Analyses on ICU and non-ICU capacity of government hospitals during the COVID-19 outbreak via multi-objective linear programming: An evidence from Istanbul

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ABSTRACT

The current infectious disease outbreak, a novel acute respiratory syndrome [SARS]-CoV-2, is one of the greatest public health concerns that the humanity has been struggling since the end of 2019. Although, dedicating the majority of hospital-based resources is an effective method to deal with the upsurge in the number of infected individuals, its drastic impact on routine healthcare services cannot be underestimated. In this study, the proposed multi-objective, multi-period linear programming model optimizes the distribution decision of infected patients and the evacuation rate of non-infected patients simultaneously. Moreover, the presented model determines the number of new COVID-19 intensive care units, which are established by using existing hospital-based resources. Three objectives are considered: (1) minimization of total distance travelled by infected patients, (2) minimization of the maximum evacuation rate of non-infected patients and (3) minimization of the infectious risk of healthcare professionals. A case study is performed for the European side of Istanbul, Turkey. The effect of the uncertain length of the stay of infected patients is demonstrated via sensitivity analyses.

1. Introduction

Coronavirus infectious disease 2019 (COVID-19) is an unprecedented and ongoing pandemic, which is caused by a new coronavirus [1]. When the earliest case of COVID-19 in Turkey was confirmed on March 11, 2020 [2], the novel coronavirus disease has already caused more than 120,000 individuals and 4613 deaths across 118 countries [3]. Nearly after seven months that the first case announced, the total reported infected individuals by September 20th had reached to 302, 867, and the total death had been 7506 in Turkey [4]. In terms of the number of deaths, COVID-19 has almost surpassed the latest influenza pandemic by 11 times [5].

The preliminarily symptoms of COVID-19 can rapidly turn into an acute respiratory distress syndrome (ARDS), which emerges the need of critical care [6]. Increasing demand of infected patients has led the need of additional ICU-beds and ventilators. In order to enlarge the service capacity, hospital-based resources had been repurposed for infected cases. Routine activities performed at operating theaters had been disrupted and replaced with intensive-care units; furthermore, medical personnel had been redeployed to COVID-19 services [7]. Likewise,

inpatient and outpatient activities, apart from emergency cases, have been cancelled or postponed in Turkey [8]. The literature demonstrates that the global surgery cancelation rate between January and April is estimated as 40% and 80% for cancer and benign disease operations, and it would take more than seven years to recover the backlog of elective cases [9]. Postponing routine medical services might be seen as a rapid approach to cope with the outbreak challenges; nevertheless, its long-term impact is discussible.

Moreover, the risk of medical staff being infected with COVID-19 should also be controlled in response to the global outbreak. An early case series from Wuhan, China demonstrated that almost 30% of infected patients were healthcare professional [10]. Medical personnel are critical to the on-going pandemic, and the absence of them is one of the greatest threats to the healthcare systems [11].

This paper focuses on a significant public health problem in the response phase of the COVID-19 pandemic and aims to empower healthcare systems. The proposed multi-objective multi-period mathematical model minimizes the total distance travelled by infected individuals, the maximum evacuation rate of non-infected patients and the infectious risk of healthcare professionals. Three decisions in medium-

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planning term are optimized: (1) infected patient allocation to capacitated hospitals, (2) additional intensive care resource deployment and (3) resource sharing degree between non-infected and infected patients.

The contributions of the proposed research can be recapitulated as following:

- This study provides a guide for hospital capacity building to healthcare managers during a pandemic outbreak. One of our contribution is assessing the government hospitals' responsiveness under limited capacity of existing hospital-based resources.
- In our formulation, additional ICUs are established by repurposing existing hospital-based resources. One of the research questions that the proposed study searching for is how to assign the limited hospital-based resources to infected patients while maintaining the routine medical operations at a certain level. In another word, the resource sharing degree between infected and non-infected patients is determined.
- To reduce the impact of delayed treatment processes, the maximum evacuation rate of non-infected cases is minimized. Thus, the collaboration among hospitals in a network is supported, which proposes a more robust plan.
- The length of the hospital stay of infected patients is considered as a stochastic parameter, which reflects the unpredictable nature of infectious disease outbreaks. Further, the resources commonly used by different type of patients are considered.
- The proposed model is generic and can be adjusted to other regions and outbreaks. We demonstrate the outcomes of the mathematical formulation on a real case of the ongoing COVID-19 pandemic for the European side of Istanbul, Turkey. By conducting a weighted method, the results obtained by this study illustrate how to design an effective multi-objective resource optimization model in the aspect of pandemic outbreak.

In this section, the progression of the COVID-19 outbreak, and the related problems are stated. In section 2, the literature related to the logistics aspect of infectious disease outbreak and hospital capacity planning for disaster responses is briefly reviewed. Problem description, mathematical model formulation and the weighted sum method are presented in section 3. Section 4 provides the data used in this study, and the case study performed for the European side of Istanbul, Turkey. The discussions of this study is presented in section 5. The conclusions and statement about future directions are given in section 6.

2. Literature review

In recent years, the increasing number of disasters enhances the significance of humanitarian logistics operations. In this sub-section, the related researches considered the application of Operations Research/Management Science (OR/MS) tools in common with our own proposed model are reviewed. First, we searched for the past studies related to infectious disease outbreaks. Then, we set out a brief analyze of literature related to the hospital capacity planning and allocation modelling for disaster responses.

Infectious disease outbreaks are one of the biological disasters [12], which has life-threatening impact. Dasaklis et al. [13] published one of the first comprehensive reviews for the application of logistics operations in epidemic outbreaks. Another review study introduced by Adivar and Selen [14] demonstrated that the content of reviewed articles mostly focused on influenza outbreaks. Further, the impact of epidemic diseases on supply chain is analyzed by Queiroz et al. [15]. Similar to Ref. [14], Queiroz et al. [15] demonstrated that influenza drawn the highest level of attention from the researchers; on the other hand, studies which reported the COVID-19 disease has already been placed in the literature.

Researchers applied mathematical optimization tools, such as linear and integer programming [16–18], non-linear optimization [19] and

stochastic programming [20–23] to determine optimal solution for logistics issues such as resource allocation, facility location, transportation and distribution. One of the important logistics challenges that decision makers encounter during an outbreak is managing limited resources. A hierarchical multi-objective mathematical model was introduced by Koyuncu and Erol [24] in order to allocate physical supplies under limited budget in a possible influenza outbreak. Different than [24], Sun et al. [25] introduced a multi-period multi-objective mathematical formulation to optimize resource and patient allocation decisions under limited hospital-based resources, such as ICUs, hospital beds and ventilators. For COVID-19 pandemic, Sarkar et al. [26] proposed a data-driven decision-making tool to optimize the allocation of infected patients. A bi-objective optimization mathematical model is conducted by AbdelAziz et al. [27] to optimize COVID-19 patient distribution to hospitals. An optimization model minimizing the total logistical cost of medical supplies in case of an influenza outbreak was developed by Liu et al. [28]. Sy et al. [18] suggested a linear programming methodology to minimize the number of total deaths considering hospital capacity and COVID-19 drugs. For West African Ebola Virus Epidemic, Yin and Buyuktahtakin [29] developed to optimize resource allocation strategies. Further, Yin et al. [30] proposed multi-stage stochastic programming model optimizing the allocation decision of ventilators to control COVID-19. For the logistics aspect of vaccination, scholars applied mathematical programming [16,20,31–33]. Recently, a mix-integer linear programming model was conducted by Tavana et al. [34] to distribute COVID-19 vaccines in developing countries. Similarly, Shukla et al. [35] focused on the assignment and scheduling problem of COVID-19 vaccines. Considering the uncertain demand and lead time, Manupati et al. [36] proposed a mathematical model optimizing the location of COVID-19 vaccine storage facilities. To prevent the spread of influenza infection during COVID-19 Pandemic, an inventory-location model for influenza vaccine distribution was introduced by Rastegar et al. [37].

Regarding disaster response models, the location problems combined with allocation decisions, Jia et al. [38], Murali et al. [39], Nafarrate et al. [40] and Lu and Hou [41] provided decision-making tools to locate point-of-dispensing sites, in which mass medication are provided during infectious disease attacks. Ekici et al. [42] provided a solution to a facility location and allocation problem for food distribution for the people under quarantine. Buyuktahtakin et al. [17] performed a location-allocation study, in which the optimal number, capacity and location of temporary healthcare facilities are determined. The solvability of the model had been confirmed by a real case study, Ebola outbreak in West Africa. Liu et al. [19] considered the similar problem for H1N1 outbreak while deciding on when to open and close the temporary facilities. A complex integer linear programming formulation determining the location of transitory treatment facilities, distribution of medical staff, and the transport of patients was introduced by Anparasan and Lejeune [43]. Considering stochastic parameters, Manupati et al. [44] determined the locations of plasma banks which serve for COVID-19 treatment. A different aspect of medical logistic operations in large scale outbreaks is handled by Yu et al. [45]. They suggested a methodology to locate temporary medical waste treatment centers. A multi-objective approach was developed and performed on COVID-19 pandemic in Wuhan, China. Considering uncertainty, the problem of sustainable production and waste-management was also handled by Ahmad et al. [46] for high consumed COVID-19 medical equipment.

Table 1 demonstrates the summary of the relevant studies for the logistics aspect of infectious disease outbreak planning.

Hospital decision-making for disaster responses is another significant research area related to this study. Comparing to studies considering normal operations, there are limited number of studies that analyze limited hospital-based resources and enhance the responsiveness of hospitals, during disasters [47–49]. In literature, Paul et al. [50], Al-Kattan and Abboud [51] and Cao and Huang [52], Ni et al. [53] and

Table 1
Literature review.

Study	Logistic Attribute		Objective(s)	Period Setting		Methodology						Disease	Country
	Location	Allocation		Multi-period	Static	IP	LP	ILP	MIP	MINLP	DNLP		
Koyuncu and Erol [24]		✓	Minimizing number of cases and deaths, and total morbidity.		✓						✓	Influenza	Turkey
Murali et al. [39]	✓	✓	Maximizing coverage		✓		✓	✓				Anthrax	U·S.
Ren et al. [32]		✓	Minimizing total fatalities	✓					✓			Smallpox	U·S
Sun et al. [25]		✓	Minimizing travelled distance and maximum distance	✓					✓			Influenza	U.S.
Ekici et al. [42]	✓	✓	Minimizing cost	✓					✓			Influenza	U·S
Nafarrate et al. [40]	✓	✓	Minimizing total travel time		✓					✓		Anthrax	U·S
Liu et al. [28]		✓	Minimizing cost	✓			✓					Influenza	China
Buyuktahtakin et al. [17]	✓	✓	Minimizing new infectious and fatalities	✓					✓			Ebola	West Africa
Anparasan and Lejeune [43]	✓	✓	Maximizing number of patients transported	✓				✓				Cholera	Haiti
Liu et al. [19]	✓	✓	Minimizing unsatisfied demand	✓					✓			Influenza/H1N1	China
Sy et al. [18]		✓	Minimizing fatalities		✓		✓					COVID-19	Philippine
Yu et al. [45]	✓	✓	Minimizing risk and cost	✓					✓			COVID-19	China
This study		✓	Minimizing total travelled distance, maximum evacuation rate, and risk	✓			✓					COVID-19	Turkey

Table 1 is constructed based on the table proposed in Liu et al. [19].

Gul et al. [49] conducted simulation analysis of hospital operations in a case of a large-scale disaster. Ref. [54] considered a bioterrorist attack and determined the resource need of emergency department of a hospital via simulation modelling approach. Shi et al. [55] investigated the effect of establishing dedicated clinics in an influenza outbreak. An agent-based simulation model was developed to support resource allocation decisions under different scenarios. Recently, the literature category involving hospital decision-making during pandemic outbreaks gets more attention. Weissman et al. [56] investigated the pressure of COVID-19 related demand on hospital-based resources, and the authors analyzed epidemiological parameters via Monte Carlo simulation approach. Another hospital planning decision-support tool was developed by Moghadas et al. [57]. The simulation results highlighted the importance of self-isolation regarding the drastic impact on the critical-care capacity. Aghapour et al. [58] proposed a multi-objective modelling approach to optimize the allocation decision of available hospital-based resources during disasters. Ceferino et al. [59] developed a bi-objective optimization model considering patient transfer, ambulance usage and temporary facilities to enhance the responsiveness of medical operations during disasters.

Based on this review, we revealed that there are limited number of studies considered the allocation decision of infected patients among multiple healthcare facilities in a case of a pandemic outbreak. To the best of authors' knowledge, only Sun et al. [25] addressed the aforementioned problem and developed a multi-objective, multi-period resource and patient allocation model. In addition to Sun et al. [25], our model account for the sustainability of routine medical services. We suggested a multi-objective multi-period mathematical programming model optimizing the resource sharing degree between infected and non-infected patients while minimizing the distance travelled by infected individuals, the maximum evacuation rate of non-infected patients and the transmission risk of disease at hospitals. In particular, this study allows the decision-makers re-organize hospitals and repurpose existing resources according to their priorities and the progression of the disease. Furthermore, we conduct sensitivity analysis to investigate the uncertainty of the length of the stay of infected patients.

Within the concept of hospital decision-making in disaster responses, there are very limited number of studies handle the resource allocation problem by repurposing existing hospital-based resources during large-scale disasters [47–49]. The closest study is conducted by Aghapour et al. [48]. This study demonstrated that changing the functionality of existing resources of hospitals for disaster victims could help to increase the resilience of healthcare facilities. Different than Aghapour et al. [48], we considered biological disasters and perform the mathematical model on a real case of the ongoing COVID-19 pandemic. Further, we proposed a three-objective optimization model considering a hospital network in a large urban center, not a single-hospital scale. The authors believe that this study will make a significant contribution to the literature especially during COVID-19.

In the succeeding sub-section, the problem and the developed mathematical model are described.

3. Problem description and methodology

In this section, the multi-objective multi-period linear programming model is presented, and the weighted sum method model is proposed.

Following assumptions are regarded in the proposed mathematical model.

- Since we particularly focus on the patient allocation plan of the European side of Istanbul, it is assumed that the European and Anatolian side of the city do not share their own resources and only serve to their residents.
- Infected people arrive to hospitals from districts, in which can also be described as demand points.
- Non-intensive care unit beds, intensive care unit beds and ventilators are the limited resources of hospitals.
- Hospitalized COVID-19 patients are classified into two main types in terms of their infectious severity and resource requirement. Basically, patients with serious severity are stated as type a patient, and patients with moderate severity are stated as type b patient. They differ in terms of the resources they occupy and the length of hospitalization. Type a patient is expected to be healed or succumbed to the infectious disease. Healed type a patients seize resources at ICU first, and then they are transferred to non-ICUs. Type a patients, who are expected to be died, only occupy ICU resources. Although same type of infected patients requires the same unit capacity, the length

of hospitalization is not identical and reflect stochasticity on the capacity utilization. Detailed explanation is given in Section 4.

- We assume that the total capacity of resources remains the same during the progression of the outbreak.
- At the beginning of each time period, the state of the system changes in terms of new arrivals, departures and the available capacity.
- In order to increase the service capacity, additional intensive-care resources are provided by setting up hospitals' operating rooms. Additional and existing resource allocation decisions are made at the beginning and stabilized for the remaining time periods.

The remaining part represents the proposed mathematical model.

3.1. Mathematical model formulation

3.1.1. Indices and sets

i, I : Index and set of districts, $i \in I$
j, J : Index and set of hospitals, $j \in J$
t, k, T : Time periods, $t, k \in T$

3.1.2. Parameters

d_{ij} : Distance between district i and hospital j
ar : Attack rate
mp_j : Number of medical personnel at hospital j
$HealA_i^{tk}$: Demand of type a patient in district i who need intensive care at time period t and transferred to non-ICUs at time period k
$DeathA_i^{tk}$: Demand of type a patient in district i who need intensive care at time period t and died at time period k
$HealB_i^{tk}$: Demand of type b patient in district i who need hospitalization at time period t and discharged at time period k
h : Hospital length of the stay of type a patient (including ICU and non-ICU length of stay)
$AvICU_j$: Number of available ICU beds at hospital j, $AvICU_j = ICU_j(1 - OcpICU_j)$
ICU_j : Total number of ICU beds at hospital j
$OcpICU_j$: Occupancy rate of ICU beds at hospital j
$AvVen_j$: Number of available ventilators at hospital j, $AvVen_j = Ven_j(1 - OcpVen_j)$
Ven_j : Total number of ventilators at hospital j
$OcpVen_j$: Occupancy rate of ventilators at hospital j
γ : Number of ICU beds that can be established at an operating room
OR_j : Number of operating rooms at hospital j
$nonICU_j$: Total number of non-ICU beds at hospital j
$OcpnonICU_j$: Occupancy rate of non-ICU beds at hospital j
u : Upper bound for the evacuation rate of non-infected patients
$IntubRate$: Intubation rate of type a patient

3.1.3. Decision variables

HA_{ij}^{tk} : Number of type a patients who are allocated to hospital j from district i at time period t and transferred to non-ICUs at time period k
DA_{ij}^{tk} : Number of type a patients who are allocated to hospital j from district i at time period t and died at time period k
B_{ij}^{tk} : Number of type b patients who are allocated to hospital j from demand point i at time period t and discharged at time period k
e_{max} : Maximum evacuation rate of non-infected patients at hospitals
e_j : Evacuation rate of non-infected patients at hospital j
$SeizeA_j^t$: Number of type a patients who seize ICU bed at hospital j at time period t
$ReleaseA_j^k$: Number of type a patients who release ICU bed at hospital j at time period k

$SeizeB_j^t$: Number of type b patients who seize non-ICU bed at hospital j at time period t
$ReleaseB_j^k$: Number of type b patients who release non-ICU bed at hospital j at time period k
$SeizeTrA_j^t$: Number of type a patients who are transferred from ICUs and seize non-ICU bed at hospital j at time period t
$ReleaseTrA_j^k$: Number of type a patients who are transferred from ICUs and release non-ICU bed at hospital j at time period k
$CovICU_j^t$: Number ICU beds dedicated to COVID-19 patients at hospital j at time period t
$newICU_j$: Number of new established ICU beds at hospital j
$CovVen_j^t$: Number of ventilators dedicated to COVID-19 patients at hospital j at time period t
$newVen_j$: Number of new established ventilators at hospital j
$CovnonICU_j^t$: Number of non-ICU beds dedicated to COVID-19 patients at hospital j at time period t

$$\text{Min } f_1(x) = \sum_{i=1}^{I} \sum_{j=1}^{J} d_{ij} \left(\sum_{t=1}^{T} \sum_{k=t}^{T} \left(HA_{ij}^{tk} + DA_{ij}^{tk} \right) + \sum_{t=1}^{T} \sum_{k=t}^{T} B_{ij}^{tk} \right) \quad (O1)$$

$$\text{Min } f_2(x) = e_{max} \quad (O2)$$

$$\text{Min } f_3(x) = ar \left[\sum_{j=1}^{J} mp_j \left(\sum_{i=1}^{I} \sum_{t=1}^{T} \sum_{k=t}^{T} \left(HA_{ij}^{tk} + DA_{ij}^{tk} \right) + \sum_{i=1}^{I} \sum_{t=1}^{T} \right. \right.$$
$$\left. \left. \times \sum_{k=t}^{T} B_{ij}^{tk} \right) \right] \quad (O3)$$

Subject to

$$e_{max} \geq e_j , \ \forall j \in J \quad (1)$$

$$\sum_{j=1}^{J} HA_{ij}^{tk} = HealA_i^{tk}, \ \forall i \in I, \ \forall t, k \in T \quad (2)$$

$$\sum_{j=1}^{J} DA_{ij}^{tk} = DeathA_i^{tk} , \ \forall i \in I, \ \forall t, k \in T \quad (3)$$

$$\sum_{j=1}^{J} B_{ij}^{tk} = HealB_i^{tk}, \ \forall i \in I, \ \forall t, k \in T \quad (4)$$

$$\sum_{i=1}^{I} \sum_{k=t}^{T} HA_{ij}^{tk} + DA_{ij}^{tk} = SeizeA_j^t, \ \forall j \in J, \ \forall t \in T \quad (5)$$

$$\sum_{i=1}^{I} \sum_{t=1}^{k} HA_{ij}^{tk} + DA_{ij}^{tk} = ReleaseA_j^k, \ \forall \in J, \ \forall k \in T \quad (6)$$

$$\sum_{i=1}^{I} \sum_{k=t}^{T} B_{ij}^{tk} = SeizeB_j^t, \ \forall j \in J, \ \forall t \in T \quad (7)$$

$$\sum_{i=1}^{I} \sum_{t=1}^{k} B_{ij}^{tk} = ReleaseB_j^k, \ \forall j \in J, \ \forall k \in T \quad (8)$$

$$\sum_{i=1}^{I} \sum_{t=1}^{k} HA_{ij}^{tk} = SeizeTrA_j^k, \ \forall \in J, \ \forall k \in T \quad (9)$$

$$\sum_{i=1}^{I} \sum_{k=t}^{T} HA_{ij}^{tk} = ReleaseTrA_j^{t+h}, \quad \forall j \in J, \ \forall t \in T \left| t \leq T - h \right. \quad (10)$$

$$ReleaseTrA_j^t = 0 , \quad \forall j \in J, \ \forall t \in T \left| t \leq h - 1 \right. \quad (11)$$

$$CovICU_j^0 = AvICU_j + newICU_j, \; \forall j \in J \qquad (12)$$

$$newICU_j \leq \gamma OR_j e_j, \; \forall \in J \qquad (13)$$

$$CovVen_j^0 = AvVen_j + newVen_j, \; \forall j \in J \qquad (14)$$

$$newVen_j \leq \gamma OR_j e_j, \; \forall j \in J \qquad (15)$$

$$CovnonICU_j^0 = nonICU_j\big(1 - OcpnonICU_j\left(1 - e_j\right)\big), \quad \forall j \in J \qquad (16)$$

$$e_j \leq u, \quad \forall j \in J \qquad (17)$$

$$CovICU_j^{t+1} = CovICU_j^t + ReleaseA_j^{t+1} - SeizeA_j^{t+1}, \; \forall j \in J, \; \forall t \in T \,\big|\, t \leq T - 1 \qquad (18)$$

medical personnel (mp_j). The number of infected patients assigned to hospitals and the attack rate (ar) of COVID-19 disease are proportional to the relevant risk. Although this equation primarily minimizes the risk of healthcare professionals, it mitigates the risk of non-infected patients simultaneously since the infectious risk at hospitals increases as the number of admitted COVID-19 patients increase. To represent the quantity of infected individuals who are not admitted to government-owned hospitals, a dummy hospital is introduced in this mathematical model. Indeed, the dummy hospital describes the required amounts of capacity which can be provided by non-government hospitals during the pandemic outbreak. The dummy hospital's capacity, in terms of ICUs, non-ICUs, ventilators, is relatively a large number. Note that we let the number of medical personnel and the distances between dummy hospital and districts be relatively a large number. Equation in (1) bounds e_{max} below. Herein, the minimum value that this variable can take is the maximum evacuation rate of infected patients. Equations in (2-3) guarantee that the total number of *type a* patients, who are supposed to

$$CovVen_j^{t+1} = CovVen_j^t + IntubRate\left(ReleaseA_j^{t+1} - SeizeA_j^{t+1}\right), \; \forall j \in J, \; \forall t \in T \,\big|\, t \leq T - 1 \qquad (19)$$

$$
\begin{aligned}
CovnonICU_j^{t+1} = CovnonICU_j^t &- \left(SeizeB_j^{t+1} + SeizeTrA_j^{t+1}\right) \\
&+ \left(ReleaseB_j^{t+1} + ReleaseTrA_j^{t+1}\right), \; \forall j \in J, \; \forall t \in T \,\big|\, t \leq T - 1
\end{aligned} \qquad (20)
$$

$$SeizeA_j^t \leq CovICU_j^0, \; \forall j \in J, \; \forall t \in T \qquad (21)$$

$$ReleaseA_j^t \leq CovICU_j^0, \; \forall j \in J, \; \forall t \in T \qquad (22)$$

$$CovICU_j^t \leq CovICU_j^0, \quad \forall j \in J, \; \forall t \in T \qquad (23)$$

$$IntubRate\left(SeizeA_j^t\right) \leq CovVen_j^0, \quad \forall j \in J, \; \forall t \in T \qquad (24)$$

$$IntubRate\left(ReleaseA_j^t\right) \leq CovVen_j^0, \quad \forall j \in J, \; \forall t \in T \qquad (25)$$

$$CovVen_j^t \leq CovVen_j^0, \; \forall j \in J, \; \forall t \in T \qquad (26)$$

$$SeizeB_j^t + SeizeTrA_j^t \leq nonICU_j^0, \; \forall j \in J, \; \forall t \in T \qquad (27)$$

$$ReleaseB_j^t + ReleaseTrA_j^t \leq CovnonICU_j^0, \; \forall j \in J, \; \forall t \in T \qquad (28)$$

$$CovnonICU_j^t \leq CovnonICU_j^0, \quad \forall j \in J, \; \forall t \in T \qquad (29)$$

be healed or died, are assigned to hospitals at the time period that they need hospitalization. We let $healA_i^{tk}$ and $deathA_i^{tk}$ be the demand occurred at time period t. Also, k denotes the time period that *type a* patients depart from ICUs. Equation in (4) guarantees that the total number of cases with moderate disease, *type b* patients, are assigned to hospitals at the time period that they need hospitalization. Equation in (5) calculates the total number of *type a* patients, who seize an ICU bed. Similarly, Equation in (6) calculates the total *type a* patients who release ICU bed. Herein, $ReleaseA_j^k$ is the number of departed *type a* patients, who are expected to be transferred to non-ICUs or died. Equations in (7-8) assign the total number of *type b* patients who occupy and release non-ICU beds. Equation in (9) determines the total number of *type a* patients who are transferred to non-ICUs for each time period. The total number of *type a* patients who release non-ICU beds and discharged is demonstrated by equation in (10). Herein, we consider that h is a constant number. For instance, *type a* patients who are supposed to be healed stay for h time periods and discharged from hospitals at time period $t + h$. Equation in (11) prevents to assign any transferred *type a* patient before the first discharged time period. For instance, if *type a* patients are expected to be discharged from non-ICUs at the third time period after they are admitted to ICUs, equation in (11) prevent to assign transferred *type a* patient at previous time periods.

Equation in (12) assigns the ICU beds dedicated to COVID-19 patients at the initial time period. Equation in (13) calculates the number of new ICU at each hospital. Herein, γ indicates the number of ICUs can be established in an operating room. Also, we let e_j denotes the percentage of operating rooms transformed to ICUs at each hospital.

$$
\begin{aligned}
&HA_{ij}^{tk}, DA_{ij}^{tk}, B_{ij}^{tk}, e_{max}, e_j, \; SeizeA_j^t, \; ReleaseA_j^k, SeizeB_j^t, \; ReleaseB_j^k, SeizeTrA_j^t, \\
&ReleaseTrA_j^k, CovICU_j^t, newICU_j, CovVen_j^t, newVen_j, CovnonICU_j^t \; \geq 0, \; \forall i \in I, \; \forall j \in J, \; \forall t, k \in T
\end{aligned} \qquad (30)
$$

Three objectives (O1, O2, and O3) are formulated in the proposed model. The first objective function (O1) minimizes the total distance travelled by infected patients. The second objective function (O2) minimizes the maximum evacuation rate of non-infected patients at hospitals. Third objective function (O3) minimizes the infectious risk of

Equations in (14,15) help to assign the initial number of ventilators at the beginning of the outbreak. Equation in (16) is necessary to determine the number of non- ICU beds devoted to COVID-19 patients. $OcpnonICU_j$ is a rate standing for the percentage of the beds occupied by non-infected patients. The number of available beds dedicated to COVID-19 patients increases as the number of beds occupied by non-

infected patients reduces. Herein, the evacuated non-ICU beds are directly related to dedicated operating rooms since the number of non-ICU beds will be emptied due to the lack of elective surgical operations. Equation in (17) controls the upper bound of the evacuation rate of non-infected patients. With the help of equations in (18-20), the available number of ICU beds, non-ICU beds and ventilators are updated simultaneously. Here, the calculation is done as follows: the available capacity remained at previous time period plus the number of patients departed minus the number of patients admitted. Equations in (21-22) ensure that the number of infected patients, *type a*, cannot be more than the capacity dedicated to COVID-19 cases. Equation in (23) prevents any hospital to assign more ICU beds than its capacity assigned at the beginning of the pandemic. Equations in (24-26) are used to prevent any hospital to accept intubated type a more than its initial capacity. Similarly, equations in (27-29) apply capacity restrictions. The non-negativity restrictions are demonstrated by equation in (30).

3.2. The weighted sum method

Since we have three objectives in the developed model, to determine efficient solutions from the Pareto frontier a well-known approach, weighted sum [60], is applied (31a, 31b, 31c and 31d). In multi-objective problems, typically, objectives conflict. Therefore, only consensus solutions are applicable. Thus, the weighted sum method is applied, and the beneficial explanations are provided as follows:

In the multi-objective model, the normalized objective functions are considered, in particular, each objective function' range is determined. Let f_l^n be the worst (nadir point) objective function values for objectives l, and f_l^u the best (utopia) values for each objective l if they are optimized individually. Once the range for each objective function determined the normalization operation is embedded into the multi-objective problem. The normalized equation is given in equation in (31a). Let f_l be the objective function value of objective l in the multi-objective problem and f_l^{norm} be the normalized objective function value for objective l (all objectives are minimized).

$$f_l^{norm} = \frac{f_l - f_l^u}{f_l^n - f_l^u} \tag{31a}$$

Note that, usually, all objectives do not have the same importance for decision makers. Thus, importance weights are pre-defined, and let w_l be the importance of objective l, where $\sum_{l=1}^{L} w_l = 1$. Then the multi-objective mathematical model is proposed as:
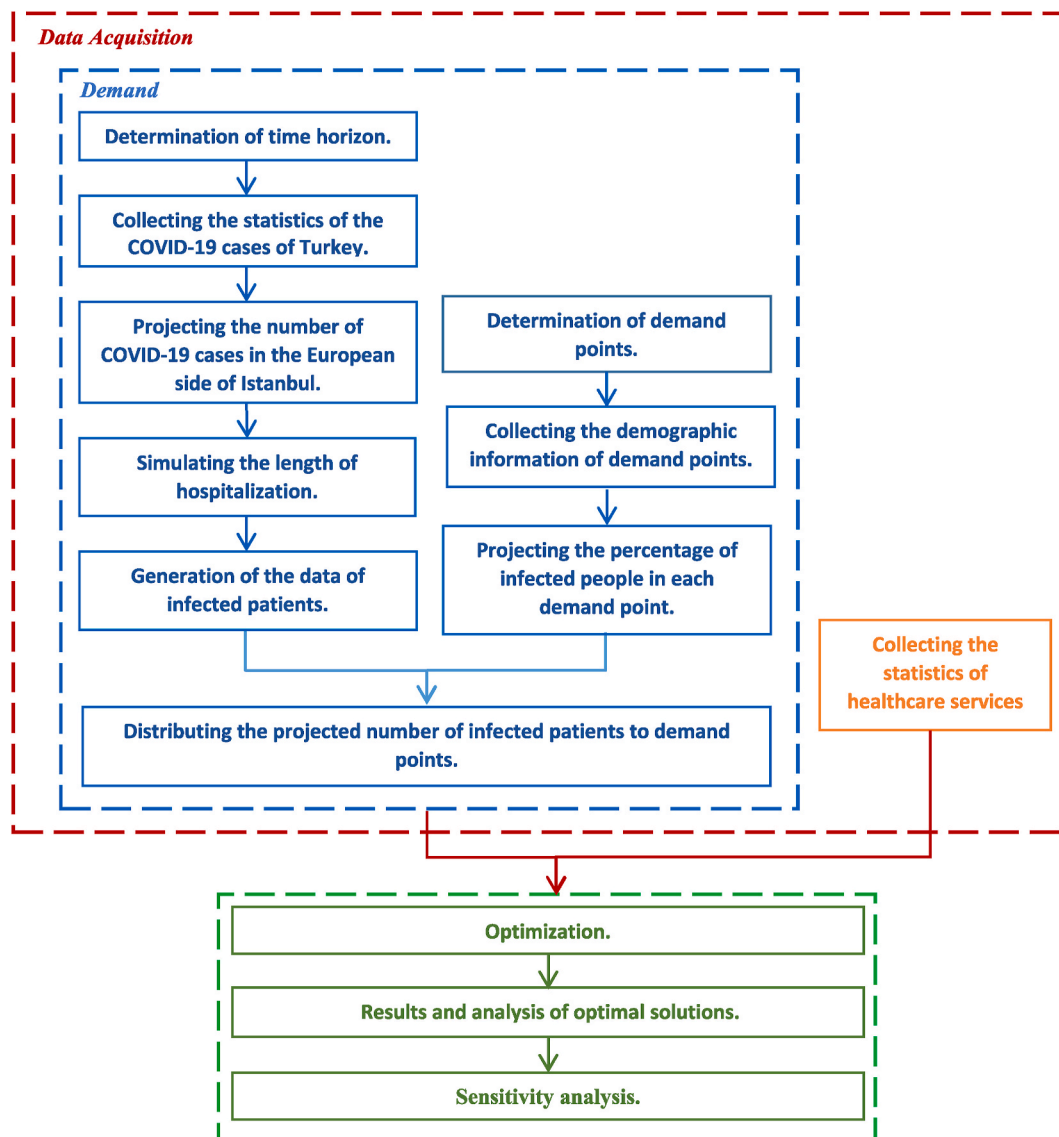

Fig. 1. The processes of data generation and multi-objective optimization.

$$\textbf{Min } \Phi = \sum_{l=1}^{L} w_l f_l^{norm} \tag{31b}$$

Subject to :

$$f_l^{norm} = \frac{f_l - f_l^u}{f_l^n - f_l^u}, \ \forall l \in L \tag{31c}$$

and $(O1, \ O2, \ O3, 1 - 30)$ (31d)

As it is stated in Ref. [60], if the value of all w_l are positive then the minimum of (31b) is Pareto optimal, in particular to get Pareto optimality minimizing (31b) is sufficient. Note that in this study, each objective function ($f_1(x), f_2(x), f_3(x)$) is linear.

4. Application: data, results and sensitivity analysis

A real case study considering the COVID-19 pandemic in the European side of Istanbul is conducted to validate the proposed mathematical model. Fig. 1 demonstrates the steps followed in data generation and multi-objective optimization.

4.1. Data acquisition

In this section, the data for the COVID-19 pandemic in Turkey and information about healthcare services in the European side of Istanbul, Turkey are provided. Ministry of Health (MoH) of Turkey, Turkey Radio and Television Corporation (TRT)-official television station of Turkey, Istanbul Metropolitan Municipality (IMM) and several published academic journals and gazette publications are the base sources of this research paper.

4.1.1. Time horizon
MoH, Turkey published the first COVID-19 situation report of Turkey on June 30, 2020, which summarizes statistics associated with COVID-19 cases between March 11, 2020 and June 28, 2020 [61]. In the authors' point of view, the first COVID-19 situation report [61] is one of the first official document including data of infected cases recorded in Istanbul, Turkey. For the sake of data integrity, we take the same time interval presented in the report and set the final period as of June 28, 2020. The optimization model is solved for 16 consecutive time periods, in which each period represents seven days. Note that the last period of the planning time horizon includes only five days to not exceed the specified time interval.

4.1.2. Number infected patients
According to the first COVID-19 Situation Report of Turkey [61], almost 55% of infected cases are reported in Istanbul. Based on IMM [62], the European side of the city approximately hosts 65% of Istanbulers. Therefore, we basically assume that 65% of projected number of infectious are emerged in the considered part of the city.

The number of confirmed COVID-19 deaths, recoveries, severe cases and other related statistics are gathered from the website of TRT [63]. Note that all of the data and relevant statistics used in this research paper are valid for the time interval between March 11 and June 28,

2020. In Ref. [61], the cumulative number of infected and hospitalized individuals are reported as 198,284 and 105,416 respectively. By following the given information, the number of hospitalized infected patient in each day is estimated as 53% of new records. Moreover, the ratio of intubated patients among COVID-19 associated hospitalization is taken as 8% by considering the data given in Ref. [61].

In order to investigate the relation between the deaths and intubated patients, we compare different statistics. First, based on the data given by TRT [63], it is agreed that all COVID-19 associated deaths are only sourced from intubated patients. Such an inference is made, because the crosschecks validate that the daily deaths, and the value calculated from the product of daily intubated patients and "intubation/death" ratio are equal. Further, the cumulative number of death and intubated patient are reported as 5097 and 7775 respectively [61]. Therefore, by following the given statements, it is assumed that 66% of intubated patients cannot survive.

Likewise, in order to estimate the number of infected patients who need ICU, two different sources are assessed. Regarding the average ratio of "intubated patient/patient in ICU" given by TRT [63], we consider that approximately 50% of patients who occupy ICU bed need respiratory support. The intubation rate is given as 4% in overall COVID-19 cases [61]. Following the information given by TRT [63] and MoH, Turkey [61], it is assumed that 8% of COVID-19 cases will need intensive care support. Table 2 shows the percentages of hospitalization, ICU admission and intubation considering the total number of cases reported except the last row. Information given in Table 2 is generated by using the data collected from various resources, which are also provided in Table 2.

The number of daily hospitalized patients is obtained by the product of new cases and the percentages are given in Table 3. Note that the information introduced in Table 3 is generated based on the ratios provided in Table 2. As it is illustrated in Tables 3 and 8% of the newly recorded cases are the infected individuals with critical severity, and 45% of them are the infected individuals with moderate severity. Consequently, 53% of daily recorded infected people need hospital care in a time period. While all *type b* patients are expected to be recovered, 32% of *type a* patient are defeated by the deathful coronavirus. For instance, the cases reported on April 8th, 2020 in Turkey are 4117. Then, the number of *type a* patients who are expected to be healed in the European side of Istanbul is basically calculated as follows: $4117x0.53x0.65x0.08x0.68 = 77.1559 \approx 77$. Please consider that the value given in the last row of the third column of Table 3 illustrates the death rate in the overall COVID-19 associated cases.

4.1.3. ICU and hospital length of stay
In this study, the uncertainty of an infectious disease on healthcare system is imitated via using randomness on the time duration that individuals seize resources. We generate the hospital length of stay for each individual by using discrete-event simulation. The parameters, ranges and distributions given by Weissman et al. [56] are used. The summary of the relevant data is presented in Table 4.

Based on the parameters provided by Ref. [56], a gamma distribution with the mean of 12 days is assumed for the hospital length of the stay of *type b* patients. Similarly, a gamma distribution with the mean of eight days is assumed for the ICU length of the stay of *type a* patient. Patients who get over the acute period of disease and discharged from ICUs are transferred to non-ICUs to complete their recovery period. It is assumed

Table 2
Parameters and data sources.

Parameters	Percentage	Data Source
Cases recorded in Istanbul	55%	[61]
Population of the European side of Istanbul	65%	[62]
Hospitalization	53%	[61]
ICU admission	8%	[61,63]
Intubation (in the overall infected cases)	4%	[61]
Death	66%[a]	[61,63]

[a] Percentage of death in the overall intubated patient.

Table 3
Patient data.

Patient type	Percentage in new cases	Death	Recovered
Type a	8%	32%	68%
Type b	45%	0%	100%
Total	53%	2.57%[a]	97.5%

[a] Percentage of death in the overall recorded cases.

Table 4
ICU and hospital length of stay.

Length of stay (days)	Patient type		
	Type a		Type b
	Healed	Died	Healed
ICU	Gamma (32.47,0.27)	Gamma (32.47,0.27)	–
Hospital	21	–	Gamma (136.21,0.09)

that *type a* who are supposed to be recovered complete their hospitalization period at non-ICUs to 21 days starting from the first day they are admitted to ICUs. We generate random numbers by using MATLAB R2018a (9.4.0.813654) 64-bit (maci64) and rounded to the nearest integer. The simulation based expected results and the proportioned based expected results are given in Fig. A.1.

4.1.4. Demand points

Districts are considered as demand points. To predict the number of infected individuals at each district, we consider the demographic structure. The relevant data is acquired from IMM [62]. The distribution of infected people across demand points is determined by the following notations and formulations given in Appendix C. The results are demonstrated in Fig. A.2 and Table B.1.

4.1.5. Hospitals and hospital-based resources

26 government-owned hospitals are classified as Public Hospitals (PH), Education Research Hospitals (ERH), Public Medicine Faculty Hospitals (MFH) and New Established Hospitals (NEH). Table B.2 demonstrates the relevant hospitals and their service information. Fundamentally, Public Hospitals Statistics Report-2017 published by MoH of Turkey [64], is taken into the account for the data of government-owned hospitals. In the related report [64], 37 hospitals located at the European side of Istanbul are given. We do not take 17 of them into account due to the different medical professions of hospitals or insufficient infrastructure in terms of medical equipment. Further, Public Hospitals Statistics Report [64] doesn't include the hospitals established after 2017 and medicine faculty hospitals (MFH). For this reason, we apply various resources along with [64]. In Table B.2, j1-j20 are categorized as PH and ERH, and the relevant data is gathered from Ref. [64]. j21 is a PH established in 2018 [65]. j22 and j23 are MFHs of two public universities [66,67]. Moreover, in the last few months, four largely capacitated hospitals (j19, j24, j25, j26) had been established in the European side of Istanbul [68–71]. The constructions of these hospitals were completed on March 30, 2020 (j19) [68], May 21, 2020 (j26) [71] and May 31, 2020 (j24, j25) [69,70]. Therefore, patients are

allowed to be allocated to new established hospitals in the last 13 (j19), five (j26) and four time periods (j24, j25) within the planning horizon. Prof. Dr. Cemil Taşçıoğlu City Hospital (j19) was in the reconstruction stage before the COVID-19 pandemic. Due to the expected overflow of infected patients, the new project was immediately finalized and started to serve on March 30, 2020. The layout was reorganized, and resources were renewed; therefore, the relevant data are collected from various resources [64,68,72]. Please note that j19 is also one of the ERH.

By following the general health statistic summaries published by MoH, Turkey [72], we accept that 77% of ICU beds are seized by non-infected cases. The number and occupancy rate of ventilators are taken same with ICUs. Please note that the given number of ICUs of PH and ERH are the sum of pediatric and adult ICUs (see Table B.2). We assume that the bed occupancy rate term in Table B.2 stands for non-ICU beds. The occupancy rate of (j1-j20) is given in Ref. [64]; however, this information is not available for (j21-j26). For this reason, we take the fundamental statistics published by MoH, Turkey [72] into account, and assume that the bed occupancy rates of PHs and MFHs are 68% and 70% respectively [72].

Operating rooms can be transformed to ICUs to struggle with the demand surge at hospitals. Based on the medical consultant opinions, it is assumed that the number of operating rooms in a hospital is 5–7% of its bed capacity, and two ICU beds can be established in each operating room. For the sake of computation effectiveness, our assumptions are made based on 5% of the total bed capacity, and the results are rounded to the nearest integer. Note that the number of operating rooms of (j22, j23, j24 and j26) is available at the resources and reported as given in Table B.2. The number of healthcare professionals at ERHs and PHs is obtained from Ref. [64]. For MFHs and NEHs, the hospital with the closest number of available beds is considered as base example, and the same number is assigned.

4.1.6. Other

Distances between districts and hospitals are collected from google.com/maps [73]. The shortest distance between nodes is taken. Moreover, we assume that the attack rate of disease is 0.52, which corresponds to $R_0 = 2$ [57].

5. Results

The multi-objective, multi-period linear programming model is solved in GAMS (Version 23.5.2) by using CPLEX optimization program. Three objective functions are optimized separately, and the utopia and nadir points are determined as given in Table 5. The conducted model is linear, and the obtained results are optimal. Note that the optimized objective function values in Table 5 include a dummy hospital, which represents the need of resources.
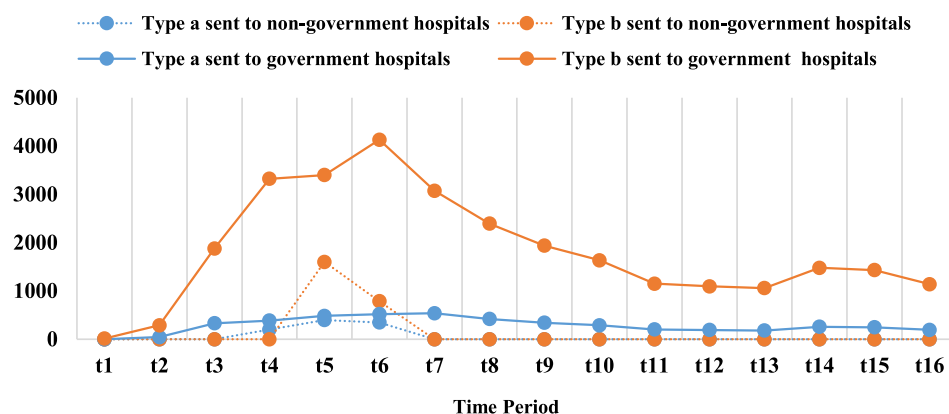

Fig. 2. Patient allocation to government and non-government hospitals.

Table 5

Single solutions of each objective function and their utopia and nadir points.

	$Min f_1(x)$: Total travelled distance	$Min f_2(x)$: Maximum evacuation rate	$Min f_3(x)$: Risk	f_l^u	f_l^n
$f_1(x)$	213185.528	1708661.479	801798.099	213185.528	1708661.479
$f_2(x)$	0.8	0	0.8	0	0.8
$f_3(x)$	16586460	30876950	11781900	11781900	30876950

Table 6

Dispersed weight vectors and solutions of generated cases.

Case ID	Dispersed weight vector			Objective function value				CPU
	w_1	w_2	w_3	Z	$f_1(x)$	$f_2(x)$	$f_3(x)$	
1	0.50	0.25	0.25	0.283	254269.838	0.800	13278910	30.039
2	0.25	0.50	0.25	0.365	944364.830	0.160	22618240	17.88
3	0.25	0.25	0.50	0.280	332465.560	0.800	12165770	21.678
4	0.60	0.30	0.10	0.315	383599.974	0.588	16803320	17.694
5	0.10	0.60	0.30	0.322	1266162.445	0.023	26682720	18.752
6	0.30	0.10	0.60	0.136	332367.223	0.800	1216640	23.243
7	0.80	0.10	0.10	0.121	220624.407	0.800	14939620	14.931
8	0.10	0.80	0.10	0.157	1307036.769	0.000	27709780	20.092
9	0.10	0.10	0.80	0.115	423121.487	0.800	11811820	17.915
10	0.40	0.40	0.20	0.358	564763.008	0.398	18035360	18.774
11	0.20	0.40	0.40	0.368	618344.746	0.398	1728590	19.679
12	0.40	0.20	0.40	0.237	294699.820	0.800	12508160	18.601
13	1/3	1/3	1/3	0.350	557223.428	0.441	16923820	18.206
14	0.70	0.20	0.10	0.220	223702.310	0.800	14652500	18.038
15	0.20	0.10	0.70	0.128	383444.451	0.800	11916320	16.930
16	0.10	0.70	0.20	0.240	1322457.034	0.000	27573870	17.864

Z: Weighted objective function value.

A single objective function is converted from the proposed three-objective mathematical model. For the sake of emergency cases, the upper bound of evacuation rate is set to 0.8. In order to provide broad solution framework to decision makers, 16 cases are conducted based on the weight vectors presented by Samanlioglu, [74]. By doing so, the proposed model enables decision makers to receive various suitable plans. In Table 6, the weight vectors and 16 different cases along with their optimal objective function values and CPU times (in seconds) are represented.

5.1. Base case study

In this subsection, Case 13, in which the weights are equal (1/3, 1/3, 1/3), is examined. First, we illustrate the optimal allocation decision of infected patients. Further, the utilization of government hospitals and hospital-based resources which are dedicated to infected patients are evaluated.

As it is demonstrated in Table 6, the total distance travelled by the infected patients is determined as 557,223.428 km while 44.1% of non-

Table 7

Allocation of infected patients from districts to government and non-government hospitals.

			Percentage of infected patient					
			Government hospital			Non-government hospital		
ID	District	Allocation of government hospital	Total	Type a	Type b	Total	Type a	Type b
i1	A.köy	j1	96.9%	0%	100%	3.1%	100%	0%
i2	Avcılar	j2, j6, j18	78.8%	58.2%	81.2%	21.2%	41.8%	18.8%
i3	Bağcılar	j1, j3, j4, j13, j14, j15, j16, j18, j23	83.1%	64.1%	85.4%	16.9%	35.9%	14.6%
i4	B.evler	j2, j3, j7, j13, j14, j17, j20, j22, j23	86.7%	61.7%	89.7%	13.3%	38.3%	10.3%
i5	B.köy	j3, j14, j17, j20, j22	98.2%	82.8%	100%	1.8%	17.2%	0.0%
i6	B.şehir	j1, j4, j18, j25	97.8%	78.1%	100%	2.2%	21.9%	0.0%
i7	B.paşa	j5, j8, j16, j17, j19, j20, j22, j23	99.7%	97.3%	100%	0.3%	2.7%	0.0%
i8	Beşiktaş	J9, j10, j12, j16, j19	99.7%	96.9%	100%	0.3%	3.1%	0.0%
i9	B.düzü	j6, j9, j11, j21	92.3%	65.5%	95.5%	7.7%	34.5%	4.5%
i10	Beyoğlu	j8, j9, j10, j12, j16, j17, j19, j20, j23	99.7%	97.2%	100%	0.3%	2.8%	0.0%
i11	B.çekmece	j6, j11, j21	98.5%	80.0%	100%	1.5%	20.0%	0.0%
i13	Esenler	j5, j8, j13, j15, j16, j17, j19, j20, j23	100%	100%	100%	0%	0%	0%
i14	Esenyurt	j2, j6, j7, j11, j14, j18, j21, j25	87.1%	59.8%	90.4%	12.9%	40.2%	9.6%
i15	E.sultan	j8, j12, j16, j17, j19, j22, j23	81.4%	60.3%	83.9%	18.6%	39.7%	16.1%
i16	Fatih	j8, j12, j16, j17, j20, j22, j23	100%	100%	100%	0.0%	0.0%	0.0%
i17	G.paşa	j5, j8, j9, j12, j15, j16, j17, j19, j20, j22, j23	99.7%	97.4%	100%	0.3%	2.6%	0.0%
i18	Güngören	J3, j5, j13, j14, j16, j17, j20, j22, j23	98.5%	85.7%	100%	1.5%	14.3%	0.0%
i19	Kağıthane	j8, j9, j10, j12, j15, j16, j19	91.6%	68.1%	94.4%	8.4%	31.9%	5.6%
i20	K.çekmece	j1, j2, j3, j4, j13, j14, j18, j21, j25	99.7%	97.0%	100%	0.3%	3.0%	0.0%
i21	Sarıyer	j9, j12, j20	99.5%	95.0%	100%	0.5%	5.0%	0.0%
i22	Silivri	j11	78.6%	55.6%	80.9%	21.4%	44.4%	19.1%
i23	S.gazi	j1, j4, j5, j8, j9, j10, j12, j15, j19, j23	100%	100%	100%	0%	0%	0%
i24	Şişli	j9, j10, j12, j19	81.3%	58.5%	84.1%	18.7%	41.5%	15.9%
i25	Z.burnu	j17, j20, j22	99.7%	97.1%	100%	0.3%	2.9%	0.0%
		Total	**90.6%**	**75.1%**	**92.5%**	**9.4%**	**24.9%**	**7.5%**

infected patients are evacuated from government-owned hospitals. With the combination of equal weights, the infectious risk is measured as 116,923,820.

5.1.1. Allocation of infected patients

Table 7 demonstrates the optimal patient distribution plan obtained in Case 13. As it is shown in Table 7, the important number of infected patients is sent to government-owned hospitals. For instance, almost all infected individuals in Arnavutköy (i1), Bakirkoy (i5), Bahcesehir (i16), Bayrampasa (i7), Besiktas (i8), Beyoglu (i10), Buyukcekmece (i11), Esenler (i13), Fatih (i16), Gaziosmanpasa (i27), Gungoren(i18),Kucukcekmece (i20), Sariyer (i21), Sultangazi(i23) and Zeytinburnu (i25) are served by government-owned hospitals. On the other hand, the need of non-government hospitals emerges for the districts where the significant number of infected individuals are expected. With parallel to the expected intensity, approximately 15% of COVID-19 associated patient in dense areas (i2, i3, i4, i14, i23, i24) utilize non-government hospitals' resources. Herein, Çatalca (i12) is not demonstrated in tables and figures since based on the simulation analysis, there is no infected patient expected from this area (see Fig. A.2). In addition, Yeşilköy Prof. Dr. Murat Dilmener Emergency Hospital (i24) and Başakşehir Çam and Sakura City Hospital (i26) are not demonstrated in tables and figures since the optimization model does not send any infectious to these hospitals.

The values in Fig. 2 demonstrate the allocation decision of infected patients at each time period. Patients with critical disease (*type a*) are allocated to non-government hospitals time periods between *t3* and *t7*. Similarly, non-government hospitals are utilized by patients with moderate disease (*type b*) time periods between *t4* to *t7*. Regarding the projected number of infected cases, the need of hospital-based resources boosts at time period *t2* and rises until *t7*. Even though the utilization of non-ICUs does not go under 100% at time periods between *t5-t8* (see Fig. 3), the number of *type b* sent to non-government hospitals reduces after *t5* (see Fig. 2). This situation can be explained by the number of active cases generated in the simulation analysis. Based on the experiment, a drastic reduction is observed in the number of arrival *type b* at *t6* and further time periods. This situation leads resource availability at government-owned hospitals and enable the LP model to allocate patients in the relevant time intervals.

5.1.2. Service level of government and non-government hospitals

Fig. 4 demonstrates the percentage of *type a* and *type b* patients served in government-owned and non-government hospitals. As it is illustrated in Fig. 4 (a) and (b), 16.9% and 8.9% of patients with critical and moderate symptoms are sent to non-government hospitals. In particular, this result emphasizes the need of ICUs and non-ICUs which can be provided by external resources. Moreover, the comparison of the unmet demand of *type a* and *type b* might point out the necessity of ICUs. Since a part of *type a* patient is expected to be healed and transferred to

non-ICUs, the results do not only emphasis the importance of preparedness at ICUs but also at non-ICUs as well.

In this part, government-owned hospitals are classified into four different groups to assess the impact of patient influx at healthcare institutions: (j1, j2, j3, j4, j5, j6, j7, j8, j9, j10, j11, j21) are PH. (j12, j13, j14, j15, 16, j17, j18, j20) are classified as ERH. MFH are given as (j22, j23). Last, (j19, j25) are assessed as NEH. Please note that j24 and j26 are also NEHs; however, the usage of the hospitals is recorded as 0 in Case 13. Therefore, they are not illustrated in the related tables and figures. Based on the number of beds given in Table B.1, ERH and MFH are considered as large capacitated hospitals while PHs are assessed as medium-capacitated. According to the percentages in Fig. 4(c), while nearly 34% of COVID-19 associated patient is sent to PHs, ERHs (including j19) provide healthcare services to half of the infected patients. The rest of the demand are satisfied by MFHs and NEHs. As mentioned earlier, one of the ERH, Dr. Cemil Tasoglu City Hospital (j19), was not available at the beginning of the COVID-19 outbreak due to the ongoing reconstruction project. Despite the posterior opening of Dr. Cemil Tasoglu City Hospital (j19), it provides healthcare services to the significant number of COVID-19 associated cases. 4.6% and 4.7% of *type a* and *type b* are sent to j19; therefore, we conclude that j19 have critical role in the current public health emergency.

5.1.3. Utilization of hospital-based resources at government hospitals

The utilization of hospital-based resources at four type of hospitals in terms of ICU beds and non-ICU beds is shown in Fig. 5. While the usage of PHs isn't fluctuating as much as ERHs and MFHs (see Fig. 5 (c), (d), (e), (f)), it is demonstrated that, the utilization of large-capacitated hospitals tends to decrease after the peak time periods. Especially, a drastic decrease is observed at MFHs (e, f). When we compare the state of each hospital class, it is seen that the utilization of PHs (c, d) is steadier than ERHs and MFHs in the last 9 periods.

The statement of PHs is more stable since their initial capacity are not as large as the capacity of ERHs and MFHs. Further, the proposed optimization model tends to allocate infected patients to hospitals which have less healthcare professionals to decrease infectious risk. Therefore, the utilization of medium-capacitated hospitals is likely to be more than large-capacitated hospitals after the peak time periods. Fig. 5 (g) and (h) demonstrate the utilization of hospital-based resources at new established hospitals (NEHs). As we mention previously, j19 has a critical role. In Fig. 5, the utilization of j19 dramatically decreases at the end of time period *t8*. Since it is a large-capacitated hospital, the statement of j19 shows similarity to other ERHs. Due to late establishment of j25, we do not observe its behavior at the peak time periods.

5.1.4. Dedicated hospital-based resources

ICUs, ventilators and non-ICUs dedicated to COVID-19 patients are summarized in Table B.3. It is noteworthy that the evacuation rate of
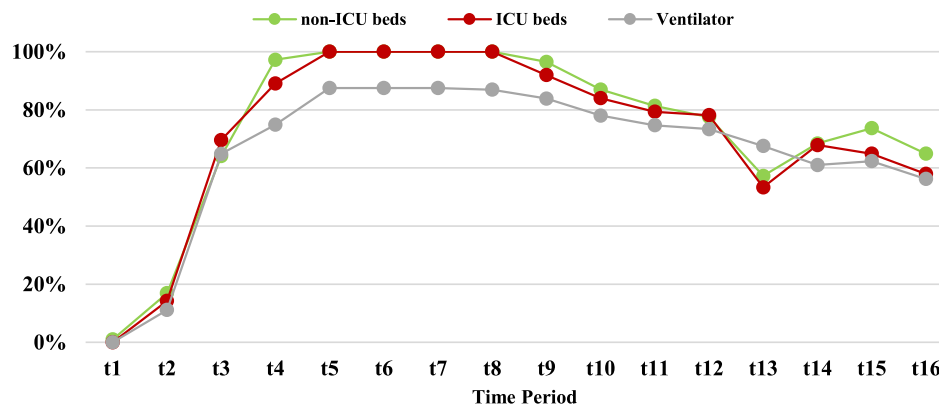

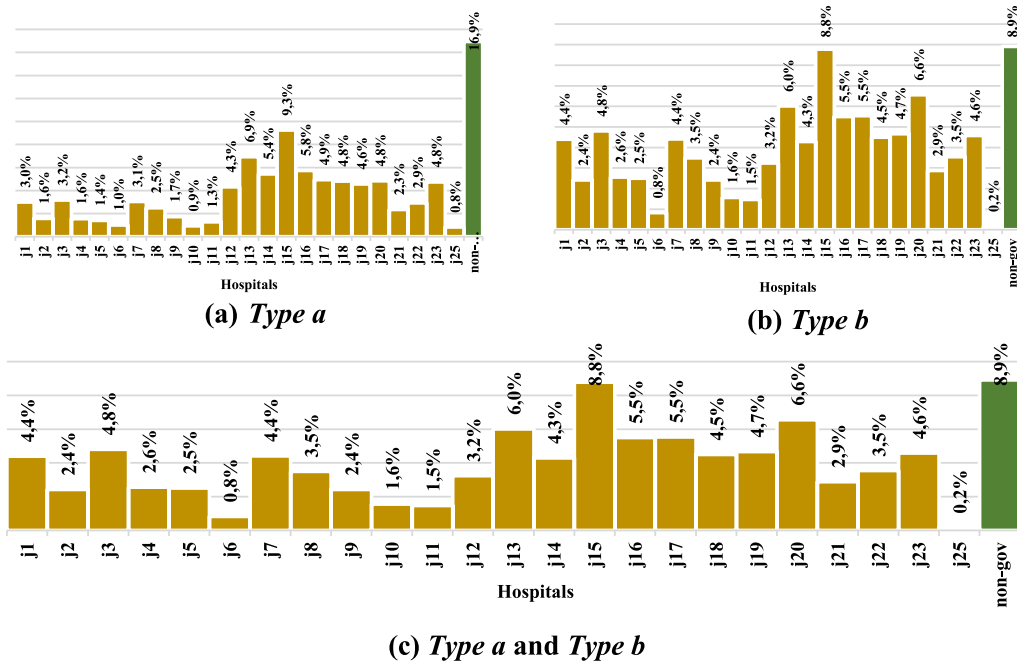**Fig. 3.** Average utilization of hospital-based resources.

(a) *Type a*

(b) *Type b*

(c) *Type a* and *Type b*

Fig. 4. Patient allocation to government and non-government (non-gov) hospital.

(a) non-ICU utilization of PHs

(b) ICU utilization of PHs

(e) non-ICU utilization of MFH

(f) non-ICU utilization of MFH

(c) non-ICU utilization of ERHs

(d) ICU utilization of ERHs

(g) non-ICU utilization of NEHs

(h) non-ICU utilization of NEHs
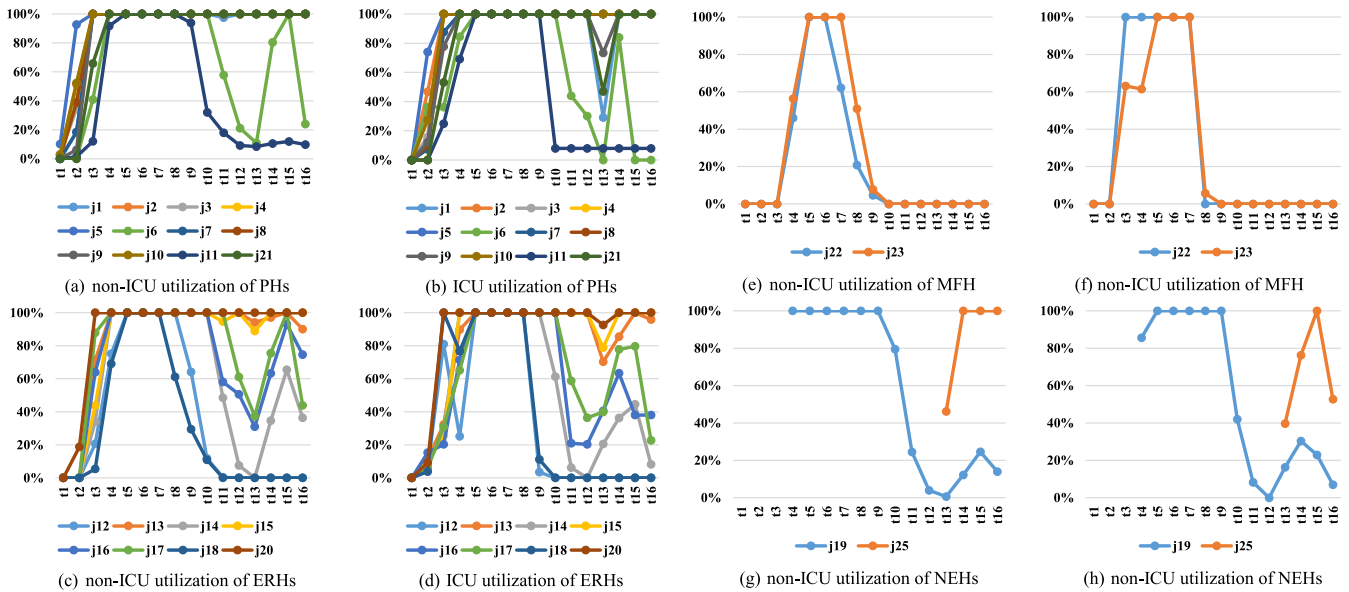
Fig. 5. Average utilization of ICUs and non-ICUSs at PHs, ERHs, MFHs and NEHs.

non-infected patients from non-ICUs is directly proportional to the dedication rate of operating rooms, which are allocated to COVID-19 ICUs. It means that ICUs and non-ICUs are repurposed for COVID-19 cases at the same time.

In Fig. 6, the number of available and new established ICUs (a) and ventilators (b) are shown. From Fig. 6, it is seen that the majority of the additional hospital-based resources in terms of ICU beds and ventilators are established at ERHs (j12-j20) and MFHs (j22-j23) which are classified as large-capacitated hospitals. Fig. A.3 demonstrates the utilization of ICUs, non-ICUs and ventilators in each government hospital. When the number of new established resources (see Fig. 6) and the utilization of hospital-based resources are compared (see Fig. 5), it is seen that the hospitals where the majority of the additional resources (j12-j20) are established do not use their capacity as much as (j1-j10). The reason for

this fact is explained as follows. In the LP model, the initial capacity is optimized under time-dependent demand constraints, which enforce to allocate patients to government-owned hospitals as much as possible at the busiest period. Since a large unit of hospital beds at ERHs and MFHs are dedicated to infected patients at the beginning of the pandemic, new ICUs and ventilators are established in large capacitated hospitals. Yet, the utilization rates reduce as the number of infectious in the European side of Istanbul decreases. For these reasons, a reduction is observed.

5.2. Sensitivity analysis

In this subsection, the results of 16 cases generated based on various weight vectors, suggested by Samanlioglu [74], are analyzed. Further, we discuss the impact of critical parameters by varying the time duration
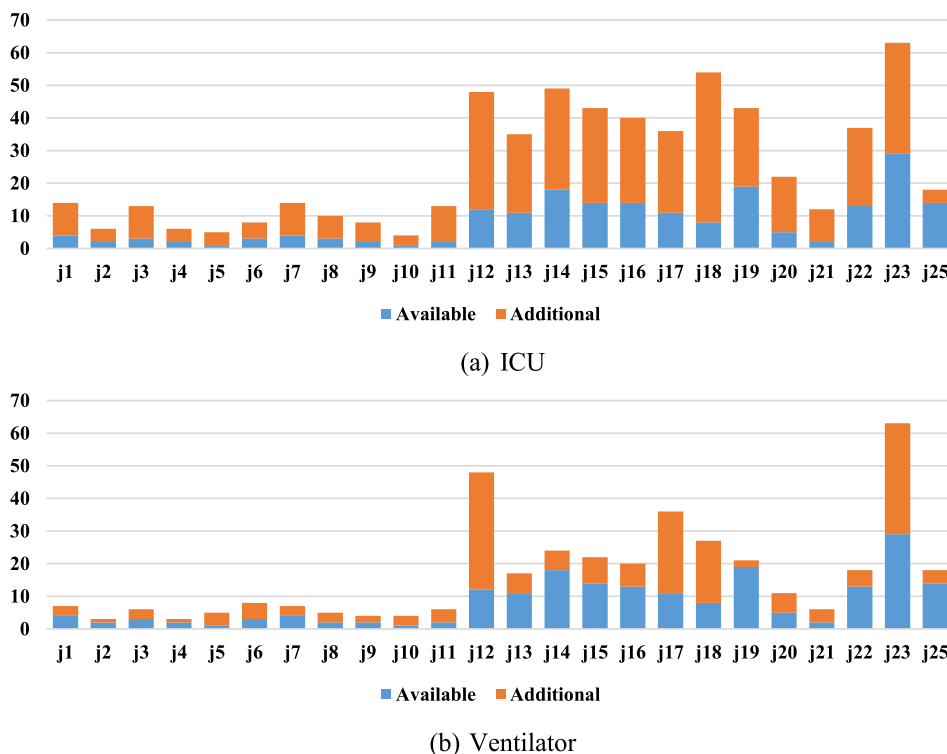
(a) ICU

(b) Ventilator

Fig. 6. ICUs and ventilators dedicated to infected patients.
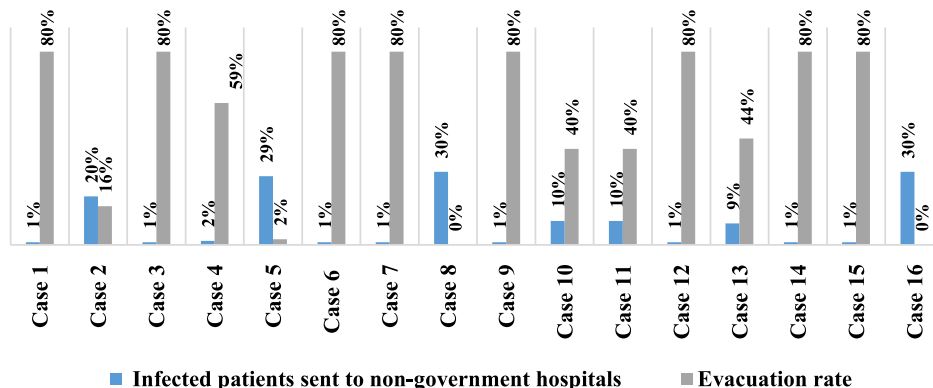

Fig. 7. Percentage of infected patients sent to non-government hospitals and the evacuation rates of non-infected patients.

that resources occupied by different types of patients.

Fig. 7 illustrates the percentage of total infected patients sent to non-government hospitals and the evacuation rate of non-infected patients at healthcare institutions. Case 2, Case 5, Case 8 and Case 16 demonstrate the behavior of the linear programming model when the highest priority rate is assigned to the second objective function, which corresponds to the minimization of maximum evacuation rate. In the aforementioned cases, we observe that the percentage of infected patients sent to non-government hospitals increases as the evacuation rate of non-infected patient decreases. For instance, when no non-infected patients are evacuated (Case 8 and Case 16), 30% of infected patients sent to non-government hospital. Moreover, as demonstrated in Fig. 7, the effect of different priority rates assigned to the first and third objective functions doesn't influence the percentage of patient assigned to non-government hospital when $f_2(x)$ remains constant. For instance, the weights are interchanged between $f_1(x)$ and $f_3(x)$ in Cases 1–3, Cases 7–9 and Cases 10–11. It is observed that the interchanged rates do not

influence the evacuation rate and the percentage of patients sent to non-government hospitals.

Fig. 8 shows the number of infected patients sent to government and non-government hospitals. Herein, government-owned hospitals are illustrated in four different groups. Different than the assessment in Fig. 7, changing the weights of $f_1(x)$ and $f_3(x)$ results in different patient allocation decisions. With respect to the infectious risk of medical personnel, the number of infected patients sent to PHs get closer to the number of patients sent to ERHs. Similar results are obtained in Case 6, Case 9 and Case 15, where the highest weight is assigned to risk minimization function. In contrast, larger w_1 causes the linear programming model to allocate more patients to large-capacitated hospitals (Case 1, Case 4, Case 7 and Case 14). From Fig. 8, we also observe that the number of patients served by new established hospitals increase when $f_2(x)$ and $f_1(x)$ dominate other objective functions. Therefore, it is concluded that NEHs help to cope with the overwhelming number of infected patients and contribute to the maintenances of routine
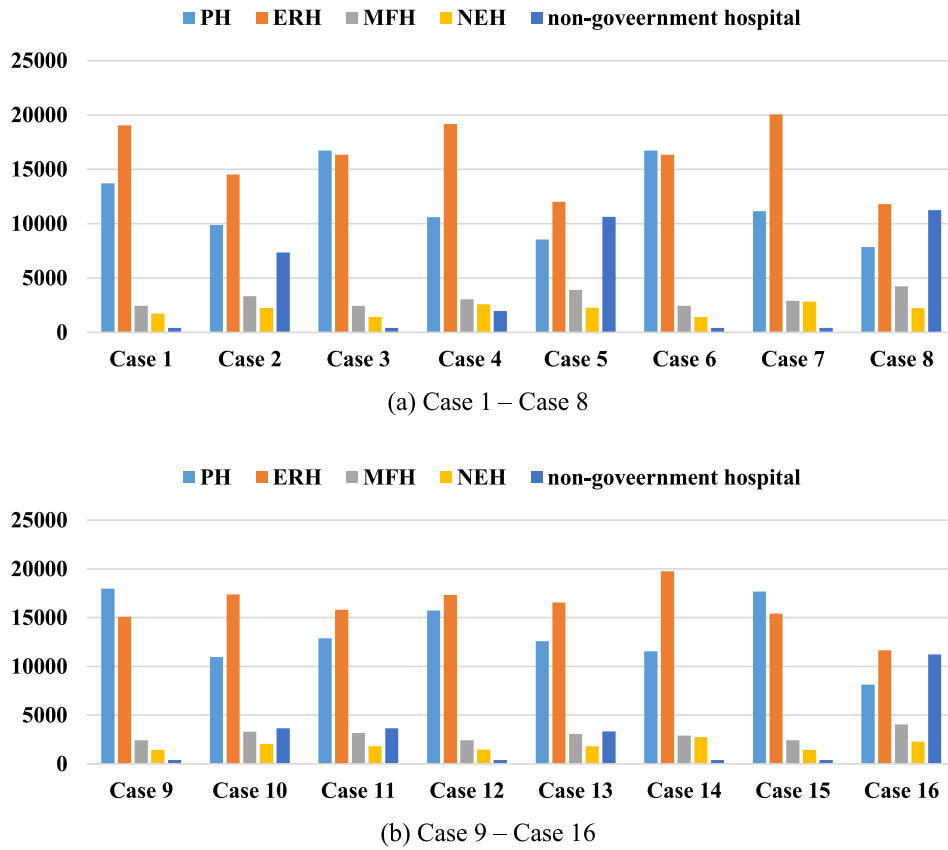
(a) Case 1 – Case 8

(b) Case 9 – Case 16

Fig. 8. Number of infected patients sent to PH, ERH, MFH, NEH and non-government hospital.
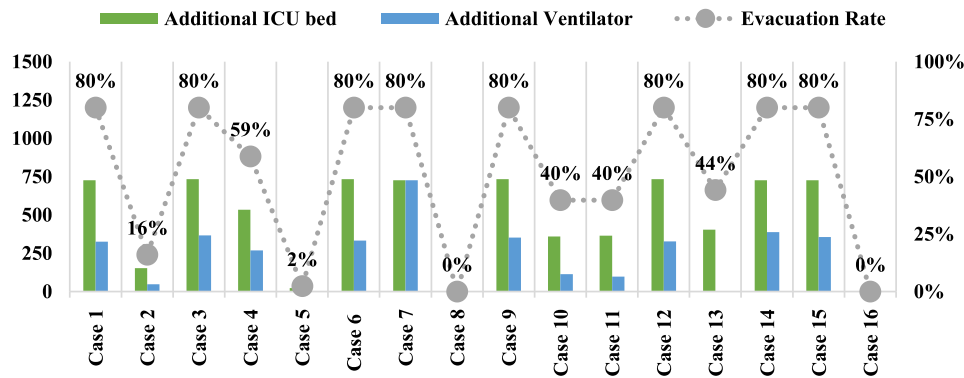

Fig. 9. Evacuation rate of non-infected patients and additional hospital-based resources.

healthcare services. Please note that the benefit of j24, j25, and j26 during the peak time period of the pandemic are not reflected on the results due to their late establishment date.

By considering the obtained results, it is concluded that when the decision makers give priority to the distance minimization, capacious hospitals such as ERH are more suitable. On the other hand, utilizing medium-capacitated hospitals minimizes the risk of disease spread at healthcare institutions. With respect to the evacuation rate of non-infected patients, infected patients are allocated more homogeneously to all type of hospitals. We also observe that the new established hospitals, assist the healthcare system to cope with the current public health crisis when distance minimization and evacuation rate are regarded primarily.

Fig. 9 demonstrates the relationship between the evacuation rate and the number of additional ICU beds and ventilators. As expected, the increase in evacuation rate leads the mathematical model to dedicate more medical resources to infected patients.

The relation between the number of new established resources and the weight factors of first and third objective function are demonstrated in Fig. 10. Based on the weights of objectives, it is seen that interchanging weights of distance minimization function and risk minimization function do not impact the number of additional hospital-based resources.

5.2.1. Results of data variation based on the hospital length of stay

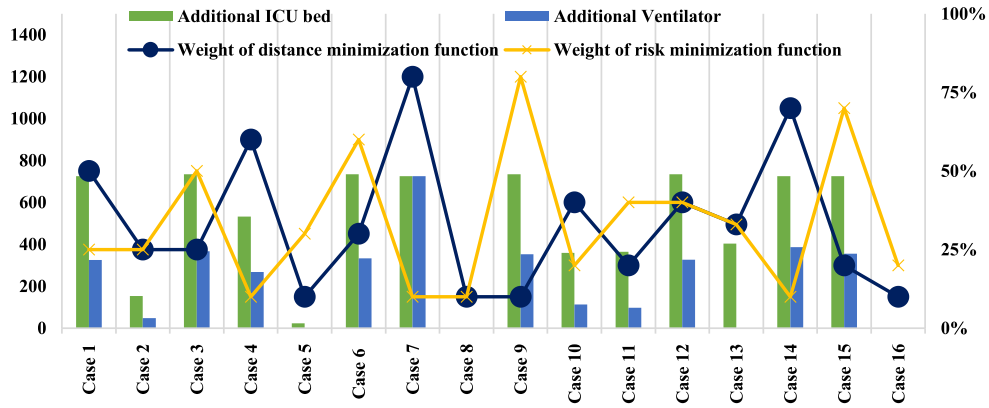We perform a sensitivity analysis to investigate the impact of

Fig. 10. Additional hospital-based resources and the weights of first and third objective functions.

Type a

Type b

(a) 8 days

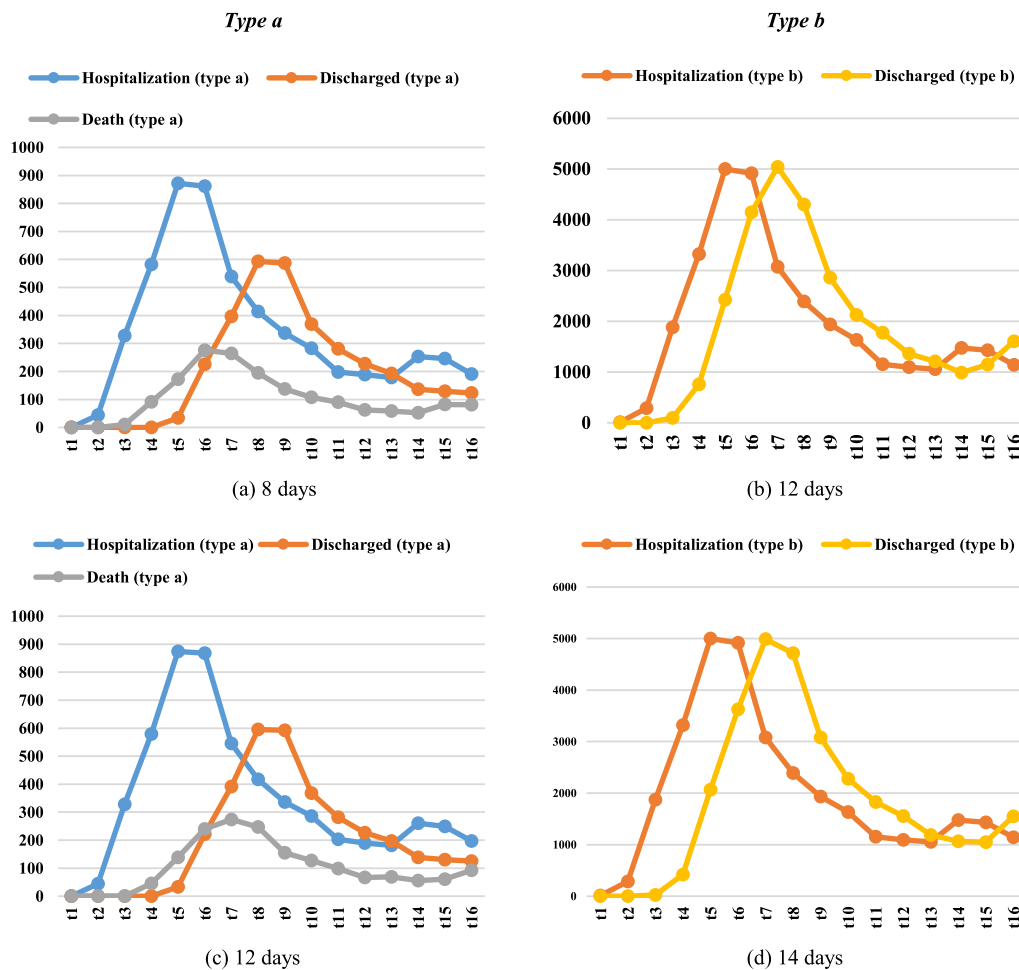(b) 12 days

(c) 12 days

(d) 14 days

Fig. 11. Simulation-based results of sensitivity analysis.

different time durations that ICU beds, ventilators and non-ICU beds are occupied. In this section, different scenarios are generated to examine the behavior of stochastic parameters on the imitated system. The base scenario, Case 13, is solved with new parameters. We vary the stochastic parameters which are the ICU and hospital length of the stay of patients by conducting the simulation analysis.

First, we vary the parameters represented by Weissman et al. [56]. In the base case, a gamma distribution with the mean of eight days is assumed for the ICU length of stay for *type a* patient (see Table 4). For the

simulation analysis, different parameters are considered. Respectively, we generate random numbers based on gamma (15.254, 0.393) with the mean of six days, and gamma (61.017, 0.197) with the mean of 12 days. Same experiment is repeated for *type b*. In the base case, a gamma distribution with the mean of 12 days is assumed for the hospital length of stay for *type b* patients (see Table 4). In the sensitivity analysis, random numbers are generated for the parameters which follow gamma (44.545, 0.1575) with the mean of seven days and gamma (178.182, 0.079) with the mean of 14 days. Fig. 11 demonstrates the conducted simulation

Table 8
Results of the objective function values of generated scenarios.

$f_1(x)$: Total travelled distance (km)			
	LoS of type a		
	6	**8**	**12**
LoS of type b			
7	316356.401	324543.506	377731.362
12	573328.547	555534.415	541317.385
14	607868.841	623333.569	605950.975
$f_2(x)$: Maximum evacuation rate (%)			
	LoS of type a		
	6	**8**	**12**
LoS of type b			
7	0.392	0.388	0.357
12	0.414	0.439	0.482
14	0.524	0.503	0.545
$f_3(x)$: Risk			
	LoS of type a		
	6	**8**	**12**
LoS of type b			
7	13835990	13975340	14775710
12	17282170	16915940	16618840
14	18324310	18585630	18184540

LoS: Length of Stay.

Table 9
Type a and *type b* patients sent to non-government hospitals and the number of new established ICUs based on generated scenarios.

Type a sent to non-government hospitals			
	LoS of type a		
	6	8	12
LoS of type b			
7	722	804	1363
12	877	915	1228
14	634	836	1094
Type b sent to non-government hospitals			
	LoS of type a		
	6	8	12
LoS of type b			
7	0	0	0
12	2632	2412	1961
14	3259	3247	2796
New ICUs			
	LoS of type a		
	6	8	12
LoS of type b			
7	356	356	327
12	378	402	441
14	475	460	500

LoS: Length of stay.

analyses for patient *type a* (a-c) and patient *type b* (b-d). Please consider that the term of discharged *type a* indicates the patients with severe symptoms who are transferred to the non-ICUs from ICUs and discharged from the hospital within 21 days after they were admitted. To distribute the number infectious to the districts, the new generated numbers are multiplied by the fractional numbers and rounded to the nearest integer after simulation analyses. Therefore, there is a slight difference in the number of hospitalizations in each scenario.

In order to summarize the effects of different hospital length of stay of two type of entities, we illustrate the results of the objective function values of nine different scenarios generated based on Case 13 in Table 8. From first row to seventh row, the expected distance travelled by infected patients when *type a* and *type b* seize hospital-based resources for various time durations are illustrated respectively. Columns eight to 14 demonstrate the values of the second objective function under the same parameters. The results of third objective functions are shown in columns 15 to 21.

Table 9 demonstrates the number of infected patients sent to non-

government hospitals and new established ICUs based on generated scenarios. When we assess the impact of the length of the stay of *type b*, the objective function values fluctuate parallelly. While the values of $f_1(x)$ and $f_3(x)$ increase, the maximum evacuation rate of non-infected patients also increases. With respect to the number of infected patients allocated to non-government hospitals, the reduction in the relevant objective function values is considered as a reasonable output. From Table 9, it is observed that as the length of stay of *type b* gets longer, the number of *type b* sent to non-government hospitals increases. On the other hand, the number of *type a* sent to non-government hospitals reduces under the same scenarios. In particular, sharp changes are observed between the scenarios generated based on the length of stay of *type b* for seven and 12 days. The dramatic change can be observed in first and second objective function values (see Table 8). Different than the steady increase in the objective function values as the length of the stay of *type b* gets longer, trade-offs between the $f_1(x)$, $f_2(x)$ and $f_3(x)$ are observed while the length of the stay of *type a* is increasing. Although a rise is reported in the number of *type a* sent to non-government hospitals, the total number of patients who were not allocated to government hospitals decrease. As a result, this reduction affects the first and third objective function values. For instance, when the average time duration of ICUs is increased to eight days from six days, a decrease in second objective function was recorded where the length of the stay of *type b* is taken as 12 and 14 days. Since the evacuation rate of non-infected patients decreased, increase in the number of infected patients sent to non-government hospitals was observed which also caused rise in first and third objective functions. On the other hand, when the length of the stay of *type a* is changed to 12 days from eight days, increases are observed in the second objective function values within the same scenarios mentioned above. At the same time, decreases are recorded in $f_1(x)$ and $f_3(x)$, which are affected by the reduced number of *type b* sent to non-government hospitals. It is important to note that the number of *type a* sent to non-government hospitals are also increased in these scenarios; however, this situation does not impact $f_1(x)$ and $f_3(x)$ dramatically due to larger decrease in the number of *type b* sent to non-government hospitals. When the length of stay of *type b* increase, the number new established hospital-based resources increased. Herein, the impact of the increasing evacuation rate leads the allocation of new hospital-based resources.

6. Discussion

The burden of coronavirus disease has obligated the healthcare providers to reorganize hospitals and rebuild the existing capacity. The new infectious disease has disturbed thousands of lives; nevertheless, the number of patients affected by the postponed routine medical services has not surfaced yet [75]. Further, the healthcare professionals in frontline, have been impacted by infectious risk physically and mentally [7,76,77]. The purposes of the Pandemic Preparation plan are providing qualified healthcare services, maintaining routine medical operations and preventing the spread of infectious disease [5]. Parallel to the requirements indicated in the relevant preparation plan, our study provides a beneficial decision-making tool to healthcare providers. In particular, optimizing the allocation of infected patients under capacity restrictions prevent exceeding the capacity of hospitals and maintains the quality of treatment services. Further, by optimizing the resources sharing degree between infected and non-infected patients and minimizing the maximum evacuation rate of non-infected patients, we aim to sustain regular healthcare services at a reasonable level. Last, the distance minimization of non-infected patients and the infectious risk at healthcare facilities help to keep the spread of disease under control. Therefore, our study encounters the purposes of Pandemic National Preparation Plan. 16 different cases are generated. The cases which prioritize evacuation rate suggest distributing infected patients more homogeneously than others. On the other hand, utilizing medium-capacitated hospitals rather than capacious ones is found more

appropriate while minimizing infectious risk. If the distance minimization is considered, the evacuation rate of non-infected patients reaches the upper bound. Therefore, the majority of hospital-based resources are repurposed for infected patients. As a result, we conclude that different action plans can be taken according to the progression of the outbreak. Another significant result of this study is about new established hospitals (NEH). For instance, Prof. Dr. Cemil Taşçıoğlu City Hospital (j19), which regained its functionality immediately on March 30th [68], has increased the healthcare service responsiveness. Moreover, its large capacity helps to deal with the overwhelming number of infected patients during the peak time periods. Therefore, the percentage of served infected patients in j19 emphasizes the importance of enhancing health service capacity during the pandemic. Other new established hospitals (j24, j25, j26) were not available to serve first. Therefore, we cannot record the advantage of these field hospitals during the peak time periods. Nevertheless, the results demonstrate that they are significant healthcare providers when the decision makers consider the minimization of evacuation rate of non-infected patients. They also help to maintain routine medical services and decrease the infectious risk while sharing patient-log. Similar to other natural disasters, there is no way to prevent the emergence of new infectious disease. As the importance of preparedness is pointed out by the famous Benjamin Franklin quote, "By failing to prepare, you are preparing to fail" [7], effective operations are the outcomes of powerful preparation. In this study, we apply the Operations Research methodologies, which provide powerful decision-making tools for humanitarian logistics planning and healthcare-management [78–81]. In particular, we are motivated by the need of effective hospital capacity planning for infected and non-infected patients during an epidemic disease. In the epidemic logistics view, scholars have used the OR tools for the distribution of medications [18,38–40], vaccines [16,20,31–33], medical equipment [24], consumable supplies [42] and healthcare capacity planning [17, 19,25,31]. To the best of authors' knowledge, similar to this study, only Sun et al. [25] considered the multi-objective, multi-period resource and patient allocation problem among multiple hospitals during a pandemic. Different than Sun et al. [25] and other studies associated with healthcare management in pandemics, this research focuses on the need of balanced resource optimization for infected and non-infected patients under capacity restriction. Further, we regard to the infectious risk of healthcare professionals. We also account to the hospital-based resources shared between patients with critical and moderate disease. Last but not least, different than business logistics, we believe that humanitarian logistics operations during the large-scale outbreaks aim to maximize the medical service responsiveness. Therefore, we do not consider cost-driven function.

7. Conclusions

In this research, three-objective multi-period linear programming model for patient allocation and capacity planning in a pandemic outbreak is presented. Specifically, the suggested mathematical model considers the scarcity of existing resources while determining resource sharing degree between infected and non-infected patients. Three conflicting objectives, (1) the total distance travelled by infected patients, (2) the maximum evacuation rate of non-infected patients and (3) the infectious risk of healthcare professionals are minimized simultaneously. The performance of the suggested mathematical model is analyzed with a case study based on the COVID-19 pandemic in the

European side of Istanbul, Turkey. First, the base case is assessed, and then numerous cases are generated based on various weight vectors to show the effectiveness of Pareto optimality. Then, solutions are analyzed in terms of evacuation rate of non-infected patients, infected patients sent to government hospitals and non-government hospitals. Last, sensitivity analysis is conducted by varying the hospital length of the stay of infected patients.

We believe that different allocation plans can be required for different time intervals during the outbreaks. The proposed mathematical model enables decision makers to prioritize three different criteria. For instance, since distance minimization decreases infectious risk in public, decision makers can prioritize the first objective function as such in Case 1, Case 4, Case 7 and Case 14 when the number of reported infected individuals increases. In the considered cases, the evacuation rate of non-infected patients is high. On the other hand, postponed routine cases and the infectious risk of healthcare professionals gain importance as the outbreak progresses. In time intervals when the number of infected individuals is considerably low, decision makers can give consequence to non-COVID patients as such in Case 2, Case 5, Case 8 and Case 16 and risk reduction at hospitals as such in Case 3, Case 6, Case 9 and Case 15. Therefore, allocation decision can be optimized for different time intervals. By minimizing the maximum evacuation rate of infected patients throughout hospital network, the proposed mathematical model provides a more robust solution.

This study has limitations: various published resources are taken into account for model parameters; therefore, the considered data may not be corresponded to the practiced environment. Even though the length of the stay of ICUs reflect the uncertain behavior of the pandemic outbreak, the length of the hospitalization of severely symptomatic patients is taken as a constant parameter. Moreover, our assumptions are made based on that infected patients with severe symptoms who recover or who have died occupy the resources for the same time duration. These assumptions may cause poor prediction for the needed hospital-based resources. For the future studies, stochastic parameters such as the absence of medical personnel may be included in order to stimulate the capacity uncertainty. The solution time is satisfied for the considered case study; however, time complexity may be appeared for the larger instances. Therefore, a heuristic algorithm can be developed to deal with larger size of data. Last, to project the progression of COVID-19 disease, various modelling approaches such as compartmental models, generic programming and machine learning techniques can be integrated with the proposed mathematical model.

Declaration of interest competing

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

Appendix A

(a) Number of COVID-19 death

(b) Number of COVID-19 recovered patient

(c) Number of COVID-19 patient in ICU

(d) Number of intubated COVID-19 patient

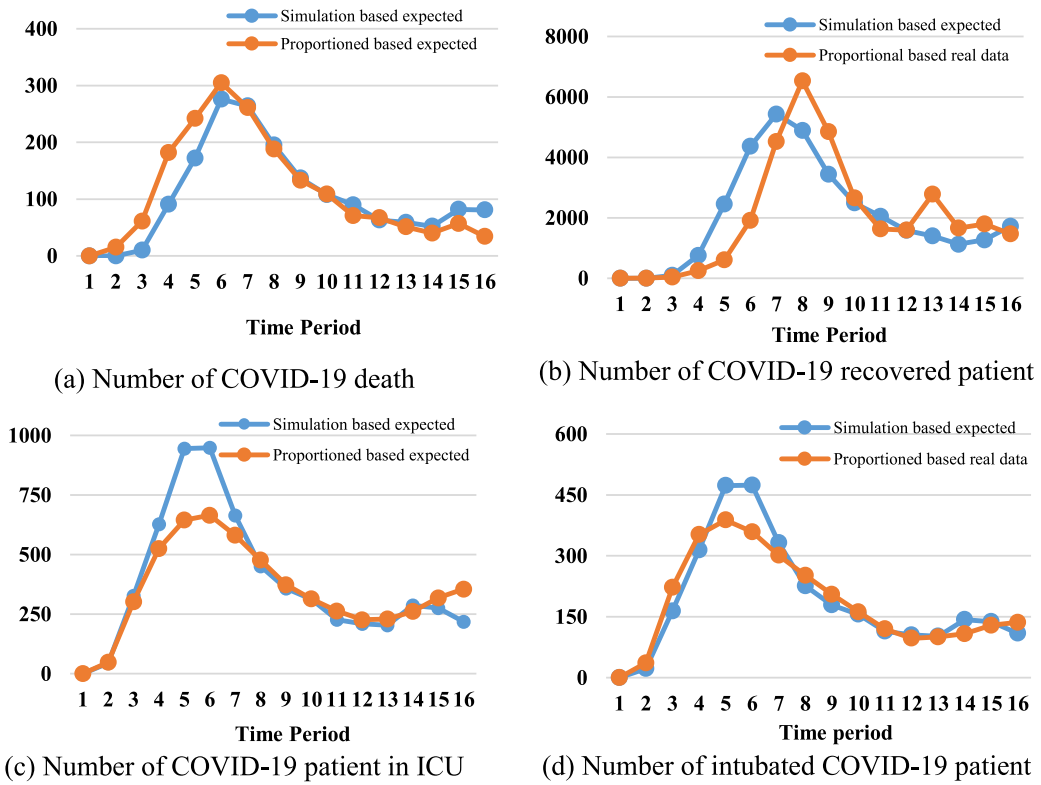**Fig. A.1.** Comparison between the proportional-based and simulation-based results.

Fig. A.2. Distribution of infected patients.

(a) Non-ICU
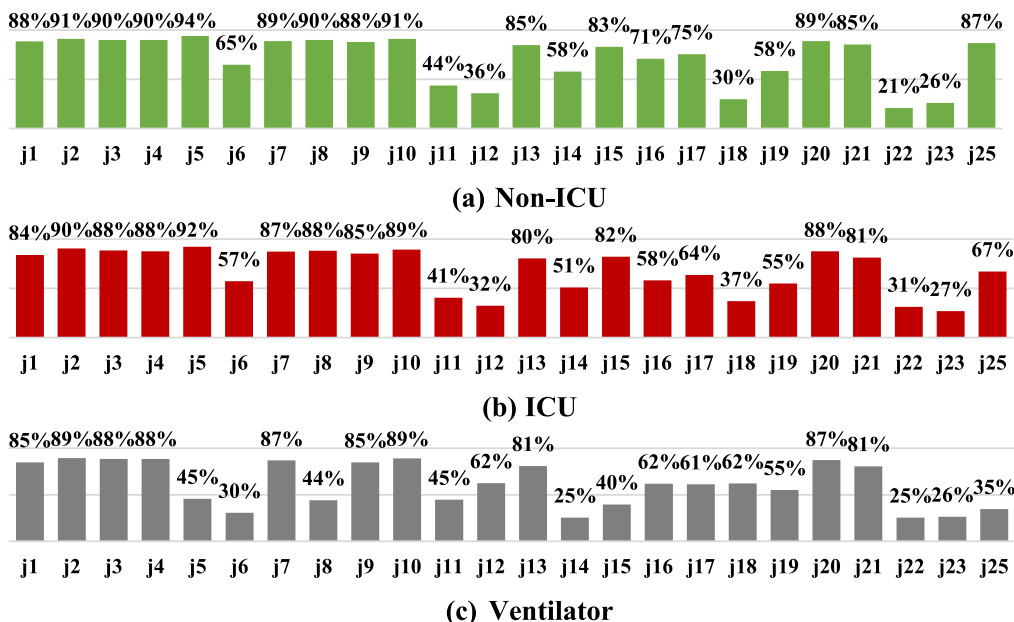

(b) ICU

(c) Ventilator
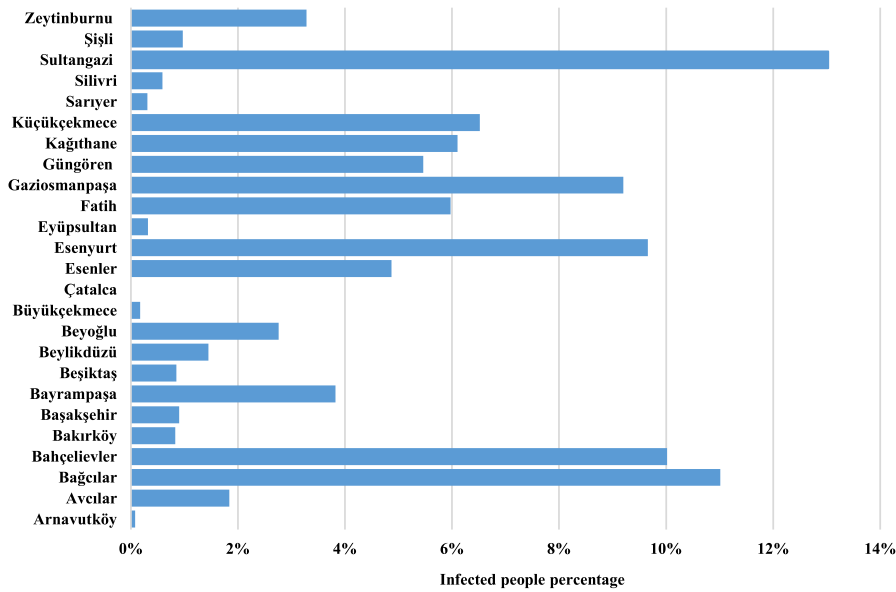
Fig. A.3. Average utilization of hospital-based resources.

Appendix B

Table B.1

Demographic information of the districts and the distribution of infectious across the European side of Istanbul

ID	District	Demographic information				
		Population (p_i)	Surface area (s_i) (km^2)	Population density (β_i) (Population/km^2)	Percentage of Population (α_i) (%)	Normalized population density (η_i)
i1	Arnavutköy	282,488	453	624	2.806	0.033
i2	Avcılar	448,882	50	8978	4.459	0.479
i3	Bağcılar	745,125	23	32,397	7.4	1.727
i4	Bahçelievler	611,059	17	35,945	6.07	1.917
i5	Bakırköy	229,239	29	7905	2.277	0.421
i6	Başakşehir	460,259	107	4301	4.572	0.229
i7	Bayrampaşa	274,735	9	30,526	2.729	1.628
i8	Beşiktaş	182,649	18	10,147	1.814	0.541
i9	Beylikdüzü	352,412	39	9036	3.5	0.482
i10	Beyoğlu	233,323	9	25,925	2.318	1.382
i11	Büyükçekmece	254,103	173	1469	2.524	0.078
i12	Çatalca	73,718	1142	65	0.732	0.003
i13	Esenler	450,344	19	23,702	4.473	1.264
i14	Esenyurt	954,579	43	22,200	9.482	1.184
i15	Eyüpsultan	400,513	228	1757	3.978	0.094
i16	Fatih	443,090	15	29,539	4.401	1.575
i17	Gaziosmanpaşa	491,962	12	40,997	4.887	2.186
i18	Güngören	289,441	7	41,349	2.875	2.205
i19	Kağıthane	448,025	15	29,868	4.45	1.593
i20	Küçükçekmece	792,821	44	18,019	7.875	0.961
i21	Sarıyer	347,214	177	1962	3.449	0.105
i22	Silivri	193,680	29	6679	1.924	0.356
i23	Sultangazi	534,565	10	53,457	5.31	2.85
i24	Şişli	279,817	37	7563	2.779	0.403
i25	Zeytinburnu	293,574	12	24,465	2.916	1.304
	Total	10,067,617	2717			

Table B.2

Hospital service information [64,66–70,72,82,83].

ID	Government-owned hospital	non-ICU bed	ICU bed	Total	Bed occupancy rate (%)	Healthcare Professionals	Estimated number of operating room
j1	MoH, Turkey İstanbul Arnavutköy Public Hospital	201	16	217	59.4	233	11*
j2	MoH, Turkey İstanbul Avcılar Murat Kölük Public Hospital	100	9	109	59.7	194	5*
j3	MoH, Turkey İstanbul Bahçelievler Public Hospital	205	13	218	73.4	319	11*
j4	MoH, Turkey İstanbul Başakşehir Public Hospital	100	8	108	59.6	195	5*
j5	MoH, Turkey İstanbul Bayrampaşa Public Hospital	100	4	104	73.8	237	5*
j6	MoH, Turkey İstanbul Çatalca İlyas Çokay Public Hospital	100	13	113	78.3	155	6*
j7	MoH, Turkey İstanbul Esenyurt Necmi Kadıoğlu Public Hospital	199	18	217	62.0	312	11*
j8	MoH, Turkey İstanbul Eyüpsultan Public Hospital	140	14	154	66.9	225	8*
j9	MoH, Turkey İstanbul İstinye Public Hospital	128	9	137	66.0	201	7*
j10	MoH, Turkey İstanbul Kağıthane Public Hospital	51	4	55	45.2	149	3*
j11	MoH, Turkey İstanbul Silivri Public Hospital	223	9	232	64.8	312	12*
j12	MoH, Turkey İstanbul Şişli Hamidiye Etfal Education Research Hospital	756	54	810	79.4	1117	41*
j13	MoH, Turkey İstanbul Bağcılar Education Research Hospital	498	48	546	90.9	856	27*
j14	MoH, Turkey İstanbul Bakırköy Dr. Sadi Konuk Education Research Hospital	612	79	691	86.1	980	35*
j15	MoH, Turkey İstanbul Gaziosmanpaşa Taksim Education Research Hospital	600	63	663	59.0	728	33*
j16	MoH, Turkey İstanbul Haseki Education Research Hospital	554	55	609	84.7	811	30*
j17	MoH, Turkey İstanbul Education Research Hospital	507	49	556	79.4	775	28*
j18	MoH, Turkey İstanbul Kanuni Sultan Süleyman Education Research Hospital	1010	33	1043	56.1	1447	52*
j19	MoH, Turkey İstanbul Prof. Dr. Cemil Taşcıoğlu City Hospital (Okmeydanı Education Research Hospital)	709	81	790	74.0	978	27
j20	MoH, Turkey Yedikule Chest Diseases and Thoracic Surgery Training and Research Hospital	350	22	372	82.4	349	19*
j21	MoH, Büyükçekmece Mimar Sinan Public Hospital	200	10	210	70.0*	233*	11*
j22	İstanbul University-Cerrahpaşa Medical Faculty Hospital	1306	57	1363	70.0*	1551*	27
j23	İstanbul University Medical Faculty Hospital	1353	126	1479	70.0*	1551	39
j24	Yeşilköy Prof. Dr. Murat Dilmener Emergency Hospital	576	432	1008	68.0*	1447*	16
j25	Hadımköy Dr. İsmail Niyazi Kurtulmuş Hospital	42	59	101	68.0*	237*	5*
j26	Başakşehir Çam and Sakura City Hospital	2682	490	3172	68.0*	2500*	90

*Parameters are given based on estimation.

Table B.3

Dedicated hospital-based resources to infected patients in government-owned hospitals

		Initial Capacity			New established resources	
ID	Government hospitals	Non-ICU bed	ICU bed	Ventilator	ICU bed	Ventilator
j1	Arnavutköy PH	135	14	7	10	3
j2	Avcılar Murat Kölük PH	67	6	3	4	1
j3	Bahçelievler PH	121	13	6	10	3
j4	Başakşehir PH	66	6	3	4	1
j5	Bayrampaşa PH	59	5	5	4	4
j6	Çatalca İlyas Çokay PH	56	8	8	5	5
j7	Esenyurt Necmi Kadıoğlu PH	130	14	7	10	3
j8	Eyüpsultan PH	88	10	5	7	3
j9	İstinye PH	81	8	4	6	2
j10	Kağıthane PH	38	4	4	3	3
j11	İstanbul Silivri PH	142	13	6	11	4
j12	Şişli Hamidiye Etfal ERH	422	48	48	36	36
j13	Bağcılar ERH	245	35	17	24	6
j14	Bakırköy Dr. Sadi Konuk ERH	318	49	24	31	6
j15	Gaziosmanpasa Taksim ERH	402	43	22	29	8
j16	Haseki ERH	291	40	20	26	7
j17	İstanbul Education ERH	283	36	36	25	25
j18	Kanuni Sultan Süleyman ERH	694	54	27	46	19
j19	Dr. Cemil Taşcıoğlu CH	416	43	21	24	2
j20	Yedikule ERH	190	22	11	17	6
j21	Büyükçekmece Mimar Sinan PH	124	12	6	10	4
j22	İstanbul University-Cerrahpaşa MFH	795	37	18	24	5
j23	İstanbul University MFH	824	63	63	34	34
j25	Hadımköy Dr. İsmail Niyazi Kurtulmuş Hospital	26	18	18	4	4
	Total	**6013**	**601**	**389**	**404**	**194**

PH: Public Hospital; **ERH:** Education Research Hospital; **CH:** City Hospital; **MFH:** Medical Faculty Hospital.
Results are rounded to the nearest integer.

Appendix C

Parameters:	
p_i	Population of district i
s_i	Surface area of district i
β_i	Population density of district i
α_i	Percentage of population in district i
η_i	Normalized population density of district i
ρ_i	Percentage of infected people who need hospitalization in district i
$Infected^{tk}$	Total number of infected people who need hospitalization at time period t and healed or died at time period k in the European side of Istanbul.
θ_i^{tk}	Number of infected people who need hospitalization in district i at time period t and healed or died at time period k.

Formulation:

$$\beta_i = \frac{p_i}{s_i}, \ \forall i \in I \quad \text{Eq.(C1)}$$

$$\alpha_i = \frac{p_i}{\sum_{i=1}^{I} p_i}, \ \forall i \in I \quad \text{Eq.(C2)}$$

$$\eta_i = \frac{I\beta_i}{\sum_{i=1}^{I} \beta_i}, \ \forall i \in I \quad \text{Eq.(C3)}$$

$$\rho_i = \frac{\alpha_i \eta_i}{\sum_{i=1}^{I} \alpha_i \eta_i}, \ \forall i \in I \quad \text{Eq.(C4)}$$

$$\theta_i^{tk} = \rho_i \, Infected^{tk}, \ \forall i \in I \quad \forall t, k \in T \quad \text{Eq.(C5)}$$

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