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A decision support system to reorganize medical service network in pandemic

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Abstract: The advent of the Covid-19 pandemic has posed severe challenges to health care networks in various countries. The overcrowding of hospitals and the lack of medical staff and beds in multiple wards are among the main problems of governments. A new virus wave also exacerbates these problems. Also, the lack of information and the variability of the incidence rate and severity of the disease in different waves make it difficult to estimate the number of patients accurately. In this respect, this study develops a mixed-integer linear programming model to reorganize the medical service network. A fuzzy approach is employed to estimate the number of patients in each period. The result obtained from the model, apart from preventing the shortage of hospital beds, demonstrates a 60% reduction in visits to these centers.

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Keywords: Covid-19 pandemic management; Medical service network design, Fuzzy approach; Decision support system; Alternative care facilities.

1. INTRODUCTION

Since December 2019, when coronavirus disease (COVID-19) emerged in Wuhan city, it is rapidly spread worldwide. The current medical service network (MSN) is facing severe problems. Thus, the existing treatment networks - which now have to serve patients with Covid 19 and their primary and routine tasks - have serious issues. Consequently, the centers that can fully help severe patients in most cities are minimal. One of the main problems of these centers is the crowding of patients - including people with severe coronavirus, people with underlying diseases, healthy people for tests, and patients with other diseases - in the reception and triage.

When a new wave occurs (due to virus mutations, occasions, and annual celebrations), the number of patients multiplies, which consequently leads to a decrease in the level of service to patients and an increase in casualties. In this situation, planning the needs of these centers, the number of staff, and the number of beds in different departments (especially the ICU) is significant (Massonnaud et al., 2020). One way to deal with these problems is to reorganize the MSN and medical requirement planning for a specific period, a few weeks after the diagnosis or prediction of a new wave. Therefore, two options could be of help: 1) Establishing alternative care facilities (ACF) to manage the flow of clients, 2) Perform outpatient services, testing, and screening, as well as the use of off-duty staff and trained volunteers, increase the level of MSN service to an acceptable level. An ACF can be built in places with ample space and belong to government agencies, such as parks, stadiums, large pharmacies, etc. The experience of the COVID-19 outbreak illustrated that the first option seems more practical and economical (Ivanov, 2020). The main goal of an ACF is to create an additional capacity for hospitals, reduce the number of patients referred to hospitals, perform triage and ultimately maximize the rate of providing medical services to patients. The construction of these centers

and the management of medical personnel in parallel will cause a significant increase in the rate of medical services and reduce the number of casualties.

In this paper, an optimization model for emergency response therapy is developed to focus on reorganizing the current treatment network when a new wave of coronary heart disease occurs. The major decisions of this model are to locate and allocate ACFs to on-demand centers and hospitals, determine the number of beds required for each hospital to prevent a shortage of beds, and allocate trained volunteer staff and specialized medical staff to each medical center.

2. LITERATURE REVIEW

In the post-disaster management literature, special attention has been paid to the two issues of "minimizing post-disaster casualties" and "maximizing the rate of medical services provided." Meanwhile, the term "emergency response medical center" is more commonly used to refer to facilities built quickly after a crisis and provide part of a health care service for a short period of time. For the first time, Drezner (2004) addressed this problem with the title of "casualty collection points" and assessed the performance of the proposed model with different objective functions. Ko et al. (2016) propose a model that locates emergency medical centers and allocates patients to them in a given region under the closest assignment rule. The model also decides on the rate of increase of capacity for each medical facility according to the maximum possible capacity of each facility. The objective is to minimize the number of total subsidies from the government. Oksuz and Satoglu (2020) provide a two-stage stochastic model to locate temporary medical centers by considering the locations of the existing hospitals, casualty classification (triage), and the capacities of these centers. This study also demonstrates that prioritizing patients by triage process and then assigning them to appropriate medical centers significantly affects increasing medical service. Aimed at establishing new emergency care

facilities, Caunhye and Nie (2018) introduce a three-stage stochastic solution to model the triage process. They categorize patients after which medical centers are assigned to react to a large-scale disaster. The authors use the term ACF to determine the newly established health centers. They also conclude that the establishment of the ACFs has a high effect on decreasing the final death toll. These centers are responsible for performing triage and some outpatient medical services.

Furthermore, Mulyasari et al. (2013) represent a framework for hospital preparedness parameters and indicators, in which, items such as buildings, equipment and facilities, patients, and medical and support staff are referred to "vulnerability elements" and items such as the number of medical staff used, hospital beds, triage of tags and tents for emergency medical service are called "health service indicators." In this regard, Schroder & Washington (1982) evaluate various medical service indicators and their effectiveness in improving patients. They concede that one of the critical indicators in the process of providing medical services is the existence of a sufficient number of hospital beds and the number of medical staff used. In the same context, Rådestad et al. (2013) also state that an adequate number of beds and sufficient medical staff significantly impact the final result of the service provided. Accordingly, we use the term "Staff-Patient Ratios" - suggested by Sacks (2006) and Schroder & Washington (1982) - to ensure that an acceptable minimum level of medical service will be met.

Indeed, one of the main challenges of the pandemic is the severe fluctuations in the number of patients and the subsequent allocation of out-of-service personnel and trained volunteers (Hanfling, 2006). Accordingly, we also use ACF for new emergency medical facilities, trained volunteers for staff serving in the ACFs, and specialized personnel for off-duty doctors and nurses. On the other hand, uncertain characteristics of some parameters in any modeling approach are very challenging. Accordingly, the problem is converted to a network design with disruption (Jahani et al., 2017; Jahani et al., 2018). Exploring the literature on Covid 19 related issues, we found that one of the widely used methods is the fuzzy approach to deal with demand uncertainty (Melin et al., 2020). Fuzzy optimization modelling approach represents a compelling method for solving healthcare problems which are associated with uncertainty (Kargar et al., 2020). Accordingly, we use a fuzzy system to deal with problem uncertainty. We also restructure our MSN as a supply chain network design with a mixed integer programming method that is known as a typical model in the literature (Jahani et al., 2019; Gholizadeh et al., 2021; Homayouni et al., 2021)

Based on what was described and to the best of our knowledge, this is the first study to provide a model for reorganizing the existing medical network to prevent a shortage of hospital beds and redistributing available medical staff to maximize the level of health care provided, when a new wave of coronary heart disease occurs.

3. PROBLEM DEFINITION

In our new network model, the flow of public referrals is first redistributed to the ACFs. People with more severe illnesses

are referred to hospitals for admission to general wards or ICUs. The details of this process are described in Figure 1.

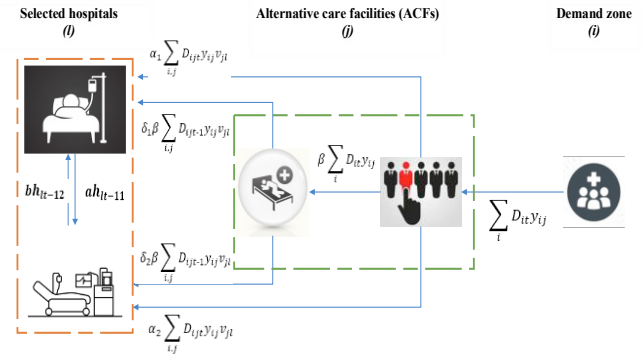


Figure 1 - Overview of patients' allocation and transition in our reorganized medical service network

It is assumed that all decisions are made immediately after identifying the possibility of a new wave and one week before planning to deal with the consequences of this wave. Based on this, the demand for each period is the expected demand for the next period. The period is suggested to be considered a week or two weeks because the outbreak's duration is mostly around one to three months. Also, all applicants are directed to do corona diagnostic tests in the ACF centers using public information. The number of people who go directly to hospitals will be excluded accordingly.

4. MODEL FORMULATION

The indices, parameters, and variables used to formulate the concerned COVID-19 new MSN design problem are described below:

Indices

- i Demand $i = 1, \dots, I$ zones;
- j Candidate locations for ACFs; $j = 1, \dots, J$
- l Selected hospitals; $l = 1, \dots, L$
- k The service level of a hospital; $k = 1, 2$
- t Time period; $t = 0, 1, \dots, T$
- q Quarantine levels; $q = 0, 1, 2$

Parameters

- dis_{ij} Distance from medical service applicant point i to ACF j
- D_{it} Demand of medical service applicant point i in time period t
- $Capa_j$ Capacity of candidate location j
- Wa Wage of trained volunteer for a time period
- Sa Salary of trained volunteer for a time period

Ce_{lk}	Cost of adding a unit of hospital capacity in level k for hospital l	<i>Variables</i>
PA	Maximum allowed number of ACF for construction	x_j Binary variable determining construction of ACF j
β	Percentage of referrals to ACF j, who will be admitted to the same center.	y_{ij} Binary variable determining the allocation of hospital l to ACF j
Ini_{lk}	Number of people hospitalized at the beginning of planning	η_{lt} Number of specialized personnel allocated to hospital l in time period t
$CapIn_{lk}$	Initial capacity of candidate locations j to admit patients in service level k	h_{lkt} number of people admitted to hospital l with demand for service level k in time period t
ext_{lk}	Maximum number of beds added to the hospital l capacity for service level k	Cap_{ltk} admission capacity of hospital l for service level k in time period t
Hr_{ltk}	Initial number of people serving in hospital l for service level k in time period t	ex_{ltk} Number of beds added to the hospital l capacity for service level k in time period t
μ_{jt}	Upper limit of the trained volunteers assigned to candidate location j in time period t	r_{jt} Number of additional trained volunteers allocated to ACF j in time period t for better service
η_{mt}	Upper limit of the specialized personnel assigned to candidate location j in time period t	p_{ltk} Number of additional forces allocated to hospital l in service level k in time period t
α_k	Percentage of patients admitted with the service level of service k	<p>The optimization model minimizes the objective function (Eq. (1)) which is the total cost of the network containing the fixed and variable costs. The reorganized MSN and opening ACFs compute the fixed cost. The variable costs include transportation costs of flows between facilities, salaries for volunteers and specialists, the desirability of allocating more medical staff to each medical center, and the cost of adding medical equipment to increase the capacity of intensive care units.</p> $minf = \sum_{i,j,t} dis_{ij} D_{it} y_{ij} + Wa \sum_{j,t} (\mu_{jt} + r_{jt}) + Sa \sum_{l,t} (\eta_{lt} + p_{ltk}) - \sum_{l,t,k} des_{lk} r_{jt} + \sum_{l,t,k} Ce_{lk} ex_{ltk} \quad (1)$ $\sum_j x_j \leq PA \quad (2)$ $\sum_i y_{ij} \leq Mx_j, \forall j \quad (3)$ $\sum_j y_{ij} = 1, \forall i \quad (4)$ $\beta \sum_i D_{it} y_{ij} \leq Capa_j, \forall t, j \quad (5)$ $h_{l0k} = Ini_{lk}, \forall l, k \quad (6)$ $h_{lt1} \geq \lambda_1 h_{lt-11} + \alpha_1 \sum_{i,j} D_{it} y_{ij} v_{ijl} + \delta_1 \beta \sum_{i,j} D_{it-1} y_{ij} v_{jl} + ah_{lt-12}, \forall t, l \quad (7)$ $h_{lt2} \geq \lambda_2 h_{lt-12} + \alpha_2 \sum_{i,j} D_{it} y_{ij} v_{ijl} + \delta_2 \beta \sum_{i,j} D_{it-1} y_{ij} v_{jl} + bh_{lt-11}, \forall t, l \quad (8)$ $Cap_{l0k} = CapIn_{lk}, \forall l, k \quad (9)$ $h_{ltk} \leq Cap_{ltk}, \forall t, l, k \quad (10)$ $Cap_{ltk} \leq Cap_{lt-1k} + ex_{lt-1k}, \forall t, l, k \quad (11)$
ε_k	Estimated error rate for per capita rate of hospitalized patients	
δ_k	Percentage of patients admitted to the ACF in the previous period who are transferred to the level of service k ward in the current period.	
P	Comparative utility of allocating more specialized personnel hospital in one time period	
Tr_k	Minimum Staff-Patient Ratios for service level k	
a	Percentage of patients who stay in the same hospital and ward in service level k=1 in the next period.	
b	Percentage of patients who stay in the same hospital and ward in service level k=1 in the next period.	
T	Number of trained volunteers who can serve in each time period	
ι	Inverse of the number of patients that a trained volunteer can provide triage service over a period of time.	
ξ	Inverse of the number of patients that a trained volunteer who can provide health care service in a ACF over a period of time.	
v_{jl}	Binary parameter that indicates the assignment of ACF j to hospital l	
M	A large number	

$$\sum_t ex_{ltk} \leq ext_{lk}, \forall l, k \quad (12)$$

$$\mu_{jt} \leq Mx_j, \forall t, j \quad (13)$$

$$\eta_{lt} + Hr_{ltk} + p_{ltk} \geq Tr_k(1 + \varepsilon_k)h_{ltk}, \forall k, t, l \quad (14)$$

$$\mu_{jt} + r_{jt} \geq (\iota \sum_i \beta D_{it} y_{ij} + \xi \sum_i D_{it} y_{ij}), \forall j, t \quad (15)$$

$$\eta_{lt} + \sum_k p_{ltk} \leq \eta m_{lt}, \forall t, l \quad (16)$$

$$\mu_{jt} + r_{jt} \leq \mu m_{jt}, \forall t, j \quad (17)$$

$$x_j, y_{ij}, \in \{0,1\}, \forall i, j, k, l, q, t \quad (18)$$

$$\eta_{lt}, \mu_{jt}, h_{ltk}, Cap_{ltk}, ex_{ltk}, r_{jn}, p_{ltk}, v_{jl} \geq 0, \forall i, j, k, l, q, t \quad (19)$$

Constraints (2-4) are related to the construction and allocation of AFCs to the network. Constraint (5) controls the capacity of each ACF not to exceed the demand allocated to the ACF. The initial number of patients admitted to each hospital is managed by Constraint (6). Constraints (7,8) state that the number of patients admitted to each hospital ward is the percentage of people referred to the established ACFs and then referred to hospitals as a percentage of the number of patients admitted in the previous period. Constraint (9) indicates the initial capacity of each hospital. Constraint (10) ensures that the number of people admitted to each hospital in each period does not exceed the capacity of that hospital in that period. The capacity of each hospital in each period is determined by Constraint (11), which includes the capacity added in the previous period and the capacity of that period. Constraints (12) limit the number of beds in each inpatient ward and period. Constraints (13) check each ACF to be opened once a trained volunteer is assigned to it. Constraint (14) controls the number of professional personnel in each hospital with the services provided to admitted patients to that center. The number of patients requested for triage is met by the number of trained volunteers assigned to an ACF in Constraint (15). Constraints (16)-(17) also express the requirement to observe an upper limit for the number of staff assigned to each hospital or ACF. Constraints (18) and (19) are related to decision variables boundaries.

5. SOLUTION APPROACH

Given the historical data on the number of Covid 19 patients in the last two years, we can use the fuzzy approach to estimate the weekly demand for different wards of hospitals. In this vein, D^l , D^r and D^m are defined as the most pessimistic, the most optimistic and finally, the most possible predicted amounts for demand. Therefore, the demand is articulated as a triangular fuzzy number: $\tilde{D} = (D^l, D^m, D^r)$. According to the fuzzy ranking approach developed by Pishvae and Khalaf (2016), the demand can be defuzzified as follows:

$$D = \left(D^m + \frac{\varphi^D + \varphi'^D}{3} \right) \quad (20)$$

Where the parameters φ^D and φ'^D are lateral margins of the triangular fuzzy number and defined as follows:

$$\varphi^D = D^m - D^l \quad (21)$$

$$\varphi'^D = D^r - D^m \quad (22)$$

Accordingly, the objective function and constraints (5), (7), (8), (15) could be converted to the following equivalent crisp model:

$$\begin{aligned} \min f = & \sum_j RA_j x_j + \sum_{i,j,t} dis_{ij} \left(D_{it}^m + \frac{\varphi_{it}^D + \varphi'_{it}{}^D}{3} \right) + \\ & Wa \sum_{j,t} (\mu_{jt} + r_{jt}) + Sa \sum_{l,t} (\eta_{lt} + p_{ltk}) - \sum_{l,t,k} des_{lk} r_{jt} + \\ & \sum_{l,t,k} Ce_{lk} ex_{ltk} + \\ & \sum_{t,q} CQ_q u_{tq} \end{aligned} \quad (23)$$

$$\sum_{i,t} \left(D_{it}^m + \frac{\varphi_{it}^D + \varphi'_{it}{}^D}{3} \right) y_{ij} \leq Capa_j, \forall t, j \quad (24)$$

$$\begin{aligned} h_{lt1} \geq & \lambda_1 h_{lt-11} + \alpha_1 \sum_{i,j} \left(D_{it}^m + \frac{\varphi_{it}^D + \varphi'_{it}{}^D}{3} \right) y_{ij} v_{ijl} + \\ & \delta_1 \beta \sum_{i,j} D_{it-1} y_{ij} v_{jl} + ah_{lt-12}, \forall t, l \end{aligned} \quad (25)$$

$$\begin{aligned} h_{lt2} \geq & \lambda_2 h_{lt-12} + \alpha_2 \sum_{i,j} \left(D_{it}^m + \frac{\varphi_{it}^D + \varphi'_{it}{}^D}{3} \right) y_{ij} v_{ijl} + \\ & \delta_2 \beta \sum_{i,j} D_{it-1} y_{ij} v_{jl} + bh_{lt-11}, \forall t, l \end{aligned} \quad (26)$$

$$\mu_{jt} + r_{jt} \geq \left(\iota \sum_i \beta \left(D_{it}^m + \frac{\varphi_{it}^D + \varphi'_{it}{}^D}{3} \right) y_{ij} + \xi \sum_i \left(D_{it}^m + \frac{\varphi_{it}^D + \varphi'_{it}{}^D}{3} \right) y_{ij} \right), \forall j, t \quad (27)$$

6. REAL_WORLD CASE STUDY

As mentioned earlier, the main application of this model is in areas with high population density. In this regard, we have practiced the operation of the model and the analysis of its results in a case study based on the most populous city of Iran, Tehran. This city is the capital of Iran and consists of 22 districts with a total area of 615 km² and about 9 million people. Since the coronavirus outbreak in Iran, on average, 13% of all patients in the country have always been related to the city of Tehran. The government and the Ministry of Health of Iran have identified and publicly announced nine specialized hospitals to provide all services to coronary patients. Still, two major problems have reduced the rate of patient care and increased the number of casualties: 1. Lack of beds and staff 2- Excessive congestion in the reception areas. We used this city and its data to investigate the applicability of our model.

After implementing the model, we see some costly decisions for the problem. The results show that, on average, the ratio of the number of special staff to the number of people admitted to different wards of hospitals increases by 22%. Moreover, the ratio of the number of beds in the ICU to the number of patients in the same ward increased by 40%. But one of the

main goals of the model is to reduce the number of unnecessary visits to hospitals. The results shown in Figure 2 represent that after implementing the model, the number of referrals to each hospital decreases significantly, so, on average, the total number of referrals with the model decreases by almost 60% (from 635 to 225).

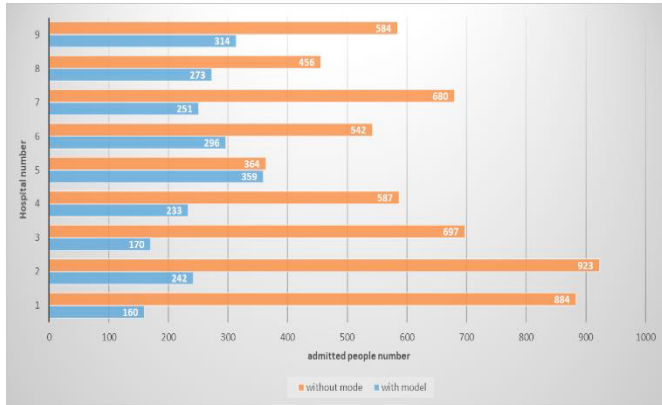


Figure 2 - Average number of people referred to hospitals before and after implementing the proposed model

Another major application of the proposed model is staff replanning and reassignment. In fact, the ratio of patients to assigned personnel is one of the most important indicators for measuring the level of medical care. In this regard, Figure 3 shows the average ratio of the number of patients to special staff for each hospital. As shown in the figure, after the implementation of the model, the difference between the upper and lower limit of the obtained ratio has decreased by about 40% (from 0.244 to 0.152) while the average of this ratio increases by about 22% (from 0.185 to 0.226).

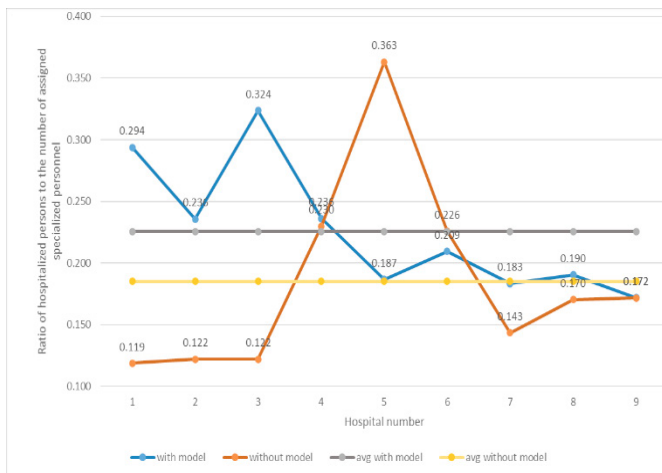


Figure 3 - Average ratio of the number of patients to special staff for each hospital

7. CONCLUSIONS

This study introduces a mathematical model for a decision support system to reorganize an MSN in a pandemic. We use a fuzzy approach when the incidence rate and the number of cases increase significantly. The main decisions to be made in this model are 1- Location-allocation of ACF centers for

triage, outpatient services, and screening. 2- Planning medical needs by increasing the number of beds in different hospital wards and the optimal allocation of volunteers and off-duty medical staff to medical centers.

The model results show that if the model is implemented, the number of direct referrals to hospitals and the level of service provided by the network will increase significantly, which will lead to minimizing losses.

For future research, several supporting decisions could be considered in the model, including 1) applying different levels of quarantine, 2) the application of space capacity limits in the form of maximum allowable space for extra beds in the entire planned period, 3) dealing with model uncertainty by multi-period stochastic programming, 4) long-term planning for equipping other small hospitals to provide medical services at different levels in long-term pandemics, 5) use chance-constraint and α -reliable approaches to express main problem constraints such as capacity constraints and medical staff allocation constraints.

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