

Transportation Scheduling Method for Patients in MCI using Electronic Triage Tag

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Abstract—A method for determining the priority of patients treatments called *triage* is used to direct rescue activities during a Mass Casualty Incident (MCI). In present disaster medicine, patients with the highest priority (with a red tag attached) are transported to the hospital in random order, although their expected probability of survival (Ps) may differ. Recently, an electronic triage tag (E-triage) that is able to sense the patient's vital signs in real time has been developed. Moreover, based on the sensed vital signs, the physician's remarks about the patient, and medical treatment statistics, each patient's Ps can be estimated. In this paper, utilizing E-triage and the latest medical treatment statistics, we first formulate the problem of determining a transportation order of patients that maximizes the life-saving ratio, given the latest vital signs and temporal variation in the survival probability of each patient, the time for an ambulance to transport the patient to an appropriate hospital, and other factors. Since this problem is NP-hard, we propose a heuristic algorithm based on a greedy method that transports patients in the increasing order of their expected survival probability at the time they will arrive and be treated at the hospital. To prevent the case that rescuing a patient earlier results in the death of two or more patients, our proposed algorithm also considers, for each low survival probability patient, the two cases of rescuing the patient or not and derives the transportation order that keeps the most patients alive. Through simulations, we confirmed that the proposed method can transport about a 25% larger number of patients to the hospital before their expected survival probability gets lower than a marginal probability than conventional methods.

Keywords-ambulance scheduling; disaster management; disaster medicine; electronic triage.

I. INTRODUCTION

Recently, natural disasters, terrorist attacks, and large-scale accidents have occurred all over the world. In a mass casualty incident (MCI, hereafter), rescue teams are likely to be confronted with too many patients, overwhelming the medical resources, such as the number of rescuers (responders, paramedics, and physicians), ambulances, and the capacities of hospitals. The lack of adequate medical resources makes it difficult to allocate necessary resources to each patient, resulting in a *Preventable Trauma Death (PTD)* in some cases. In such events, the rescuers are supposed to apply *triage* to patients, which is a paper tag with four categories (red is the most serious) attached to each

patient to determine the priority of the medical treatment among the patients in a short time. Patients with paper tags are then carried to the hospital based on their categories. However, attaching paper tags is a time consuming task and prone to human errors. Moreover, inherently, paper tags cannot reflect changes in a patient condition for the worse. Paper-based triage, then, has the following critical drawback: there is no priority among the patients of the same category and the rescue commander cannot grasp the patients' conditions in detail, resulting in random order of transportation of the same category patients. Therefore, in an MCI, the transported patient is not always the one who needs first aid most urgently.

Worldwide, many research efforts have examined ways to improve the life-saving ratio and efficiency in an MCI. There is a project "Advanced Wireless Communication Technology for Efficient Rescue Operations" that is developing an electronic triage tag (E-triage) [1]. The E-triage is a small embedded device that can sense the vital signs of patients such as heart rate, respiration rate, and blood oxygen level (SpO₂) in realtime. Moreover, the E-triage can send the sensed information to a medical server through built-in ZigBee radio communication. E-triage can help reduce the triage operation time, avoid human error, and quickly reflect changes in the patient condition.

Some studies focused on estimation of the patient's survival probability from medical statistics have also been applied to emergency medicine. The *Trauma and Injury Severity Score (TRISS)* methodology estimates the *probability of survival (Ps)* based on the patient's vital condition and the site of trauma [2]. Ps has a closer relationship to the actual mortality rate and it is known that more than 75% of the patients whose Ps is under 30% at the time of arrival at the hospital will die. Utilizing E-triage and the survival probability estimation method together, we believe that it is possible to schedule a transportation order of patients that maximizes the overall life-saving ratio.

In this paper, we propose a new method for scheduling a near-optimal transportation order of the patients from an MCI, taking into account available medical resources and estimating the temporal deterioration of their survival

probability. The purpose of the proposed method is to maximize the average survival probability of all patients at the time of arrival at the hospital as well as the number of patients whose survival probability is more than a marginal level $\alpha\%$ (where α is constant number, such as 30) while satisfying several constraints such as the hospital capacity. The transportation scheduling problem of patients scattered over multiple disaster sites is NP-hard and the number of possible schedules exponentially increases as the number of hospitals, ambulances, disaster sites, and patients increases. Therefore, it is difficult to derive an optimal solution in real-time. In the proposed method, assuming that the vital signs of each patient and an estimation function of P_s 's temporal deterioration are available from a server, we calculate a value called the *marginal treatment time* when each patient's survival probability gets lower than a predefined marginal level $\alpha\%$, and generate a transportation list based on the ascending order of the patients' marginal treatment time. However, this greedy method may produce cases where transporting a patient will cause two or more other patients' death (i.e., the hospital arrival time will be after their marginal treatment time). To prevent such cases, we propose a more sophisticated algorithm that explores, for each patient of top k order in the list calculated by the greedy algorithm, the two cases of rescuing the patient or not, and derives the transportation order that keeps the most patients alive.

Through computer simulations, we compared our proposed method with some existing approaches. As a result, we confirmed that the proposed method transported about a 25% larger number of patients to the hospital before their marginal treatment time than those existing methods.

II. RELATED WORK

In this section, we briefly survey related work in the following two categories: disaster medicine and patient transportation scheduling.

A. Application of ICT to Disaster Medicine

Unlike ordinary medical treatment where sufficient medical resources are provided for each patient, in an MCI, rescuers must provide the best treatment for many patients with limited time and resources. In primary triage, the responders attach paper tags to patients according to the START method [3]. Four color codes are used to distinguish the severity of the patients' injury. Patients with red tags have the highest priority and need an immediate treatment for survival. For patients with yellow tags, a few hours delay in treatment may not influence their survival probability. Patients with green tags do not need a specific treatment. Patients with black tags are already dead or considered to have no chance of survival and are given null priority.

Rescuers transport patients to a first aid station within the disaster site according to their color code and secondary triage is performed there. In secondary triage, paramedics

perform a re-triage, schedule the transportation order of the patients, and decide the hospitals to which they will be transported. Secondary triage aims to increase the life-saving ratio by determining in a short time the transportation order of patients taking into account the severity of their injuries. In an MCI, this operation must be finished within one minute for each patient. However, the paper triage tag method has the following problems:

- Even when the patients' conditions change, their triage tags cannot reflect the change.
- Since there is no priority among patients with the same color tag, they are transported in random order.
- Human errors cannot be avoided.
- The responder's feeling of oppression (on a possible wrong diagnosis) in deciding the color code for each patient is heavy.

1) *Electronic Triage Tag*: Many studies have addressed computerization of the triage method. Gao et al. developed the AID-N electronic triage system with electronic triage tags using biomedical sensors [4] [5]. This system monitors the vital signs of patients and delivers the patient's information to first responders. The Advanced Wireless Communication Technology for Efficient Rescue Operations project also studied computerization of the triage method [1] [6] [7] [8]. This project developed an embedded sensor device called the *electronic triage tag (E-triage)* capable of sensing a patient's vital signs and wirelessly sending/receiving the sensed information with ZigBee. The vital signs monitored by the E-triage are the heart rate, respiration rate, and blood oxygen level (SpO₂). Moreover, the E-triage performs a semiautomatic triage using the patient's vital signs based on the START method and sends the collected information as well as the triage result (color code) to the server located at the rescue commander's site. This project aimed to construct an Emergency Medical Service (EMS) system that monitors, aggregates, and visualizes patients' information in real-time. Suseki et al. proposed a system that collects vital signs from patients equipped with E-triage in realtime and decides the priority of treatment based on deviation of the patient's vital signs from a predefined threshold [9].

2) *Estimation of Probability of Survival*: The TRISS method, which combines Revised Trauma Score (RTS) and Injury Severity Score (ISS), is used to estimate the probability of survival for patients [2]. RTS can be calculated from vital signs such as the respiration rate and blood pressure which can be measured. On the other hand, ISS can be calculated based on the patient's diagnosis given by a physician.

Recently, various trauma data have been registered in a trauma database. Some studies have provided more accurate models to calculate the patient's probability of survival than the TRISS method by using a trauma database. A model called the Harborview Assessment for Risk of Mortality (HARM) was developed using 33,990 trauma data items

registered in the Harborview Medical Center Trauma Registry [10]. In addition, the Trauma Mortality Prediction Model (TMPM) was developed using trauma data from 702,229 patients who sustained 2,207,823 instances of 1,322 distinct AIS injury codes registered in the National Trauma Data Bank (NTDB) [11]. Japan Trauma Care and Research (JTCR) makes up a report on trauma data registered in the Japan Trauma Data Bank (JTDB) every year and describes the relationship between P_s and the actual mortality rate in the report [12]. The above research results suggest that if enough trauma data can be collected, it will enable more accurate P_s estimation and thus a more accurate temporal P_s deterioration function than TRISS.

B. Patient Transportation Scheduling in MCI

In current disaster medicine, patient transportation scheduling just transports severe-condition patients (red tags) at random. The rescue commander collects information about patients and capacities of hospitals using a cell phone, a transceiver, and/or a memo, then schedules the patients' transportation order based on this collected information. Thus, the transportation order is likely to be based on the order in which the information is received. However, the transportation order by this method may be far from optimal since it cannot adapt to changes in the patients' conditions and newly arriving casualties. We need a better scheduling method to transport patients to hospitals.

Jotshi et al. proposed a transportation scheduling method considering the existence of errors in the collected information about casualties [13]. In this method, the disaster area is divided into clusters and some ambulances are allocated to these clusters depending on the following three factors: the number of patients in the cluster, the distance from the ambulance to the cluster, and the distance from the cluster to the hospital. In this method, the ambulances are dispatched to clusters rather than to patients so that an error in the patient's information does not result in a waste of the transportation resource. However, since this method does not focus on the injury type and/or the condition of the patient, it cannot identify patients who require earlier treatment for survival than others.

C. Contribution of the Proposed Method

We focus on the transportation scheduling problem after the secondary triage of the patients. Using the temporal survival probability deterioration function, we define a problem that maximizes the number of patients transported to hospitals within their marginal treatment time (the time when each patient's survival probability gets lower than a predefined marginal level). Since this problem is NP-hard as we prove in Section IV-A, we propose a heuristic algorithm that provides a semi-optimal solution in a short time, taking into account the availability of the hospitals, the locations of first-aid stations, the number of ambulances, and the

number of patients. We also conduct computer simulations to show the performance of the proposed method, supposing an instance of a large MCI.

III. PATIENTS TRANSPORTATION SCHEDULING PROBLEM

This section describes assumptions for the target MCI and formulate the patients transportation scheduling problem.

A. Assumptions

We assume that several on-site first aid stations and a rescue command center are set up when an MCI happens. In the command center, the patients' transportation schedule is planned and ambulances are dispatched to the rescue sites. We also assume that E-triage tags have already been attached to all patients in the rescue sites. Thus, the rescue command center can grasp all patients' vital signs and their location in real time. Moreover, the center can grasp the hospitals' information such as capacity, possible treatment types, location and so on, and know the transportation time between any pair of on-site first aid stations and hospitals. Based on the above information, the center makes a patients' transportation schedule and dispatches ambulances to some of the on-site first aid stations to transport patients as scheduled. We assume that the temporal deterioration of survival probability for each patient p at time t can be estimated by a function $P_s(p, t)$ that is calculated based on the latest vital signs and the injury type of the patient.

According to the statistics in the Japanese Surgery of Trauma Data Bank, 95% of patients eventually die if they cannot receive medical treatments before their survival priority gets below 10%. The mortality rate is 80% with survival probability below 20%, and 75% with survival probability below 30%. This means that in order to increase the life-saving ratio, we need to transport patients to a hospital before their survival probability falls below a certain threshold. We denote this threshold by α .

B. Problem Definition

Our target problem is to derive a schedule that maximizes the number of patients who are transported from rescue sites to hospitals before their survival probability gets lower than α . Let P , S , H , and Am denote the set of patients, the set of rescue sites (first-aid stations), the set of hospitals, and the set of ambulances, respectively. Let $tl(p) = \langle p, s, h, at, ps \rangle$ denote the transportation information of a patient $p \in P$ existing in the first aid station $s \in S$ where $h \in H$ is a hospital to which p is transported, at is the estimated hospital arrival time, and ps is p 's survival probability at time at . Let $am.TL$ denote the list of the transportation information of patients who are transported by ambulance am . For each hospital $h \in H$, let $h.cap$ denote the latest accommodation capacity.

Table I
SYMBOLS USED IN PROBLEM FORMULATION

Symbol	Meaning	Symbol	Meaning
P	set of patients	p	patient
S	set of rescue sites	s	on-site first aid station
H	set of hospitals	h	hospital
Am	set of ambulances	am	ambulance
TL	list of transportation information	$tl(p)$	transportation information for patient p
$h.cap$	accommodation capacity of hospital h	at	estimated arrival time at hospital
ps	survival probability at the hospital arrival time		

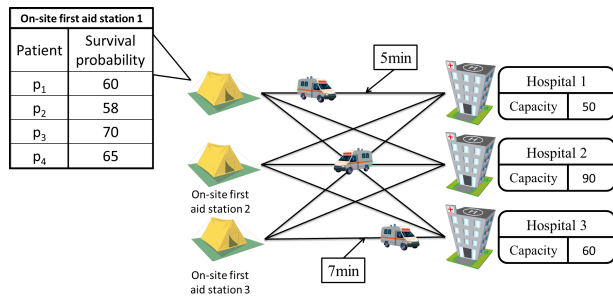


Figure 1. A Network Model for the Problem of Patients Transportation

We summarize the symbols used for the problem definition in Table I.

The patient transportation process from rescue sites to hospitals can be represented by a network as shown in Figure 1. Our target problem is deciding an optimal transportation schedule consisting of the transportation information $tl(p)$ of each patient p .

In a disaster area, many people are injured and transported to several on-site first aid stations S . After a patient receives first aid, the patient will be transported to an appropriate hospital selected from several hospital candidates H . To transport patients, several ambulances Am shuttle between on-site first aid stations and hospitals. We assume that a function $Tt(s, h)(s \in S, h \in H)$ can derive the time of an ambulance to move from on-site first aid station s to hospital h . For example, when an ambulance am located at hospital h_1 transports a patient p from on-site first aid station s to a hospital h_2 , the hospital arrival time at can be calculated by $at = t + Tt(s, h_1) + Tt(s, h_2)$. According to the assumptions in III-A, the survival probability of patient p at time at can be derived by the estimation function $Ps(p, at)$. Based on the above conditions, the transporting schedule TL for all patients can be derived. Let $count(Am, h)$ denote the

number of patients transported to hospital h in $am.TL$. The number of patients to be transported to hospital h must not exceed the accommodation capacity $h.cap$, this constraint is denoted as follows.

$$\forall h \in H, count(Am, h) \leq h.cap \quad (1)$$

The transported patient's survival probability must be no less than α , this constraint is denoted as follows.

$$\forall am \in Am, \forall tl \in am.TL, tl.ps \geq \alpha \quad (2)$$

Our goal is to maximize the number of transported patients while satisfying constraints (1) and (2). We also want to increase the average survival probability of the transported patients. Thus, we define the objective function by the following equation (3).

$$\begin{aligned} \text{Maximize : } & \frac{\sum_{am \in Am} \sum_{tl \in am.TL} tl.ps}{\sum_{am \in Am} |am.TL|} \\ & + \sum_{am \in Am} |am.TL| \\ \text{subject to } & (1) \text{ and } (2) \end{aligned} \quad (3)$$

IV. AMBULANCE SCHEDULING ALGORITHM

A. Problem complexity

We prove that the transportation scheduling problem defined in Section III is NP-hard by reducing the shortest Hamilton path problem known as a NP-hard problem to this problem.

The shortest Hamilton path problem is a problem to derive the shortest path that traverses each vertex in the given graph exactly once. Let $G = (V, E, cost)$ denote a undirected graph with weights, where V, E and $cost$ are the set of vertices, the set of edges, and the weight function $cost : E \rightarrow \mathbf{R}$.

Below, we transform a graph G to an instance of the transportation scheduling problem. We use V' and E' as variables representing the set of vertices and the set of edges, respectively. Initially, these sets are empty.

In the graph $G = (V, E)$, for each edge $(u, v) \in E$, we make two edges (u, w) and (w, v) by introducing a new vertex w which is not an element of $V \cup V'$, and put these two edges in E' and w in V' . Then, we construct a new graph $G' = (V \cup V', E', cost')$ where we define a new cost function $cost'$ as follows.

$$\forall (u, v) \in E \exists w \in V' \quad \begin{aligned} cost(u, v) \\ = cost'(u, w) + cost'(w, v) \end{aligned} \quad (4)$$

$$\forall u \in V \left(\prod_{(u, w) \in E'} cost'(u, w) \right) = 0 \quad (5)$$

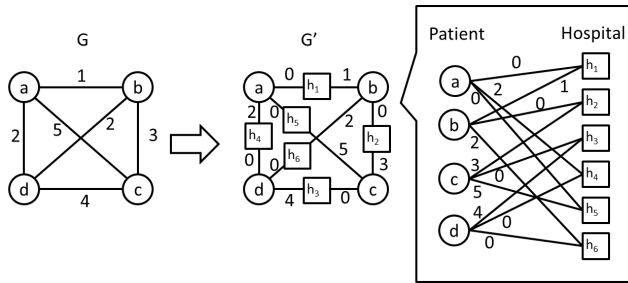


Figure 2. Transforming a graph to instance of transportation scheduling problem

The above equation (4) shows that the sum of the weights of two new edges in E' is equal to the weight of the original edge in E . The equation (5) shows that the cost of at least one edge that connects to each vertex u in V must be 0.

An example of transformation is shown in Figure. 2. In G' , we regard that V and V' correspond to the set of patients and the set of hospitals, respectively. In the figure, patients are $V = \{a, b, c, d\}$ and hospitals are $V' = \{h_1, h_2, h_3, h_4, h_5, h_6\}$. We also regard that the cost for each edge in E' corresponds to the moving time of an ambulance between the patient's location and the hospital. Moreover, let us assume that the expected survival probability of each patient monotonically decreases and equation (2) always holds.

From Figure. 2, it is obvious that solving the transportation scheduling problem for graph G' is equivalent to solving the shortest Hamilton path problem in graph G . Therefore, the shortest Hamilton path problem is a special case of the transportation scheduling problem and thus the latter problem is NP-hard.

B. Heuristic algorithms

Since the transportation scheduling problem is NP-hard, it is difficult to derive the optimal solution in a practical time. Therefore, in this section, we propose heuristic algorithms that derive a semi-optimal solution in a short time. First, we give a greedy algorithm called the *baseline algorithm* that transports patients in increasing order of their expected survival probabilities when arriving at the corresponding hospitals. Then, we give a more sophisticated algorithm called the *Depth-k Brute-Forth Search (DkbFS) algorithm* that investigates for each patient of the ordered list decided by the baseline algorithm, both cases of transporting the patient to the hospital or skipping the patient to explore the possibility of saving more patients with the later order.

1) *Baseline algorithm*: To increase the patients' survival probability, each patient must be transported to an appropriate hospital while the patient's expected survival probability

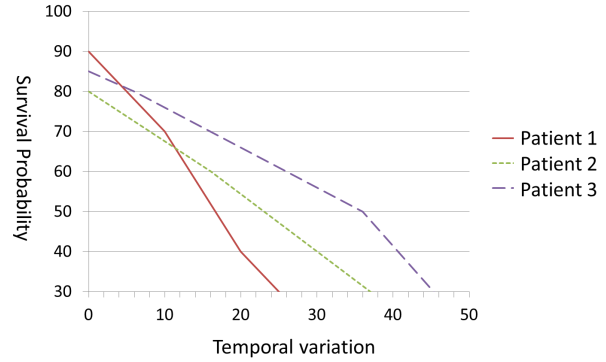


Figure 3. Example of temporal variation of survival probability

Algorithm 1 Baseline algorithm

Input: Ordered patient list PL , set of hospitals H , set of ambulances Am

- 1: $TL \leftarrow []$
- 2: **for** $i = 0; i \leftarrow i + 1; i < |PL|$ **do**
- 3: $h_c \leftarrow nearHospital(H, p_i.pos)$
- 4: $am_c \leftarrow fastAmbulance(Am, p_i.pos, h_c)$
- 5: $at_c \leftarrow am_c.nowtime + Tt(am.pos, p_i.pos) + Tt(p_i.pos, h_c.pos)$
- 6: $ps \leftarrow Ps(p_i, at_c)$
- 7: **if** $ps \geq \alpha$ **then**
- 8: $tl \leftarrow \{am_c, p_i, p_i.pos, h_c, at_c, ps\}$
- 9: $TL.append(tl)$
- 10: $am_c.nowtime \leftarrow at_c$
- 11: $am.pos \leftarrow h_c.pos$
- 12: $h_c.cap \leftarrow h_c.cap - 1$
- 13: **end if**
- 14: **end for**
- 15: **return** TL

remains higher than the threshold α . Thus, we use the expected survival probability estimation function $Ps(p, t)$ and compute the time t called *marginal treatment time* for each patient p such that $Ps(p, t) = \alpha$. Then, we build the patients list PL where the patients are sorted in increasing order of their marginal treatment time. Patients with the earlier order need earlier transportation. For example, if there are three patients p_1, p_2 , and p_3 whose expected survival probability estimation functions are given in Figure. 3 and $\alpha = 30\%$, the patients transportation list PL will be $[p_1, p_2, p_3]$.

Given the patients transportation list PL , the set of hospitals H , the set of ambulances Am , and other information such as the ambulance travel time between each patient's on-site first aid station and each hospital, we compute the ambulance scheduling list TL indicating in what order, when, and where each ambulance transports patients. We

show the baseline algorithm in Algorithm 1.

The baseline algorithm processes patients in the specified order by PL and assigns for each patient the ambulance which can transport the patient to the nearest hospital with a capacity (Algorithm 1, line 3) in the shortest time (line 4). Then, the algorithm computes the time at which the patient reaches the hospital (line 5) and the patient's expected survival probability at that time (line 6).

Since the baseline algorithm sequentially processes patients in the order specified in PL , it cannot avoid the case where two or more patients cannot be transported to the hospital before their marginal treatment time by transporting a patient with earlier order. In the following subsection, we propose an extended version of the algorithm that can avoid the above case and maximize the number of patients who are transported to the hospitals before their marginal treatment time.

2) *DkBFS (Depth-k Brute-Forth Search) algorithm:* We want to explore the possibility of "making two or more patients survive by giving up one patient." Thus, we consider for each patient p_i in PL the two cases where p_i is transported and not. If we consider two cases for each patient's transportation in PL , that is, 2^n patterns overall, we can find the optimal transportation scheduling list. However, deriving the optimal list for a large value of n is not feasible. Hence, we design the *DkBFS* algorithm so that it searches 2^k transportation patterns for the first k patients in PL and applies the baseline algorithm to the remaining $n-k$ patients for each pattern.

We say that a patient is *rescued* if the patient's expected survival probability at the time when the patient reaches a hospital is no less than α .

We show the details of the algorithm below.

- (1) Compute the number of rescued patients for all cases where each of first k patients in PL is transported and not transported. The baseline algorithm is applied to $(k+1)$ -th and later patients.
- (2) Select the pattern that has the largest number of rescued patients and put the rescued patients and their order in the pattern into the transportation scheduling list TL .
- (3) Remove the first k patients from PL and repeat the steps from (1) while PL is not empty. Finish if PL becomes empty.

For example, when $PL = [p_0, p_1, p_2, p_3, p_4, p_5]$ and $k = 3$, the *DkBFS* considers all possible patterns of transporting each of three patients p_0, p_1 and p_2 or not. The patterns are: $\{p_0\}, \{p_1\}, \{p_2\}, \{p_0, p_1\}, \{p_0, p_2\}, \{p_1, p_2\}, \{p_0, p_1, p_2\}$.

In the case of $\{p_0\}$, the algorithm transports p_0 even if equation (2) does not hold¹, but transports neither p_1 nor p_2 . The baseline algorithm is applied to the remaining

¹We consider this case because p_0 cannot reach the hospital while p_0 's expected survival probability is over α , but more patients followed by p_0 might be rescued due to ambulance movement.

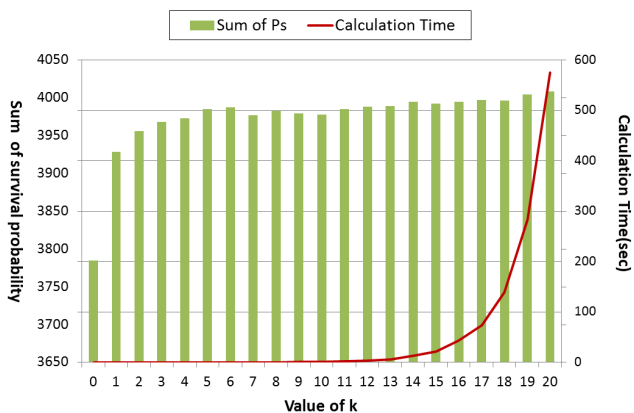


Figure 4. Computation time for different values of k

patients p_3, p_4 and p_5 , and the number of rescued patients (with at least α survival probability) as well as the average expected survival probability are derived. This process is applied to other patterns, and the pattern with the highest value for the objective function (3) is selected and added to the transportation scheduling list TL . Then, the same process is applied to the next three patients (in this example, only two are remaining).

3) *Deciding the best value for k:* To know the best value for k , we measured the total sum of expected survival probabilities for 100 patients and the computation time by changing the value of k between 0 and 20. We used the same experimental configuration as in Section V-A. We show the result computed by the average of 20 runs in Figure 4. Here, note that the case of $k = 0$ corresponds to the baseline algorithm.

Figure 4 suggests that the total sum of expected survival probability increases as k increases. In this example, the value almost converged when k is over 5. The computation time is reasonable while k is less than 13, but rapidly increases as k increases beyond 13 since the algorithm complexity is $O(2^k)$.

V. PERFORMANCE EVALUATION

We conducted simulation experiments to confirm performance of the proposed method. We compared our method with several conventional methods and show the results in the following Section V-B.

A. Simulation Configuration

We consider a large-scale disaster in the simulation experiment. The assumptions of the disaster area are collected in Table II.

Table II
THE STATUS OF THE ASSUMED DISASTER AREA

# On-Site First Aid Stations	# Patients (red)	# Hospitals	# Ambulances	Transportation Time (1-way) 3min – 18min
20	100	8	24	

Table III
SIMULATION RESULTS FOR PATIENTS WITH TYPICAL Ps FUNCTIONS

		DkBFS	BA	Jotshi-G	Jotshi-R	Greedy
# Rescued Patients (Ps ≥ 30)	Max	98	98	82	68	95
	Avg	92	89	68	59	64
	Min	85	80	39	47	44
Avg. Ps (rescued)	Max	47	44	50	72	74
	Avg	43	41	46	60	57
	Min	40	38	43	51	43
Avg. Ps (all)	Max	44	42	38	40	42
	Avg	40	37	30	36	36
	Min	36	32	19	33	31

In the disaster area, there are a total of 20 on-site first aid stations, and at each station there are 5 seriously-injured (red tag) patients. There are 8 hospitals located in the area where each hospital has 3 ambulances. Each patient’s initial survival probability is decided at random between 70% and 90%. We suppose that there are four types of Ps estimation functions that make Ps of a patient with 100% initial Ps gradually fall to 0% in 55, 65, 75, and 90 minutes, respectively. These 4 types of Ps estimation functions are equally distributed among 100 patients (25% for each). The conventional methods for comparison are shown below.

Greedy method: transports the current lowest survival probability patient first.

Jotshi’s method [13]: considers only the moving time between first aid stations and hospitals, and is denoted by *Jotshi-R*. *Jotshi-R* is close to the actual rescue transportation activity. However, this method does not decide patient transportation order and thus transports patients in random order. For fairness in comparison, we prepared a modified version called *Jotshi-G* method, which transports the current lowest Ps patient first in each on-site first aid station.

Baseline algorithm: this method was described in Section IV-B1.

Based on the results of preliminary experiments, we set the value of k to 10, and the value of α to 30%.

We simulated 1000 times and calculated average, minimum, and maximum numbers of rescued patients (patients who arrived the hospital with Ps over α) and their survival probability.

B. Results and Discussion

The simulation results are shown in Table III.

Table IV
SIMULATION RESULTS FOR PATIENTS WITH RAPIDLY DECREASING Ps FUNCTIONS

		DkBFS	BA	Jotshi-G	Jotshi-R	Greedy
# Rescued Patients (Ps ≥ 30)	Max	95	95	78	63	73
	Avg	85	82	63	54	51
	Min	74	70	43	44	37
Avg. Ps (rescued)	Max	47	44	47	71	81
	Avg	43	41	44	61	64
	Min	40	38	42	54	53
Avg. Ps (all)	Max	41	39	35	37	39
	Avg	37	33	28	33	33
	Min	32	29	19	29	28

1) *Number of Rescued Patients:* In Table III, the proposed method (DkBFS) showed the best performance among all methods. The greedy method transports the current most-serious (lowest Ps) patient first. So, if there is no changes in patient conditions, it achieves a good result (95 rescued patients for the best case). However, for the cases that patients’ conditions change, the results become worse (the average and minimum numbers of rescued patients are 64 and 44, respectively). The results of Jotshi-G are similar to the greedy method, but it showed a better performance than Jotshi-R since Jotshi-G considers patients’ current Ps. However, like the greedy method, Jotshi-G does not consider changes in patients’ conditions. For this reason, the difference from the proposed method is large. The performance of the baseline algorithm (BA) is similar to the DkBFS method, but it does not optimize the schedule, causing a gap from the DkBFS method.

2) *Average Survival Probability:* Average survival probability of rescued patients (rescued) of Jotshi-R and the Greedy method is higher than the proposed methods but the average survival probability (all) of the proposed methods is higher. These existing methods transported some patients with higher survival probability, but patients who need earlier treatment were transported later. As a result, with these methods, many patients with higher current Ps (priority should be low) are transported earlier, but the patients with lower Ps (priority should be high) are transported late and do not arrive before the marginal treatment time. On the other hand, since our proposed methods can transport patients taking into account expected Ps at the hospital arrival time, the number of rescued patients is higher than other methods.

3) *Additional Experiments:* We also conducted additional simulation experiments in two cases where patients’ Ps more rapidly and more slowly decreases, respectively. For this purpose, we changed the distribution of the four Ps estimation functions used in Section V-B2 so that 40, 30, 20, and 10% of patients have the Ps functions that make 100% initial Ps fall to 0% in 55, 65, 75, and 90 minutes, respectively, for rapid decrease case. For the slow decrease case, we used the reverse distribution: 10, 20, 30, and 40%. We show the results in Tables IV and V.

Table V
SIMULATION RESULTS FOR PATIENTS WITH SLOWLY DECREASING P_s FUNCTIONS

		DkBFS	BA	Jotshi-G	Jotshi-R	Greedy
# Rescued Patients (P _s ≥ 30)	Max	100	100	90	77	100
	Avg	97	96	76	65	89
	Min	89	86	46	52	44
Avg. P _s (rescued)	Max	48	48	50	70	73
	Avg	43	42	47	60	46
	Min	40	39	44	53	41
Avg. P _s (all)	Max	48	48	43	44	49
	Avg	42	41	36	39	41
	Min	38	34	22	34	36

Table IV shows that when more patients' P_s rapidly decreases, our proposed methods kept similar performance to the previous experiment (in Table III), whereas the results of other methods got worse.

Table V suggests that when more patients' P_s slowly decreases, the proposed methods rescued all patients in the best case and larger number of patients for average and worst cases than other methods. Other methods rescued more patients than previous cases in Tables III and IV, and the difference from our methods got smaller.

The above results suggest us that the proposed methods can more effectively schedule patients transportation in the cases where many patients need early treatment.

VI. CONCLUSION AND FUTURE WORK

In this paper, we formulated the transportation scheduling problem for patients in an MCI assuming utilization of E-triage and proved that the problem is NP-hard. To efficiently solve the problem, we proposed a heuristic algorithm that explores a search space represented by a binary tree within depth k and finds a near-optimal transportation schedule that achieves the maximal life-saving ratio. Through computer simulations, we confirmed that our method outperforms other existing methods in terms of the average survival probability and the expected number of patients surviving.

In the proposed method, we assumed that temporal deterioration of survival probability for each patient can be estimated from the type of trauma diagnosed by a physician and vital signs sensed by the E-triage tag. We believe that an accurate estimation method will be realized in the near future as studies about collection and analysis of patients' trauma data progress.

As part of our future work, we will conduct computer simulations for performance evaluation of the proposed method when patients are dynamically added and/or the conditions of patients change during transportation.

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