Resource-Constrained Model of Optimizing Patient-to-Hospital Allocation During a Pandemic

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Abstract. Healthcare management, in particular managing a hospital network, is a complex issue which requires taking into account the morbidity process dynamics, simultaneous administration of various therapies, preventive actions, drug supply and responding to emergencies, such as mass casualty traffic incidents, pandemics (e.g. SARS, MERS), etc. The overall objective is to provide appropriate, dedicated aid to patients and affected persons as quickly as possible. One of the aspects of key importance to achieving this objective is the issue of appropriate patient-to-hospital allocation within a specific area. Very often the allocation is determined by constrained resources which the healthcare facilities in the given area have at their disposal, i.e. the number of doctors with specific medical specialties, the number of nurses, the number of beds of specific types in individual hospitals, the number of available medical transportation vehicles, but most importantly, the time limits for initiating successful hospital treatment. Optimal use of constrained resources makes it possible/facilitates optimal allocation in patients, which is essential in emergency situations. The paper proposes a model of optimal patient-to-hospital allocation taking into account the constrained resources of the hospital network and emergency ambulance service which provides medical transportation. The proposed model is formulated using Binary Integer Programming (BIP).

Keywords: Optimization · Allocation problem · Emergency medical services · Patients · Pandemic

1 Introduction

Emergencies such as mass casualty traffic incidents, natural disasters or pandemics are major challenges for the healthcare system, local and state authorities, etc. In emergency situations, a large number of problems arise which must be solved simultaneously within a relatively short time. The most important problems include the appropriate triage of patients (affected/infected), ensuring quick and secure transportation to a specific hospital, providing appropriate hospital treatment and care, etc. Hospitals in a given area are very often unprepared for a large influx of a specific type of patients within a short period of time. For this reason, the so-called field hospitals are often set up,

N. T. Nguyen et al. (Eds.): ICCCI 2020, LNAI 12496, pp. 176–187, 2020.
https://doi.org/10.1007/978-3-030-63007-2_14

or selected hospitals are adapted for treating only a specific group of patients (from a disaster, pandemic, etc.).

Concerning patient triage in emergency situations, various methods are applied, such as Pandemic Influenza Triage Algorithm (PITA) [1], etc. The secure transportation of patients to the nearest appropriate hospital (i.e. one with available beds, medical specialists and equipment, such as ventilators, etc.) is usually the responsibility of the emergency ambulance service, which may be sometimes aided by military medical transportations services. Reorganization applies also to emergency departments which must be prepared for processing a larger influx of patients. Patient traffic within the hospital must also be modified accordingly.

Implementing the measures mentioned above is hindered by constrained resources, i.e. the number of doctors and nurses, the number of hospital beds of specific type, the number of ambulances and, last but not least, time. It should also be remembered that the hospitals and emergency ambulance service in a given area also provide treatment and transportation to other patients who are not casualties of a disaster or pandemic.

Consequently, the question arises: *How to optimally allocate (designate and transport) patients to hospitals in view of the abovementioned constraints?*

In order to answer this and similar questions, the paper proposes a mathematical model of optimizing patient allocation to the existing hospital network using medical transportation services, taking into account the existing constrained medical and logistic resources. To implement the model, GUROBI [2] mathematical programming and constrained programming environment and AMPL [3] modeling language were used.

2 Literature Review

Modeling the issues of resources allocation in healthcare has been broadly discussed in the literature of the subject, both in the context of pandemics of e.g. influenza-like diseases, and for situations not related to pandemics. Planning and responding during pandemics of diseases such as seasonal influenza, N1H1 or, most recently, the SARS-CoV-2 coronavirus, involves a number of aspects, including the disease spread forecast, organizing mass vaccinations (if a vaccine is available), planning and resupplying hospital resources, reorganizing the hospital network, or organizing medical transport. Mathematical models of the spread of influenza-like diseases have been presented in a number of studies [4, 5]. Hospital resources planning is another important area addressed in the literature of the subject. Using planning software, such as FluAid and FluSurge, to forecast the impact of a pandemic on the operation and resources of hospitals and other healthcare facilities was discussed in [6]. A model for optimizing nurse allocation in a hospital during an outbreak of influenza pandemic using FluSurge 2.0 software is presented in [7]. The literature concerning the issue of allocation in a hospital network (i.e. patient allocation, allocation/re-allocation of hospital resources, etc.) is quite broad and covers the issues of both long-term planning (e.g. planning for the hospital network) and short-term planning (e.g. ambulance allocation, emergency response to disasters, etc.). Concerning the former category, the literature of the subject provides a variety of location-allocation models (optimal healthcare facility locations and patient-to-facility allocation), e.g. in the studies in [8, 9]. In terms of short-term planning, there is a number of studies on modeling issues such as immediate emergency response following an earthquake, flood, hurricane or terrorist attack; ambulance allocation; allocation of the available medical resources to specific areas of operation, etc. The most interesting studies in this category include those in [10, 11]. The models related to the issues discussed herein are mostly focused on patient-to-hospital allocation/distribution, taking into account the availability of hospital beds and the patient transport time as the optimization criterion.

There are no models which would include not only the availability of hospital beds, but also of the healthcare staff, the type of available hospital beds, e.g. ventilator beds, patient classification, e.g. based on various types of TRIAGE, the medical transport capacity, etc.

The main contribution of the presented work is to propose a formal model of patient-to-hospital allocation during pandemic (Sect. 3) and an iterative method of solving it, which enables decision support in the field of patient transport and allocation (Sect. 4). The proposed model takes into account not only the limited availability of hospital beds, but also takes into account the type of available beds, the number of available healthcare staff with specific qualifications, the availability of a specific type of medical transport, etc. Moreover, the proposed model can be used both in reactive (decisions made immediately by the operator) and proactive (decisions related to the possibility of serving a specific group of patients at a specific time, moving equipment and personnel, etc.) mode. Given the high parameterization of the model, it is possible to easily improve its functionality by altering the values and meaning, and the structure of individual parameters.

3 State of the Problem and the Mathematical Model

The following assumptions were adopted in building the mathematical model of optimizing patient-to-hospital allocation:

1. A hospital network $h \in H$ is given in the specific area/metropolitan area or smaller towns and countryside – distances between healthcare facilities from several do several dozen kilometers.
2. The hospital has various types of beds $b \in B$, e.g. for general treatment, for pandemic patients, with ventilators, etc. The type of hospital bed is also the designation of the patient's category. Each hospital at the given time has a specific number of beds of the given type available $w_{h,b}$.
3. The hospital also has the fleet of available ambulances $a \in A$. The parameter $f_{a,b}$ specifies whether ambulance a can transport type b patients ($f_{a,b}= 1$ Yes; $f_{a,b}= 0$ No).
4. The hospital has employees with specific qualifications to which the relevant types of positions $g \in G$ are assigned. The applicable standards specify the maximum number of patients per the given g type employee; this is determined by the value of parameter d_g.
5. Each hospital h has a specific number of g type employees. This is determined by the value of parameter $u_{h,g}$. The parameter z_h determines the current number of patients treated in hospital h.

6. There is a given set of patients ($p \in P$). The patients are transported to the hospital by ambulances after calling the central emergency phone number, or, if the patient's condition allows it, they report directly to the emergency department. Each patient undergoes initial triage and is assigned a specific category b (type of hospital bed required).
7. In the case of patients reporting directly to the ED, if the hospital is full (no available beds of the required type b), the patients may be transported to another hospital.
8. The time of transporting each patient to each hospital $e_{p,h}$ is known, as is the required time in which the patient should be taken to the hospital j_{p}.
9. In order to ensure model cohesion and reduce its size, the so-called virtual ambulance (transporting the patient within the given hospital from the ED to the relevant ward) and virtual hospital (for all patients transported to the ED by ambulance) are introduced.
10. The developed model applies to a specific situation in time used for the so-called reactive planning. Therefore, the model can be run iteratively following an update of the resources in specified intervals, or after receiving a specific number of reports from the patients. It can also be used for proactive planning, i.e. simulating a pandemic threat in a given area, and relocating or resupplying resources as appropriate.

Considering the abovementioned assumptions for the modelled problem, a fundamental question emerges: *How to quickly and safely put the patients in the available hospitals?* Thus, two parameters are crucial: quickness, i.e. the time of transportation to the hospital, and safety, i.e. using the appropriate means of transport, and transporting the patient to the appropriate hospital, i.e. one with the available required medical personnel, hospital beds, etc. An overall diagram of the modelled problem for a case of 4 hospitals, 6 patients and transportation provided by the emergency ambulance service, is provided on Fig. 1.

On the basis of those premises, a model of optimizing patient-to-hospital allocation during a pandemic has been formulated in the form of a binary integer programming (BIP) model (1)…(10). Minimizing the patient transport time is adopted as the goal function (1). The goal function is complemented with penalties for failing to deliver the patient to the hospital (n_p), or failing to deliver the patient to the hospital on time (k_p). The model has significant constraints (2)…(9), discussed in Table 2. The key constraints arise from limited availability of resources such as hospital beds, healthcare staff, ambulances, etc. Table 1 presents indices, parameters and decisive variables of the model.

In the development of the model, an innovation in modeling decision variables of the problem was implemented. Basically, modeling the decision variable $X_{a,p,h,t}$ would suffice. With the introduction of two additional decision variables Y_p and U_p, the model will always have a solution. Obviously, if the additional variables are different than zero, the solution will not always be satisfactory, but with model of decision variables, we eliminate the risk of an "NSF" (no solution found) response of the solver and thus no information on the solution. Obtaining non-zero values of Y_p and U_p in the solution informs the decision-maker of specific missing resources, thus enabling them to make the decision on emergency resupplying and delivering the patient to the hospital.

$$\min \sum_{a \in A} \sum_{p \in P} \sum_{h \in H \cup s} \sum_{t \in T} e_{p,h} \cdot X_{a,p,h,t} + \sum_{p \in P} (k_p \cdot Y_p + n_p \cdot U_p) \tag{1}$$

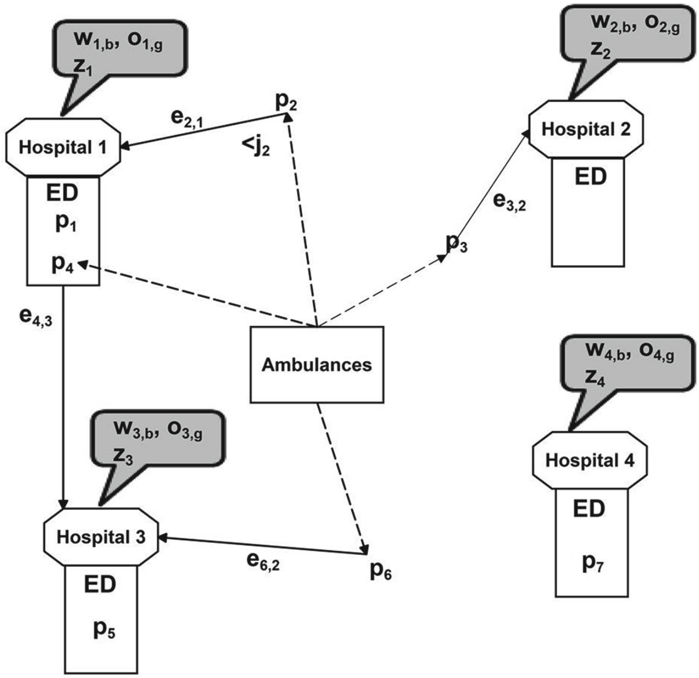

Fig. 1. Illustration of an example of data instance of the modelled problem (4 hospitals, 6 patients, centralized medical transportation

$$\sum_{a\in A\cup i}\sum_{p\in P}\sum_{h\in H\cup s} X_{a,p,h,t} + z_t \leq o_{t,g}\cdot d_g \forall t\in H\cup s, g\in G \tag{2}$$

$$\sum_{p\in P}\sum_{h\in H\cup s}\sum_{t\in H} X_{a,p,h,t} \leq 1 \forall a\in A \tag{3}$$

$$X_{a,p,h,t} = 0 \forall a\in A, p\in P, h\in H\cup s, t\in H \wedge s_{p,a} = 0 \tag{4}$$

$$\sum_{a\in A\cup i}\sum_{h\in H\cup s}\sum_{t\in H} r_{p,h}\cdot X_{a,p,h,t} + U_p = 1 \forall p\in P \tag{5}$$

$$X_{i,p,h,t} = 0 \forall p\in P, h\in H, t\in H \wedge h\neq t \tag{6}$$

$$X_{a,p,h,t}\cdot e_{p,t} - m\cdot Y_p \leq j_p \forall a\in A\cup i, p\in P, h\in H\cup s, t\in H\cup s \tag{7}$$

$$\sum_{a\in A}\sum_{p\in P}\sum_{h\in H\cup s} c_{p,b}X_{a,p,h,t} \leq w_{t,b}\forall t\in H, b\in B \tag{8}$$

$$s_{p,a} = \sum_{b\in B} f_{a,b}\cdot c_{p,b}\forall p\in P, a\in A \tag{9}$$

$$X_{a,p,h,t} \in \{0, 1\} \forall a \in A \cup i, p \in P, h \in H \cup s, t \in H \tag{10}$$

$$Y_p, U_p \in \{0, 1\} \forall p \in P$$

Table 1. Indices, sets, parameters and decision variables

Symbol	Description
Indices and Sets	
H	A set of hospitals
B	A set of bed's type
A	A set of all ambulances
G	A set of employee types
P	A set of patients
h,t	Hospital index $(h \in H)$
b	Type of bed index $(b \in B)$
a	Ambulance index $(a \in A)$
g	Employee type index $(g \in G)$
p	Patient index $(p \in P)$
i	Index of virtual ambulance traveling between the same hospital
s	Index of virtual hospital (patient reporting by phone)
Parameters	
$w_{t,b}$	The number of free beds type *b* in hospital *t* $(b \in B, t \in H)$
$f_{a,b}$	If an ambulance *a* can carry b-type patient $f_{a,b} = 1$ otherwise $f_{a,b} = 0$
d_g	How many patients can there be one employee of type *g* $(g \in G)$
$o_{t,g}$	How many employees of type *g* are in the hospital of *t* $(u \in U, t \in H)$
z_t	Current number of patients in the hospital *t* $(t \in H)$
$c_{p,b}$	If patient *p* has been classified as type *b* $c_{p,b} = 1$ otherwise $c_{p,b} = 0$
$r_{p,h}$	If the patient is in a hospital h $r_{p,h} = 1$ otherwise $r_{p,h} = 0$ $(p \in P, h \in H \cup \{s\})$
$e_{p,t}$, $e_{p,h}$	Time to bring the patient *p* to the hospital *t* $(p \in P, t \in H)$
j_p	Time required to deliver the patient *p* to the hospital
m	Very large constant
Calculated parameter	
$s_{p,a}$	If patient *p* can be overcome by ambulance a $(p \in H, h \in H)$
Parameters of the penalty function	
k_p	Penalty for failure to deliver the patient *p* within the required time $(p \in P)$
n_p	Penalty if the patient *p* cannot be delivered to the hospital
Decision variables	
$X_{a,p,h,t}$	If the ambulance *a* transports patient *p* from hospital *h* to hospital *t* $(a \in A, p \in P, h \in H \cup \{s\}, t \in T)$
Y_p	If the patient *p* cannot be delivered within the required time $Y_p = 1$ otherwise $Y_p = 0$ $(p \in P)$
U_p	If the patient *p* cannot be delivered to the hospital due to lack of places $U_p = 1$ *otherwise* $U_p = 0$ $(p \in P)$

Table 2. Description of the problem constraints

Con.	Description of constraints
(2)	The number of patients in a specific category delivered to the hospital does not exceed the number of hospital beds of the given type
(3)	Each ambulance is dispatched not more than once in the given time interval (with the exception of virtual ambulances)
(4)	The ambulance transports only patients belonging to specific categories.
(5)	Each patient is delivered to the hospital
(6)	The virtual ambulance moves within the hospital only
(7)	The patient is delivered to the hospital within the required time
(8)	The number of patients delivered to the hospital does not exceed the quantitative standards related to medical staff
(9)	The given patient can be transported by the given ambulance
(10)	Decision variables are binary

4 Methods and Implementation

The proposed mathematical model (1) .. (10) of the problem (Sect. 3) has become a central element of the decision support system regarding the allocation of patients in hospitals. In order to take into account the dynamics of changes in the availability of beds, medical transport and personnel, medical equipment etc., an iterative method of solving the modeled problem in successive time intervals (τ) was proposed with the simultaneous update of the model parameters resulting from the obtained solution. For this reason, all model parameters were divided into two sets. The first *parameter_1* specifies the parameters whose values change when the problem is solved for the period τ. The second set named *parameters_2* defines parameters with the same value for all periods τ. The diagram of the iterative approach is shown in Fig. 2. The methods of mathematical programming (including Branch & Bound method) and constraint programming (in particular constraint propagation as presolving method) were used to solve the model. Due to the nature of the modeled problem (NP-hard), with its larger size, the proposed methods may turn out to be ineffective. In the future, the hybrid approaches will be proposed, using dedicated heuristics, metaheuristics and exact methods and algorithms like constraint logic programming [12], accelerated cuckoo optimization algorithm [13], etc.

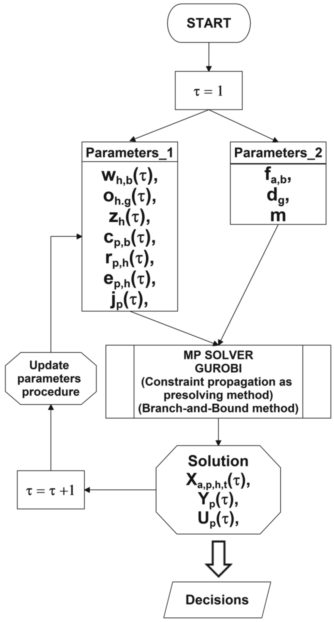

Fig. 2. Iterative approach to solving modeled problem and generate decisions in period τ

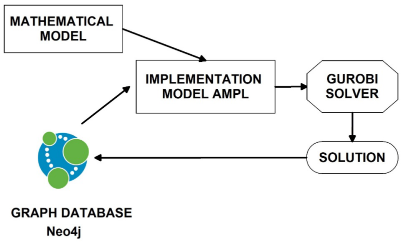

Fig. 3. Model implementation and optimization scheme

The model was implemented using AMPL modeling language, NoSQL graph database (Neo4j), into which the data instances of the modeled problem (parameters, obtained outcomes, etc.) were uploaded, and GUROBI mathematical and constraint programming solver. The method of implementation and optimization of the model is illustrated schematically on Fig. 3.

5 Computational Experiments

In order to verify the proposed model, a number of computational experiments were conducted. In the first phase, optimization was performed for the selected problem data instance *Example_1*(characterized by the following parameters: 4 hospitals, 15 patients, of which 7 reported to emergency departments by themselves, 10 ambulances, etc. – details are provided in Table 3). The results are provided in Table 4 and as a data base

Table 3. Parameter values for *Example_1*

h	z_h
1	400
2	768
3	456
4	989

b
1
2
3

g	d_g
1	50
2	50
3	70
4	80
5	80

h	b	$w_{h,b}$
1	1	6
1	2	4
1	3	4
2	1	3
2	2	3
2	3	3
3	1	2
3	2	2
3	3	3
4	1	1
4	2	1
4	3	3

h	g	$o_{h,g}$
1	1	8
1	2	9
1	3	8
1	4	7
1	5	7
2	1	20
2	2	20
2	3	15
2	4	12
2	5	12
3	1	18
3	2	29
3	3	10
3	4	8
3	5	8
4	1	20
4	2	22
4	3	17
4	4	16
4	5	16

a
1
2
3
4
5
6
7
8
9
10

a	b	$f_{a,b}$	a	b	$f_{a,b}$
1	1	1	6	1	1
1	2	1	6	2	1
2	1	1	7	1	1
3	1	1	7	2	1
3	2	1	8	3	1
3	3	1	9	3	1
4	3	1	10	2	1
5	3				

p	b	$c_{p,b}$	p	b	$c_{p,b}$
1	1	1	9	2	1
2	1	1	10	1	1
3	3	1	11	1	1
4	3	1	12	3	1
5	3	1	13	3	1
6	1	1	14	3	1
7	1	1	15	3	1
8	2	1			

p	j_p
1	100
2	100
3	70
4	70
5	70
6	100
7	100
8	880
9	80
10	100
11	100
12	70
13	70
14	70
15	701

p	h	$r_{p,h}$	$e_{p,h}$	p	h	$r_{p,h}$	$e_{p,h}$	p	h	$r_{p,h}$	$e_{p,h}$	p	h	$r_{p,h}$	$e_{p,h}$
1	1	1	0	5	1	0	60	9	1	0	70	13	1	0	15
1	2	0	53	5	2	0	68	9	2	0	64	13	2	0	65
1	3	0	86	5	3	0	75	9	3	0	63	13	3	0	99
1	4	0	70	5	4	0	18	9	4	1	0	13	4	0	85
2	1	0	15	6	1	0	86	10	1	0	69	14	1	0	58
2	2	0	65	6	2	0	36	10	2	0	73	14	2	0	9
2	3	0	99	6	3	1	0	10	3	0	77	14	3	0	38
2	4	0	86	6	4	0	63	10	4	0	15	14	4	0	73
3	1	0	70	7	1	0	70	11	1	0	69	15	1	0	70
3	2	0	64	7	2	0	64	11	2	0	51	15	2	0	64
3	3	0	63	7	3	0	63	11	3	0	48	15	3	0	63
3	4	1	0	7	4	1	0	11	4	0	14	15	4	1	0
4	1	0	91	8	1	0	70	12	1	0	81				
4	2	0	55	8	2	0	64	12	2	0	47				
4	3	0	71	8	3	0	63	12	3	0	68				
4	4	0	119	8	4	1	0	12	4	0	111				

graph on Fig. 4. Seven patients were transported to the hospitals, 2 were transported from the emergency departments to other hospitals, and the remaining 6 patients were admitted to the hospitals to which they reported. In the second phase of the experiments, the efficiency of the proposed model and implementation thereof was analyzed. The calculations were performed for 10 data instances which differed in terms of the number of hospitals, ambulances, patients, etc. The time of calculations turned out to be very short, i.e. 1–2 s. In some cases, the solution was not satisfactory, because the hospitals ran out of resources, as evident from the non-zero values of additional variables (instance 5, 7, 8 and 9). The results are provided in Table 5. Calculations were performed on a workstation with the following hardware configuration: Intel (R) core (TM) i5 4200 M CPU @ 2.50 GHZ processor, 8 GB RAM, Windows 10.

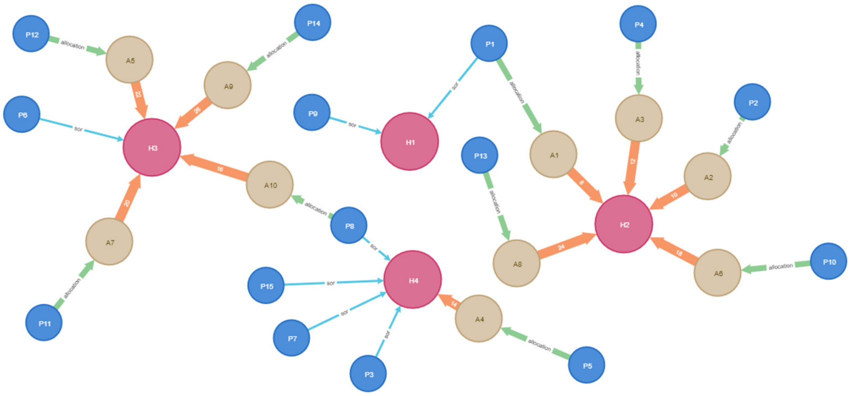

Fig. 4. Results for *Example_1* in the form of a database graph

Table 4. Results for *Example_1* (i-virtual ambulance, s-virtual hospital)

a	p	h	h	a	p	h	h
1	1	1	2	i	9	4	4
2	2	s	2	6	10	s	2
i	3	4	4	7	11	s	3
3	4	s	2	5	12	s	3
4	5	s	4	8	13	s	2
i	6	3	3	9	14	s	3
i	7	4	4	i	15	4	4
10	8	4	3				

Table 5. Results for second part of calculation experiments -number of non-zero additional variables in brackets (Y_p-U_p)

En	Number of hospitals	Number of patients	Number of ambulances	Calculation time	Number of variables	Additional variables
E1	4	6(1)	10	1	792	12(0-0)
E2	4	8(2)	10	1	1056	16(0-0)
E3	4	10(3)	10	1	1320	20(0-0)
E4	4	15(7)	10	1	1980	30(0-0)
E5	6	12(5)	10	1	3048	24(1-0)
E6	6	15(8)	10	2	3810	30(0-0)
E7	8	20(8)	20	2	13828	40(2-0)
E8	8	25(8)	20	2	15420	50(2-0)
E9	8	35(20)	20	2	16180	75(2-0)
E10	10	40(20)	25	2	28350	80(0-0)

6 Conclusion

The proposed resource-constrained model of optimizing patient-to-hospital allocation will support numerous decisions in the fields of logistics and resources directly related to saving the lives of patients during a pandemic. There are two main ways the model can be used. First, to reactively support planning decisions. This arises from the fact that the proposed implementation of the model makes it possible to integrate it with a database, which can be updated on a continuous basis by hospitals, emergency ambulance service, etc. Furthermore, as shown by the calculation experiments, the model is characterized by short time-to-solution (optimization), which allows the decision-maker/operator to make ongoing optimal decisions on patient allocation, or to identify resource deficits (non-zero values of U_p, Y_p), in order to make the appropriate allocation. The second way the model can be used is to proactively support planning decisions in the case of a hypothetical pandemic. It will be possible to determine which hospitals have sufficient resources, and identify and address potential deficits, whether the ambulance service has the necessary fleet of ambulances for a specific type of pandemic, i.e. a specific number of patients in a given category in subsequent periods of time.

In future studies, it is planned to introduce mechanisms to the model which will make it possible to take into account the potential absences of healthcare personnel (infections, work shifts, etc.). In subsequent versions of the implementation, it is also planned to use a proprietary hybrid approach [12, 14–16], fuzzy logic [17, 18], and neural networks [19] etc.

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