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RESEARCH ARTICLE

Bed Allocation Model for Infection Control During a Pandemic

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This study proposes a model of allocating beds in a hospital considering infection control during a pandemic. The problem was formulated using the quadratic assignment problem (QAP) in a multi-period planning horizon. The main objective is to minimize the spread of infection by maximizing the total distance (TD) between areas assigned to the pandemic and non-pandemic patients. Model validation using GAMS showed that the assignment of patient groups to areas is determined by the arrival rates of patients and the area's capacity. The model was able to identify periods when the sharing of space was more advantageous. The model's outcome shows that assigning more rooms to pandemic patients can affect the spread of infection, but it is necessary. It is better to have smaller shareable spaces as the inflow of pandemic patients increases. Hospital administrators may use the model for planning, enabling them to identify and prepare areas to accommodate the increasing number of infectious patients, giving them the valuable lead time to do so. Managers can direct the flow of patients with more certainty, giving them more time and energy for other pressing matters. They may also incorporate other considerations specific to the circumstances of their facilities into this model.

***Keywords**:* bed allocation, infection control, quadratic assignment problem, pandemic

JEL Classifications: D61, I18

COVID-19 has infected more than 158 million worldwide, with deaths registering over 6 million as of March 2022 (World Health Organization, 2022). The Americas recorded the highest number of cases, followed by India and Brazil. With an incredible speed of transmission, the inflow of patients in health facilities is exponential. In the early stages of the pandemic, hospitals were forced to adopt various strategies to accommodate patients by creating buffer areas between wards, separating contaminated and non-contaminated sites, and transforming acute care spaces (Łukasik & Porębska, 2022). The patient surge challenges and strains public hospitals as they experience much greater demand than capacity (Sitepu et al., 2018). The emergence of new variants, such as the omicron, causes patient surges that repeatedly overload healthcare facilities in some parts of the world (Bradsher, 2022; Fernando & Shannon, 2022).

The most common problem in hospitals is allocating space to an increasing number of patients with infectious

diseases and accommodating other patients requiring urgent medical attention. Aside from structural and space limitations, there are several challenges to consider, like turfing or preferential treatment in the allocation of beds and other resources (Remuzzi & Remuzzi, 2020). Hence, hospitals need clear guidelines based on sound projections to minimize subjectivity in managing meager resources like beds during pandemics.

The layout of a hospital is part of a range of control measures to minimize the transmission of infectious diseases, such as the separation of dirty and clean areas (Rao, 2004). For example, providing only one entry point for different kinds of patients may promote the spread of infection in the triage section. Although studies are limited regarding infection control and isolation, case studies showed that some types of isolation could prevent infection spread. The infection rate is reduced as distance increases (Atkinson et al., 2009). Minimizing the spread of infection is a concern because of the possibility of acquiring nosocomial infection (Ahn et al., 2021), which increases morbidity, mortality, and costs (Parsia & Sorooshian, 2020). C. Ma et al. (2022) emphasized the need for an active strategy to contain infection during influenza season through bed management planning. This approach can minimize bed transfers that affect staff workload and the spread of infection.

Review of Literature

Bed Allocation Problems

Bed allocation in hospitals is recurring and challenging because beds are scarce resources and determine healthcare quality, operation effectiveness, and overall patient experience (Luo et al., 2019; Noonan et al., 2019; Sitepu et al., 2018; Zhu et al., 2020). Poor bed allocation can cause work overloads for doctors and nurses and aggravate medical conflicts (Luo et al., 2019). The inherent randomness of demand and bed capacity add to the difficulty in making the best allocation to serve patient needs and achieve business objectives (Zhu et al., 2020). Machine learning, however, can be used to improve the quality of prediction of patient discharge probabilities to aid bed management (Ahn et al., 2021).

Bed allocation practice varies per hospital. A bed manager usually is responsible for allocating beds according to the hospital's rules. One rule is to assign a fixed quota for demand streams: urgent and regular elective patients to maximize revenue and equity (Zhu et al., 2020). Bed allocation rules in literature are distinct in terms of the size of the hospital, the number of hospitals, and optimization objectives. Standard bed allocation metrics include bed occupancy rate (Grübler et al., 2018; Luo et al., 2019; Nguyen et al., 2005), revenue (Belciug & Gorunescu, 2015; Zhu et al., 2020), equity (Zhu et al., 2020), and shortage (G. Ma & Demeulemeester, 2013; Sobieraj et al., 2007). Beds can either be allocated to one unit (Akkerman & Knip, 2004; Griffin et al., 2011) or the whole hospital (Novati et al., 2017; Wu et al., 2020; Zhu et al., 2020).

Solution Approaches

Recent work on bed allocation used simulation, queuing theory, multiple-criteria decision analysis, mathematical programming, and statistics to optimize bed allocation (Holm et al., 2013; Li et al., 2009; Mehrolhasani et al., 2016; Oakley et al., 2020). Mathematical programming is a popular method of solving bed allocation problems because of the flexibility in adding constraints and changing the objective function.

Bed allocation models vary according to objectives and solution methods. Luo et al. (2019) tackled the imbalance of bed occupancy rates using mixed-integer linear programming (MILP). Similar goals are minimizing the underutilization of beds (Ataollahi et al., 2013; Blake & Carter, 2002) or minimizing excess capacity (Oddoye et al., 2007). Hoff (2017) considered two objectives: maximizing the number of patients with the highest criticality and minimizing internal movements within the hospital system. It was assumed that internal movements in the system increase staff workload and the risk of nosocomial infections for the patient.

Infection and Bed Allocation

During a pandemic, one of the utmost considerations in assigning beds to patients is to prevent the spread of infection. Considering this objective, the placement of patients in the hospital becomes inherent in the bed allocation problem, where infected patients should be isolated from non-infected ones. Existing guidelines on intensive care unit bed allocation in various countries during COVID-19 did not consider the relationship between bed allocation and hospital layout (Tyrrell et al., 2021). Allocation of beds was based on priority

rules based on ethics and patient condition. In dealing with a pandemic where the disease is highly contagious, a closer look at space, such as distance between beds, number of patients in rooms, and the infection control system's location, are necessary for planning (Stiller et al., 2016). The common bed allocation problem becomes a layout-allocation problem where the objective is to accommodate patients and assign specific patients to spaces.

The layout-allocation problem in a pandemic is laden with complexities brought about by isolation requirements, bed availability, unit configurations (Hoff, 2017), uncertainties in the arrival patterns of patients (Li et al., 2009), and length of stay (Akkerman & Knip, 2004). Hospital configuration and space are unchangeable in the short run; thus, isolation requirements can only be complied with by maintaining a safe distance between patients.

The design of most hospital layouts did not adequately consider changing demands for short durations. During a flu pandemic, patients can be classified according to the severity of the condition and infection. The arrival rate is expected to increase unless the hospital administration implements adequate controls. Thus, there is a need to reallocate hospital space within a short time period in a planning horizon, making it a dynamic facility layout problem (DFLP). In this scenario, a plan must be developed considering multiple periods to minimize costs within the planning horizon. Kulturel-Konak (2007) presented conditions where this will apply, including uncertainty in terms of volume, process, and routing, among others. In the context of a hospital, volume refers to the patient arrival rate. It is generally formulated as a quadratic assignment problem (QAP), where the cost of movement and rearrangement within the time horizon is minimized. A review of methods used in the layout of healthcare facilities revealed that QAP is one of the frequently used methods (Benitez et al., 2019). Earlier applications of QAP in hospital facility layout were made by Hahn and Krarup (2001), where the focus was finding a solution to the mathematical model applied in addressing a hospital problem consisting of 30 departments. A multiperiod layout model was used by Arnolds and Nickel (2013) in a hospital environment considering multiple periods so that the costs of installing movable and non-movable walls are minimized and layout adaptations. A binary linear program was used to solve the variable ward layout problem. Parsia and Sorooshian (2020) used multiple-criteria decision-making (MCDM) to re-architect a healthcare facility in response to changing managerial strategies, medical errors, or infection.

The literature review conducted on hospital space allocation showed that the assignment of patient categories to hospital spaces was not considered to minimize the spread of infection. The current study aims to provide a model for hospital administrators to allocate space in a pandemic considering infection control, the patient surge that varies over time, and multiple time periods in a fixed planning horizon. The model will help bed managers assign patient cases that vary in terms of severity and isolation requirements to specific hospital areas.

Model Formulation

The problem in this paper was formulated using the QAP in a multi-period planning horizon. A period is defined as a week, which is usually the time horizon for planning patient stays in hospitals (Proudlove et al., 2003). The main objective is to minimize the spread of infection by maximizing the distance between areas assigned to the pandemic and non-pandemic patients. Pandemic patients (PPs) are highly infectious. There can be several groups of pandemic and non-pandemic patients (NPPs) based on the severity of the condition or the type of disease.

Assumptions

1. The arrival of patients in the hospital follows a certain probability distribution. One example is the Poisson distribution used by Asheim et al. (2019) and Deschepper et al. (2021) in hospital capacity planning.
2. The recovery rate and mortality rate of diseases per period can be estimated based on historical data. Such estimation has been done for COVID-19 (Baud et al., 2020), coronary heart disease (Barefoot et al., 2011), and chronic obstructive pulmonary disease (National Center for Chronic Disease Prevention and Health Promotion, 2021), among others. The sum of these two values is the discharge rate per period per patient group (PG).
3. The transmission of infection in the hospital is proportional to the distance between the areas where PPs and NPPs are stationed. The

distance was identified as a significant factor in preventing disease transmission (Park & Kim, 2021).

4. The hospital areas have known regular bed capacities.
5. The planning horizon of the model is known.
6. The length of stay of a patient in a hospital can be estimated. For example, Chrusciel et al. (2021) used machine learning to predict the patient's length of stay using information from electronic health records.

Notations

Sets

I = set of hospital areas
IP = set of candidate areas for PPs; where IP ⊆ I
IN = set of candidate areas for NPPs; where IN ⊆ I
IC = set of candidate areas that may be assigned for pandemic or NPP, where IC = IN ∩ IP
K = set of PGs
P = set of pandemic PGs according to severity, where P ⊆ K
N = set of non-pandemic PGs where N ⊆ K

Indices

i = hospital area, where i∈I
k = patient group, where k∈K
j = period in a planning horizon
t = period after PG k (patient group of case k) arrives at period j at the hospital, t ≠ j

Decision Variables

H_{ikj} = 1; if hospital area i will be assigned to PG k in period j
= 0; otherwise
$ACAP_{ij}$ = 1; if hospital area i (for IN and IC only) will be expanded in period j
= 0; otherwise
$ABED_{ij}$ = number of beds to be added to hospital area i (for IN only) in period j
B_{ij} = number of beds to be added in hospital area i (for IN only) in period j
HH_{ij} = 1; if hospital area i (for IC only) will be used for NPPs in period j
= 0; if hospital area i (for IC only) will be used for PPs in period j

Random Variables

AF_k = number of PG k arriving in period j
f(AFK)dAF_k = probability distribution function of the arriving PG_k

System Variables

PT_{kj} = expected number of PG k in period j (where j > 0)
Z = Total distance

Parameters

PT_{k0} = number of PG k in period 0
R_{kt} = recovery rate of PG k after t period (in reference to period j)
M_{kt} = mortality rate of PG k after t period (in reference to period j)
CAP_i = normal capacity (in number of beds) of hospital area i
$MAXB_i$ = maximum number of beds that can be added to hospital area i (for IN only)
$Dist_{ii'}$ = distance between area i (for IP only) and i' (for IN only), where i ≠ i'

Objective Function

The objective function aims to maximize the total distance (TD) between the hospital areas assigned to PPs and NPPs, as shown in Equation 1. Maximum distance was used due to the assumption that the transmission rate of infection is proportional to distance. NPPs are less likely to get the infection if their assigned hospital rooms are far from PPs. Distance between two areas will only be computed when a certain pandemic area (i) is assigned to a pandemic PG, and at the same time, a certain non-pandemic area (i') is assigned to a non-pandemic PG. To be able to maximize the total distance, as shown in Equation 1, there is a need to consider all combinations of assignments of patient group to hospital area for all periods. The combination having the maximum value will be chosen and added to other distances.

$$Max\ Z = \sum_{i\in IP} \sum_{k\in N} \sum_{j} max\{Dist_{i\in IP, i'\in IN} * H_{i\in IP, k\forall\in P, j} * H_{i\in IN, k\in N, j}\} \quad (1)$$

Constraints

Expected Number of Patients per Period

This set of equations measures the expected number of patients with each type of disease, both pandemic and non-pandemic PGs, who will be in the hospital in each period. Equation 2 quantifies the expected number of patients after one period. Equation 3, on the other hand, represents the expected number of patients in succeeding periods after the first period. Both equations consider the number of patients in the previous period, the number of recoveries, the number of mortalities, and the arrival of patients per period. These equations are applicable to both pandemic and non-pandemic PGs. The expected number of patients per period per PG will serve as inputs to the capacity constraints.

$$PT_{k1} = PT_{k0} - (PT_{k0} * R_{k1}) - (PT_{k0} * M_{k1}) + \int \quad AF_{k1} f(AF_k) dAF_k \quad \forall k \tag{2}$$

$$PT_{kj} = PT_{kj-1} - \sum_{t=1}^{j-1} \left[\int \quad AF_{kj-t} f(AF_k) dAF_k \right] * R_{kt} - \sum_{t=1}^{j-1} \left[\int \quad AF_{kj-1} f(AF_k) dAF_k \right] * M_{kt} + \int \quad AF_{kj} f(AF_k) dAF_k \tag{3}$$

Capacity Constraints

This set of constraints ensures that all admitted patients will be accommodated and will have bed assignments. Equation 4 and Equation 5 guarantee that the number of beds for PPs and NPPs, respectively, are enough for all patients per period. Equation 6 determines the bed capacity of each non-pandemic hospital area in each period. Non-pandemic areas may be allowed to expand their capacity depending on the number of patients per period. Equation 7 provides the maximum number of additional beds that can be added to every non-pandemic hospital area. Equation 8 only applies to hospital areas (IC) that may be assigned either to PPs or NPPs. If the hospital area is assigned to pandemic PGs, the said area will not be allowed to have additional beds.

$$\sum_{i=IP-IC} \quad CAP_i H_{ikj} + \sum_{i=IC} B_{ij} H_{ikj} \geq PT_{kj} \quad \forall k = P, \forall j \tag{4}$$

$$\sum_{i=IN} B_{ij} H_{ikj} \geq PT_{kj} \quad \forall j, \forall k = N \tag{5}$$

$$B_{ij} = CAP_i + ABED_{ij} \quad \forall i = IN, \forall j \tag{6}$$

$$ABED_{ij} \leq MAXB(ACAP_{ij}) \quad \forall i = IN, \forall j \tag{7}$$

$$ACAP_{ij} \leq HH_{ij} \quad \forall i = IC, \forall j \tag{8}$$

Assignment Constraints

These constraints ensure that every hospital area will be assigned to patients. Equation 9 and Equation 10 are applicable to pandemic PGs. Equation 11 and Equation 12 are applicable to non-pandemic PGs.

Equation 9 assures that every type of pandemic PG in terms of severity can have at least one hospital area assigned to it. Having multiple hospital areas assigned in a classification of pandemic PG can happen when the number of patients in that classification becomes excessively high, such that one hospital area is not enough to accommodate them. Equation 10, on the other hand, ensures that every pandemic hospital area can only be assigned to one classification of pandemic PG.

Equation 11 ensures that every classification of non-pandemic PG can be assigned to at least one hospital area, whereas Equation 12 guarantees that every non-pandemic area can be assigned to at least one classification of non-pandemic PG, provided the classifications are compatible.

Equations 13 to 16 only apply to all hospital areas (IC) that may be assigned either to pandemic or non-pandemic PGs. All these implied constraints work together to ensure that this type of hospital area can never be assigned to both pandemic and non-pandemic PG at the same time. The value of the switch variable HH_{ij} will determine if the hospital area will be assigned to a non-pandemic (i.e., $HH_{ij} = 1$) or to a pandemic PG ($HH_{ij} = 0$).

Equations 17 and 18 refer to non-negativity, integer, and binary constraint.

$$\sum_{i=IP} \quad H_{ikj} \geq 1 \quad \forall k = P, \forall j \tag{9}$$

$$\sum_{k=P} \quad H_{ikj} \leq 1 \quad \forall i = IP, \forall j \tag{10}$$

$$\sum_{i=IN} \quad H_{ikj} \geq 1 \quad \forall k = N, \forall j \tag{11}$$

$$\sum_{k=N} \quad H_{ikj} \geq HH_{ij} \quad \forall j, \forall i = IC \tag{12}$$

$$\sum_{k=N} \quad H_{ikj} \geq HH_{ij} \quad \forall i = IC, \forall j \tag{13}$$

$$\sum_{k=N} \quad H_{ikj} \leq 1 + HH_{ij} \quad \forall j, \forall i = ICj \tag{14}$$

$$\sum_{k=N} \quad H_{ikj} \leq 2HH_{ij} \quad \forall i = IC, \forall j \tag{15}$$

$$\sum_{k=P} \quad H_{ikj} + HH_{ij} = 1 \quad \forall i = IC, \forall j \tag{16}$$

$$H_{ikj}, HH_{ij}, ACAP_{ij} \in (1,0) \quad \forall i, \forall k, \forall j \tag{17}$$

$$ABED_{ij}, B_{ij} \geq 0 \; and \; integers \quad \forall i, \forall j \tag{18}$$

Results

The proposed model was validated by applying it in a hospital that contains 16 floors dedicated to admitted patients. There are 10 rooms on each floor. The hospital is designated to accept PPs that are classified using a scoring system, such as the influenza-like illness scoring system (Noonan et al., 2019), to determine if a flu patient should be hospitalized (Rodriguez-Noriega et al., 2010). It is assumed that only patients who exhibit moderate and severe symptoms are accommodated in the hospital facility because of space scarcity.

There are two pandemic PGs for PPs: PG1-moderate PPs (M) and PG2-severe PPs (S). There are also two non-pandemic PGs: PG3-NPPs (N) and PG4-critical NPPs (C). PG1 and PG2 are collectively called PPs, and PG3 and PG4 are called NPP.

The 16 floors were initially allocated to four areas. Figure 1 shows how PGs were assigned to spaces (e.g., Area 1 was assigned to moderate pandemic patients). Areas 1 and 2 are pandemic areas (PA), and Areas 3 and 4 are non-pandemic areas (NPA). PAs are chosen based on the characteristics of the space. In the case of a flu pandemic such as COVID-19, candidate areas can be retrofitted based on the guidelines specified by the World Health Organization based on the requirements for patient rooms. The model assumed that these areas are available in the hospital.

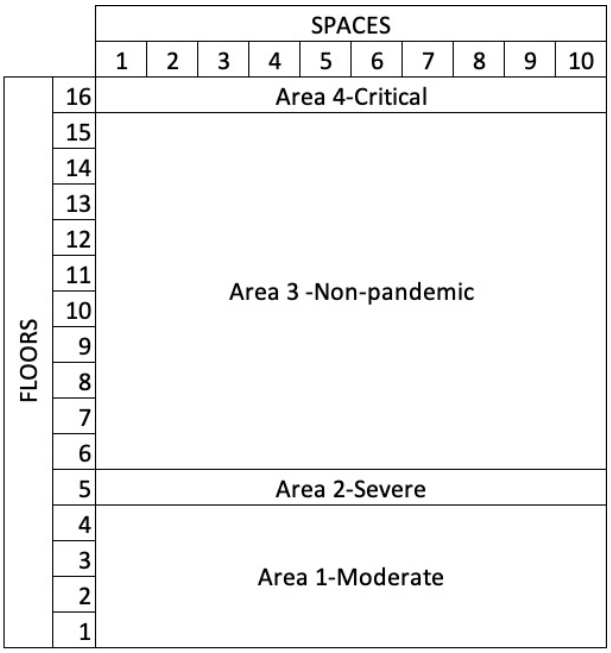

Figure 1
Initial Assignment of Patients to Hospital Areas

Pandemic areas can accommodate moderate and severe PPs. NPAs are assigned to patients who have non-infectious diseases such as obstetrics, surgery, cardiology, and so forth. However, one of the NPAs (Area 4) can be shared with PPs because it is expected that the demand for PPs will increase over the course of the pandemic life cycle. Areas 3 and 4 can be shared by NPPs if the need arises.

Rectilinear distances between the centroids of the four areas in the hospital are shown in Table 1. All distance units are measured in meters.

Table 1. *Distance Between Areas*

	Area 2	**Area 3**	**Area 4**
Area 1	8.5	16.0	28.0
Area 2		14.5	24.5
Area 3			12.0

Mortality and recovery rates were based on reported figures related to COVID-19. This rate varies per PG and per period, as shown in Table 2. It is assumed that all PPs that entered the hospital in period 1 will be discharged in period 3. However, NPPs will not all

be discharged within the planning horizon. A small percentage will stay in the hospital due to prolonged illness, such as PG 4.

The values of the arrival rates of patients belonging to different groups per period were derived outside the mathematical model. These were determined using simulation following Poisson distribution as this is one of the most common input processes in hospital queueing systems (Wu et al., 2020). The derived values are shown in Table 2. The first column, labeled "0," refers to the initial number of patients in a certain group. The arrival rate of PPs starts at a low value and increases as the pandemic worsens in period 3. However, the arrival rates of NPPs have no specific pattern.

The capacities of each area are shown in Table 3. It is assumed that Areas 1 and 2, which are allocated for PPs, are already at full capacity, and there are no additional beds that can be allocated because of social distancing control.

It was assumed that the planning horizon or the pandemic life cycle is three periods for model validation. The model assigns PGs to the hospital's different areas that maximize the distance between pandemic and non-pandemic PGs.

The sample problem was solved using GAMS, and the output of the model is shown in Figure 2. NC assignments indicate that the hospital bed manager can choose to assign separate rooms to N and C patients or combine them in either Area 3 and Area 4 or both. Thus, the NC assignments provide them with more flexibility in decision-making. The only possible concern in actual implementation is the readiness of space. It is reasonable to contain C patients in Area 4 because it has been prepared for critical patient situations. However, during a pandemic, the hospital may need to make the spaces more flexible when considering patient swelling or variable arrival rates.

In T2, C patients exceeded the capacity of Area 4, so the model combined them with N patients at Area 3 and then scattered M patients to Area 2 and Area 4. That means Area 4 will be assigned only to M patients. All C patients will be transferred to Area 3. Because it is desired to place S and C patients far from each other, the S patients were placed in Area 1. In T3, M patients had to be transferred to Area 1 because it had a larger area to accommodate a large number of M patients at that time.

Table 2. *Recovery, Mortality, and Arrival Rate per PG per Period*

	Recovery Rate			Mortality Rate			Patient Arrival Rate			
	Period			Period			Period			
	1	2	3	1	2	3	0	1	2	3
PG 1	0.1	0.3	0.57	0	0.01	0.02	2	20	100	400
PG 2	0	0.1	0.4	0.05	0.15	0.3	0	3	10	50
PG 3	0.8	0.15	0.02	0	0.02	0.01	980	750	800	800
PG 4	0	0.2	0.25	0.05	0.15	0.05	64	10	25	20

Table 3. *Area Capacities*

	Bed Capacity	Additional Bed Capacity
Area 1	600	0
Area 2	100	0
Area 3	1100	50
Area 4	70	5

	T1	T2	T3
A1	M	S	M
A2	S	M	S
A3	NC	NC	NC
A4	NC	M	NC

Figure 2.
PG Assignments Per Area

Sensitivity analysis was conducted to observe the model's performance with changes in the arrival rates of patients. The trend in the value of the objective function (total distance) is shown in Figure 3, whereas the actual assignments are shown in Figure 4.

Arrival rates of PP arrival rates were increased by increments of 10% from 0 to 30%, whereas NPPs were decreased by 20% and 40%. Figure 3 shows that for the base run, TD increased as PPs increased to 10% and then deteriorated as PPs were dispersed into several areas. The increase in TWD by 10% was caused by assigning S patients far from NPPs to prevent infection. However, as PPs continue to increase, this strategy does not result in a further increase in TWD because the surge in M patients requires that they occupy several areas. The more areas are assigned to PPs, the lower the objective function value because the PPs are now scattered all over the place. Thus, the bigger pandemic area was assigned to M patients as well as Area 4, which was designated shareable space between PPs and NPPs. The steady decline in TWD as PPs continued to increase indicates that the available space in the hospital can no longer keep up with the increased patient flow. There is a need to either control the number of patients entering the system or identify other areas for expansion.

It was apparent that the model does not expand the areas unless necessary. It tries to make use of existing space even if the objective function deteriorates. An expansion is only considered if the identified capacity of the space cannot contain the surge in the number of patients. The model highly considers putting the S and C away from each other. One way of increasing the distance is by putting a smaller number of patients in a bigger area. As such, even if S and C patients are in adjacent areas, the effective distance between patients is minimized.

Results suggest that as NPPs decrease and flu demand increases, the model allocates more space to PPs. Decreasing NPPs to 20% and 40% increased the value of the TWD even as PPs increased. This is expected because more space has become available for PPs. However, an increase of PPs to 30% caused a decrease in TWD due to the dispersion of PPs.

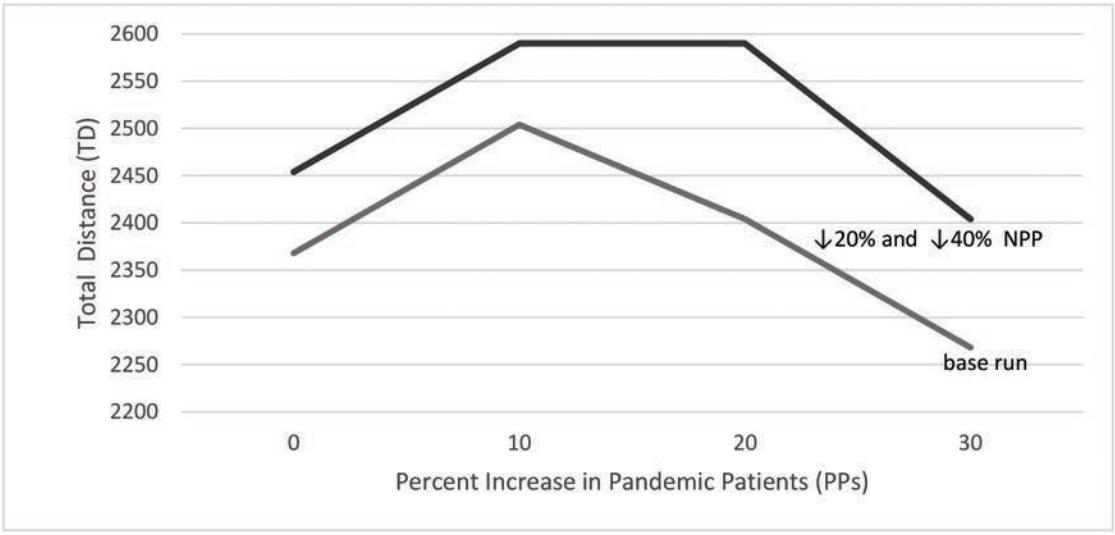

Figure 3
Sensitivity Analysis of Total Distance

increase in flu cases		Reduction in non-flu cases								
					20%			40%		
		T1	T2	T3	T1	T2	T3	T1	T2	T3
	A1	M	S	M	M	M	M	M	M	M
	A2	S	M	S	S	S	S	S	S	S
	A3	NC	NC	NC	NC	NC	NC	NC	NC	NC
	A4	NC	M	NC	NC	NC	NC	NC	NC	NC
10%	A1	S	S	M	S	M	M	S	M	M
	A2	M	M	S	M	S	S	M	S	S
	A3	NC	NC	NC	NC	NC	NC	NC	NC	NC
	A4	NC	M	NC	NC	NC	NC	NC	NC	NC
20%	A1	S	S	M	M	M	M	M	M	M
	A2	M	M	S	S	S	S	S	S	S
	A3	NC	NC	NC	NC	NC	NC	NC	NC	NC
	A4	NC	M	M	NC	NC	M	NC	NC	M
30%	A1	M	S	M	S	S	M	S	S	M
	A2	S	M	S	M	M	S	M	M	S
	A3	NC	NC	NC	NC	NC	NC	NC	NC	NC
	A4	NC	M	M	NCE	M	M	NCE	M	M

Legend: S-severe, M-moderate, NC- either C or N, NCE-expanded area for C and N

Figure 4
Assignments of Patient Groups to Hospital Areas

The model's outcome shows that assigning more spaces to PPs decreases the TWD, but it is a necessary consequence of the pandemic. It is better to allocate smaller shareable spaces from NPA to PA because these small spaces can provide hospital managers with flexibility in room assignments and still control infection.

In a hospital setting, administrators face the challenge of identifying appropriate allocation of areas that will minimize the spread of infection and maintain a service level acceptable to stakeholders. This validation only considered a small subset of hospital space but can be expanded to include more areas and PGs. However, an increase in the number of periods and departments can increase computational time. However, the number of departments is more critical than the number of periods in terms of computational time because it is more difficult to find an integer solution. The solution can be adjusted by combining some hospital areas to form one department. The use of genetic algorithm (GA) can also be explored as this is one of the best-known meta-heuristic in solving NP-hard class of combinatorial problems (Ghanei & Algeddawy, 2019).

Discussion

Controlling infection by establishing safe distance is one of the pressing concerns of hospital administrators and health practitioners facing a surge of patient admissions during a pandemic. This model can serve as a planning tool for allocating areas in the hospital during pandemics, giving administrators the valuable lead time to prepare/retrofit hospital wards according to the requirements for infection control. Controlling the spread of disease is imperative for protecting patients with non-infectious diseases and for health practitioners who deserve a safe working environment. Moreover, sanitation facilities should be installed adjacent to the areas of patients with infections so that health workers can disinfect themselves from head to foot before going to non-infectious places.

The model maximizes the distance between and among areas with patients having infectious and non-

infectious conditions. The optimum level was reached when PPs were increased by 10%, as shown in Figure 3. NPPs should be decreased to maintain that optimum distance. It is worth noting that the TWD is the same for 20% and 40% decreases in NPPs, as shown in the upper line in Figure 3. Thus, it is enough to reduce the NPPs by 20% to achieve the desired TWD. These values can affect the hospital administrator's decision not to admit NPPs who also need hospitalization. It is crucial to determine the lowest proportion of NPPs who will not be admitted to avoid deterioration of their disease condition and eventual death. Reports show a significant increase in excess deaths from non-COVID causes during the first months of the pandemic (Jacobson & Jokela, 2020).

As the arrival rates of patients with the pandemic disease increased, the model allocated patients with non-infectious diseases to one area. Hence, hospital administrators should designate an area (or set of rooms) with adequate space for this purpose, considering that the area will house a mix of patients with different conditions, age groups, needs, equipment, and so forth. Flexibility and forward planning are needed to accommodate such space requirements. Moreover, the transfer of patients from one area to the other should be such that exposure to those with infections is avoided.

Given the exponential increase in inpatient admissions, Area 4, previously designated as non-infectious, was evacuated to give way to the influx of patients with infectious diseases, as early as a 10% increase in arrival rates based on the model. It is worth noting in Figure 4 that it was only Area 4, a critical care unit, that needed to be expanded when flu cases increased by 30%. Administrators need to prepare the area ahead of time to conform to the patient's requirements, such as equipment acquisition and construction. Therefore, quick reaction time is vital, which this model facilitates.

Hospitals prioritize the admissions of patients with moderate to severe symptoms, especially for health facilities with limited space and resources. The model considered entries of PPs exhibiting moderate to severe conditions. Those with mild symptoms are usually not admitted to the hospital. However, these may develop more severe symptoms after some time. Ideally, those with mild symptoms should be placed in a dedicated place for isolation (ideally within or near the hospital) to be closely monitored just in case they progress to moderate/severe symptoms. Isolation is also beneficial for timely and appropriate management so that other people in the community will not be exposed to the infection.

Considering that a hospital is a contained space, the exponential increase in PPs will eventually reach the hospital's limits as the TWD approaches the critical levels, as shown in Figure 3. Thus, it is vital to employ additional infection control measures like barriers to make up for the distance constraints. For airborne infections like COVID-19, where adequate ventilation is essential, many hospitals resorted to placing PPs in tents in open spaces outside the hospital buildings (Peterson & Muckey, 2020).

Conclusion and Limitations

The model developed suffers from some limitations. It is computationally challenging to solve because it is an NP-hard problem. Thus, if areas, patient groups, and time periods increase, a heuristic may need to be used to identify a more promising subset of solutions to evaluate. The model also did not consider the changing value of the centroids as assignments change. The difference was deemed to be negligible in the current study. Despite these limitations, the model can be used to effectively plan the configuration and number of spaces to utilize during a pandemic. Converting spaces quickly and effectively is now a part of a hospital's resiliency plan during a pandemic. Space conversion, although possible, is not easy. Thus, the use of the model provides a basis for identifying alternative strategies to control infection and maintain a certain level of satisfaction.

Hospital administrators may use the model for planning, enabling them to identify and prepare areas to accommodate the increasing number of infectious patients, giving them the valuable lead time to do so. Managers can direct the flow of patients with more certainty, giving them more time and energy for other pressing matters. They may also incorporate other considerations specific to the circumstances of their facilities into this model.

The model may consider a macro perspective for succeeding studies wherein one area corresponds to one hospital. Having this network of hospitals where specific hospitals may be designated for infectious patients will more effectively control the transmission of the disease. In addition, an equation can be developed for disease transmission rate instead of distance.

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