m,t} - zsd_{m,t} - 2zsw_{m,t} = 0\ \forall\ m \in M_{BATCH}\ , t \tag{9}$$

$$zsu_{m,t} + zsd_{m,t} + zsw_{m,t} \leq 1\ \forall\ m \in M_{BATCH}, t \tag{10}$$

Equations (3) and (4) are related to the modeling of hospitals as batch-processes and in a special case called batch-lines. This is applied in Menezes et al. (2020) for livestock planning to determine the initial procreation of the animal batches, in which there is no accumulation of amounts of batches at each time step, as in Eq.(3). Instead, balances of batch amounts at a single time-window and the delaying and yield of amounts leaving the facility are modeled, as in Eq.(4). In the hospital facilities, new batches of patients arrive in the Triage-ER, Hospital IP, and Hospital ICU every day. The unit-operations' inventory or holdup quantity balance of pools are determined in Eq.(5) for both IP and ICU bed capacities. These constraints manage the availability of beds (holdup) to be utilized in the hospitals by controlling the a) inlet flow, when patients are dispatched outside the system or change their status to step-up or step-down; and b) the outlet flow, when the beds are needed in the hospital facilities.

Equations (5) and (6) represent the constraints for the structural transitions that allow the setup $y_{m,t}$ or startup $zsu_{m,t}$ of connected out-port-states j and in-port-states i unit-operations. When the setup of unit-operations m and m' is equal to the unitary in Eq.(6), by implication, the setup variable the arrow stream $y_{j,i,t}$ between the neighbor unit-operations must be true. In Eq.(7), addressing the hospital facilities as batch-processes, as the setup variable of m' is changed by the summation of the startups. These logic valid cuts reduce the tree search in branch-and-bound methods. The temporal transition in Equations (8) and (9) control the operations for semi-continuous blenders from Kelly and Zyngier (2007). The binary variable $y_{m,t}$ manages the start-up ($zsu_{m,t}$) switch-over ($zsw_{m,t}$) and shut-down variables ($zsd_{m,t}$), which are relaxed in the interval [0,1]. Equation (10) guarantees the integrality of the relaxed variables.

4. Results

The optimization for the proposed MILP in Figure 1 for 120 days as time-horizon with 1-day time-step is solved in 63 seconds with GUROBI 9.1.1 and 256 seconds with CPLEX 20.1.0 both at 1.0% of MILP relaxation gap using an Intel Core i7 machine at 3.4 GHz (8 threads) with 64 GB of RAM. There are 68,721 constraints for 23,765 continuous variables and 15,248 binary variables in the problem. The results in Figure 2 show that the existing facility's IP capacity could not sustain the surge of patients caused by the new strain of COVID-19 (initiated on day 63), which triggered the opening of the new field hospital by day 85.

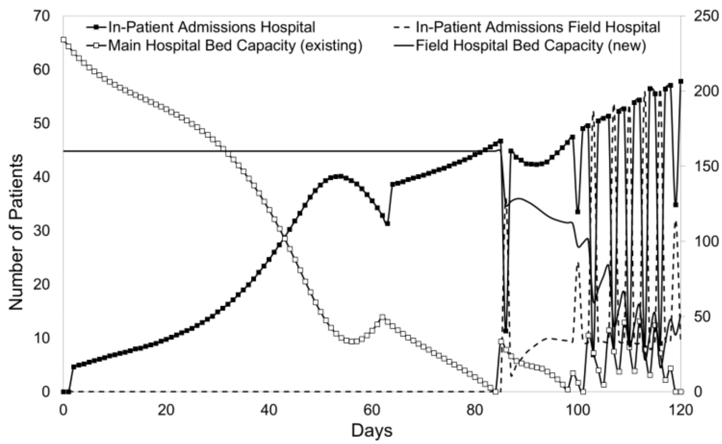

Figure 2. Design and operation of the IP facility.

Based on Figure 2, the existing hospital was only able to sustain the increase in patients for exactly 21 days (day 84), where the number of In-Patient admissions was 47 patients per day. From day 85 onwards, both facilities simultaneously received patients, which relieved the pressure on the existing facility and made the design feasible. Days 98, 101, and 119 demonstrate how the new field hospital's capacity helped sustain the operation when the main existing facility's capacity depleted. By the end of the time horizon, there were still 51 vacant IP beds in the field hospital (i.e., new facility). The lines in the plot are symmetrical as each facility worked hand in hand to handle the influx of patients.

Figure 3 demonstrates how the opening of 80 more ICU beds aided in sustaining the hospitalization of patients on days 83, 92, and onwards. The phenomenon observed from days 92 to 107, where the capacity of the field hospital remains zero, is illustrated in Figure 4.

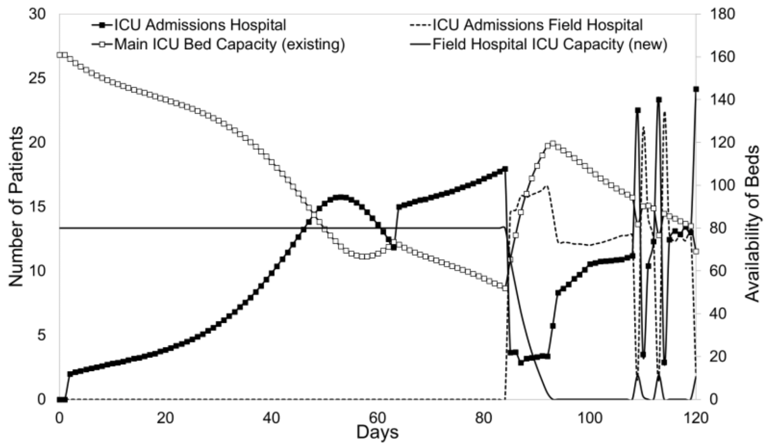

Figure 3. Design and operation of the ICU facility.

Figure 4 explains why the Field Hospital ICU capacity curve remains flat at zero from day 92 to 107, in which the capacity pool freeing up (by people being discharged) is occupied by other patients at the same rate. This phenomenon shows extreme efficiency since utilizes the limit opened capacity available, although it does not consider real-world factors such as the disinfection or preparation of ICU space.

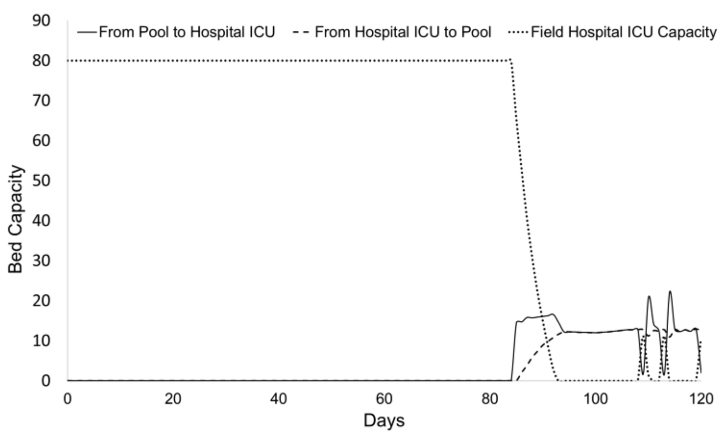

Figure 4. Pool of patients in and out causing the capacity to remain flat at zero.

5. Conclusions

It was evident from the events of COVID-19 that our world is interconnected in a way that virus outbreaks in a region can easily spread and cause impacts in a global sphere. Protecting the lives of humans entails that we must have a proper number of resources allocated in a timely and efficient manner. This work demonstrates how to be better prepared by designing and operating a healthcare treatment network with different facilities as the triage-ER, in-patient (IP), and intensive care unit (ICU) wards. The predicted epidemiology curves and the time-varying yields of the distribution of patients throughout the network served as inputs for the modeling and solving of batch-lines of patients interconnected among the facilities and their outlets. With such proposition, availability of bed capacities has been determined along the time-horizon, and installations of new field facilities for IP and ICU were necessary to handle the increased number of moderate and severe patients. Future work can implement procurement planning to ensure continuous availability of PPE and medical equipment; model staff scheduling models to ensure that no sick person is left unattended; design entire health system networks to ensure fully and optimal utilization of bed space; provide better utilization of quarantine and hotel facilities; and develop more accurate epidemiology curves to provide more reliable predictions for the potential of strains of viruses in further pandemic events.

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