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Locating trauma centers considering patient safety

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Abstract

Trauma continues to be the leading cause of death and disability in the U.S. for those under the age of 44, making it a prominent public health problem. Recent literature suggests that geographical maldistribution of Trauma Centers (TCs), and the resultant increase of the access time to the nearest TC, could impact patient safety and increase disability or mortality. To address this issue, we introduce the Trauma Center Location Problem (TCLP) that determines the optimal number and location of TCs in order to improve patient safety. We model patient safety through a surrogate measure of mistriages, which refers to a mismatch in the injury severity of a trauma patient and the destination hospital. Our proposed bi-objective optimization model directly accounts for the two types of mistriages, system-related under-triage (srUT) and over-triage (srOT), both of which are estimated using a notional tasking algorithm. We propose a heuristic based on the Particle Swarm Optimization framework to efficiently derive a near-optimal solution to the TCLP for realistic problem sizes. Based on 2012 data from the state of Ohio, we observe that the solutions are sensitive to the choice of weights for srUT and srOT, volume requirements at a TC, and the two thresholds used to mimic EMS decisions. Using our approach to optimize that network resulted in over 31.5% reduction in the objective with only 1 additional TC; redistribution of the existing 21 TCs led to 30.4% reduction.

Keywords Operations research in health services · Trauma center location · Patient safety · Bi-objective optimization

Highlights

- We address the problem of optimally locating trauma centers in a region.
- A patient safety objective is defined based on two types of mistriages.
- An optimization model and an efficient heuristic is presented to solve large-scale problems.
- Case study using real data suggested over 30% improvement in the patient safety objective.

1 Introduction

Trauma is a body wound caused by sudden physical injury likely from a motor-vehicle crash, gunshot, fall, or violence and requires immediate medical attention [1]. It is the #1 cause of death, disability, and morbidity for those under the age of 44 in the United States, resulting in almost 200,000 deaths and an economic burden of over $670 billion annually [2].

The hospitals equipped and operated to provide a designated level of care for patients suffering from major traumatic injuries are referred to as trauma centers, TCs [1]. The American College of Surgeons (ACS) has verified and categorized TCs based on

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their level of care, from Level I (L1) to Level V (L5). Both L1 and L2 are designated major trauma centers with access to high-quality medical and nursing care, and highly sophisticated surgical and diagnostic equipment. They are required to have 24/7 in-house coverage and prompt availability in surgical specialties such as orthopedic, neurology, radiology, and even burn. On the other hand, the lower level of trauma centers (L3-L5) are intermediate facilities that only provide a subset of these services, only part of the day, and serve as centers for initial care, resuscitation, and transfer to L1/L2 centers (TCs). Because L1/L2 centers are destinations for appropriate care of severely injured trauma patients, we refer to them as trauma centers (TCs) in this study; all other lower level trauma facilities and community hospitals are referred to as non-trauma centers (NTCs), which are ideal destinations for the non-severely injured trauma patients.

1.1 On-field EMS decision making

When a trauma event occurs, the subsequent Emergency Medical Service (EMS) decision making process involves two components; (i) injury assessment and (ii) destination determination. In (i), the EMS providers focuses on the extent of the injury using various diagnostic tests and underlying clinical factors to determine if the injury is severe or not. In (ii), the providers use this injury severity level and the network of hospitals nearby to determine which hospital is reachable in a certain time-frame and using what transportation mode (ground or air). Both components of the EMS decision-making are vital for the appropriate triage of the patient. An error during any step of EMS decision-making results in the mistriage of the patient. In (i), incorrect classification of the injury type (severe or non-severe) results in the 'clinical mistriage.' For instance, classifying a severely injured patient as non-severe (during the diagnosis on the scene) and subsequently transporting to NTC. While in (ii), if a patient is not transported to the right hospital based on injury severity due to any reason, then it results in 'system-related mistriage.' For example, transporting a severely injured patient to NTC is a type of 'system-related mistriage.' We included the modifier 'system-related' because these mistriages are due to system-related parameters such as network of hospitals and transportation resources that impact the determination of the hospital type (TC vs. NTC).

1.2 State-of-the art in trauma care

While a number of approaches have been proposed for injury assessment [3, 4], the impact of the underlying network on destination determination has recently received significant attention. Because trauma is a time-sensitive condition, timely access to an L1/L2 TC is one of the key determinants of outcome in a trauma care system [5, 6]. If a severely injured trauma patient is able to receive care at a L1 trauma center, then his/her survival improves by 25% relative to the care delivered at an NTC [7].

However, according to the Centers for Disease Control and Prevention, "there is no access to an advanced trauma center for nearly 45 million Americans within the golden hour (60 minutes)" [2]. The reason for this is the geographic maldistribution of TCs in the U.S.; in 2010, nearly 9 states had a clustered pattern, 22 had a dispersed pattern, and 10 had a random pattern of TC distribution in the U.S. [12]. Figure 1 shows the distribution of nearly 520 L1/L2 TCs in the U.S. with a coverage of 90.8% of the total population in 60 minutes across 30.38% land via ambulance and helicopter; for 45 minutes coverage, the coverage drops substantially to 76.72% population and 14.09% land [8, 9].

1.3 System-related mistriages

The geographical maldistribution of TCs affects the time to reach a TC from the incidence location (i.e., field) by the EMS provider, and subsequently result in either system-related under-triage (srUT) or system- related over-triage (srOT). A lack of a TC within a prespecified time (per clinical recommendations, usually 45 min upon EMS arrival) from the field can *compel* the EMS providers to take a severely injured patient to a nearby NTC, which is referred to as system-related under-triage (srUT). Figure 2a illustrates of the case of a severely injured patient transported to a nearby NTC because the nearest TC is not accessible within prespecified time (45 min) via ground and air. Note that in case of severe injuries, it is vital to transport such patients to the nearest TC, and not just to any TC which meets the prespecified time [10, 11].

Similarly, an excess (or cluster per [12]) of TCs in the vicinity of a field can *induce* the EMS providers to take a less severely injured patient to one of those TCs (instead of an NTC), which is referred to system-related over-triage (srOT), the other form of mistriage [13]. An example of srOT is shown in Fig. 2b.

Note that an appropriate clinical triage (severely injured patient identified as such) can still result in system-related under-triage because a TC is too far away, and this patient, therefore, has to be taken to a local NTC. In that sense, the EMS decision around 'destination determination' is similar to a binary

Fig. 1 Network of L1/L2 TCs in U.S. Dark dots = TCs, dark shade = 60-min coverage via ground and air, and light gray shade = U.S. population distribution

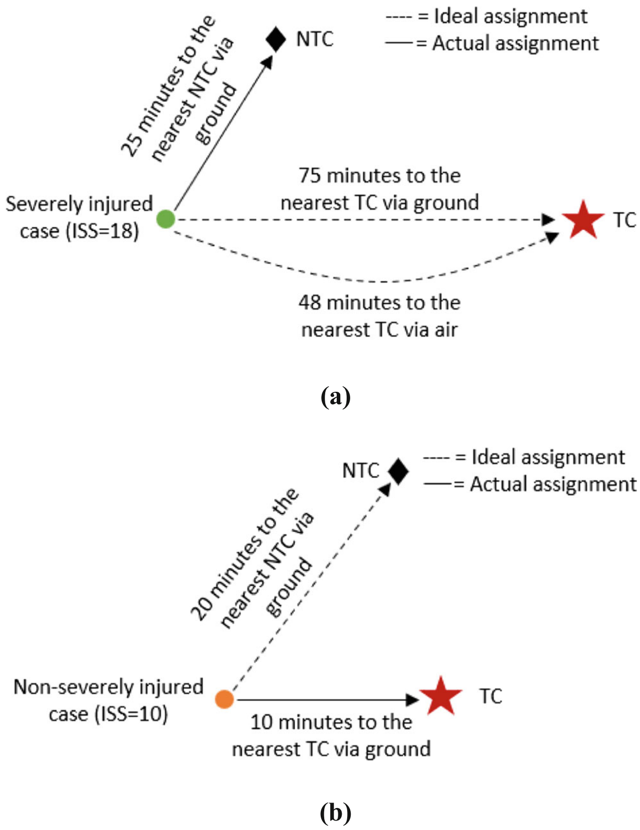


Fig. 2 **a** An example of srUT, **b** An example of srOT

classification problem with four possible outcomes; true positive (severely injured patient is taken to a TC), true negative (less severely injured patient is taken to an NTC), false positive (a less severely patient is taken to a TC, leading to srOT), and false negative (a severely injured patient is taken to an NTC, leading to srUT). The srUT rate is then calculated as (1-sensitivity), while srOT rate is calculated as (1-specificity).

Both srUT and srOT have negative implications on patient safety. srUT can cause a delay in providing definitive care and increase the likelihood of an adverse outcome such as disability, morbidity, and even mortality [4]. In contrast, srOT can cause overcrowding at emergency departments [14], unnecessary trauma activation requiring trauma providers (physicians and nurses) to suspend their care of admitted trauma patients in an operating room and/or trauma inpatient unit to attend the arriving trauma patient (who does not have major trauma injuries), and loss of other salvageable lives in mass casualty trauma [15, 16].

While the ACS has developed a guideline, Needs Based Assessment of Trauma Systems (NBATS), which suggests the number of TCs in a region using a score derived based on trauma providers' experiences, it does not suggest the locations of these TCs and cannot evaluate the impact of these TCs on srUT and srOT rates. A few studies have emerged that attempt to use optimization-based approaches (see Section 2), but they do not account for srOT and provide insights on the effect of changes in the system parameters (e.g., weights for srUT and srOT rates, required volume at TC, and thresholds used to mimic EMS decision making) on the optimal network of TCs.

1.4 Focus of this work

Our work contributes to this field by addressing the questions posed to us by our collaborating trauma decision-makers and researchers, but cannot be done so using existing approaches: (i) *What is the optimal network of TCs that minimizes the weighted sum of mistriages (i.e., srUT and srOT)? and* (ii) *How sensitive is the network to changes in system parameters?* To address these questions, we propose the Trauma Center Location Problem (TCLP) of determining the optimal number and locations of TCs in order to minimize the Weighted Sum of Mistriages (WSM) and present a bi-objective optimization model.

The key contributions of our approach are as follows.

- *First*, we present a bi-objective optimization model for TCLP that determines which hospitals, among candidate locations, should be TC or NTC such that the weighted sum of srUT and srOT rates are minimized. Essentially, our model optimizes the network's performance in terms of patient safety. This model extends the multi-facility and multi-customer location models by incorporating individual customer characteristics and individualized network-dependent allocation, along with multi-transportation modes.
- *Second*, the patient safety surrogates (i.e., srUT and srOT rates) are estimated based on actual incidences; incidences are typically used in the Trauma literature to estimate srUT and srOT as the population may not always be a good surrogate [17]. This is done through our proposed high-fidelity modeling of the mistriages via a notional tasking algorithm that emulates the 'destination determination' part (subsequent to the injury assessment part) of the EMS decision making process. We consider a variety of factors including the network of TCs (x_j), thresholds (α and β; see Appendix 1 for details), the severity of the injury (S_i), and ambulance and helicopter parameters. We also use estimated driving times (using Google Distance Matrix API) and air times (using the Haversine formula) from the field to all the candidate hospital locations.
- *Third*, we propose a heuristic using binary particle swarm optimization to efficiently solve the proposed MIP model for the TCLP for real world instances. The complexity of the resulting mixed integer programming model limited the use of state-of-the-art optimization solvers for realistic problem size (1000s of cases in a network of over 150 hospitals).
- *Fourth*, we evaluate the sensitivity of our solutions to trauma volume, choice of weights that dictate the emphasis on srUT vs. srOT rates, and threshold values for srUT and srOT estimation. In so doing, we provide quantitative guidance to state trauma policy makers on appropriate

choices of these parameters and their impact on patient safety across the state. For our experiments, we use a representative sample of 6002 de-identified trauma patient data from 2012 available from the US state of OH. We illustrate the use of our approach through a case study based on the actual network of this US state where we derive a 'greenfield' design and also a 'redistribution' of the TCs existing in 2012.

Our findings suggest that there is a direct relationship between the number of TCs in the region and the corresponding srUT and srOT rates. That is, as the number of TCs increases, for severely injured patients the access to these TCs becomes easier, which can lower the srUT rate. However, a larger number of TCs in the vicinity can prompt the EMS providers to transport less severely injured patients to these TCs, leading to a higher srOT rate. While the number and location of TCs are sensitive to the choice of weights that dictate the contribution of srUT and srOT rates in the objective function, they are also sensitive to the volume requirements and the threshold values. The application of our approach on the real 2012 trauma network in OH demonstrated over 31.5% decrease in the weighted objective (51.8% decrease in srUT rate and 1% increase in srOT rate) with only one additional TC. Redistribution of the 21 TCs led to a 30.4% decrease in the weighted objective (46.6% decrease in srUT rate and 4.95% decrease in srOT rate). Essentially, our approach not only provides a benchmark to evaluate an existing trauma network in the state, but can also be used to redistribute TCs (within a region or the entire state) to unearth latent benefits in terms of patient safety.

The rest of the paper is organized as follows. Section 2 summarizes relevant literature, Section 3 presents the mathematical model that involves the estimation of srUT and srOT rates based on the mathematical programming-based formalization of a notional tasking algorithm (that approximates the EMS decision making process). Our proposed Binary PSO is detailed in Section 4 and insights based on our experimental study with a real dataset are presented in Section 5. Section 6 presents a case study where we use our approach to identify greenfield and redistribution networks for OH. Finally, Section 7 summarizes our work and offers guidance in future research in this area.

2 Literature review

The literature on healthcare facility location is vast and includes locating long-term health care facilities [18], blood bank locations [19], organ-transplant centers [20], tuberculosis testing laboratories [21], and mobile healthcare units [22]. See Reuter-Oppermann et al. [23], Ahmadi-Javid et al. [24], and Gunes et al. [25] for a comprehensive review of healthcare facility location models. These models vary in their objectives, may it be cost-based or patient safety-based. Several cost-based models have been proposed; e.g., location-allocation of organ-transplant centers [26], design of medical service [27], and health centers for traumatic brain injury [28, 29]. Because the focus of our work is on patient safety, we now summarize key literature below.

Access to a facility has often been used as a surrogate for patient safety; for instance, (i) minimizing the total distance or time traveled across all constituents and (ii) maximizing the demand coverage within a fixed assess time. Objective (i) has been used to improve access to healthcare facilities [30]; e.g., optimizing the locations of organ transplant centers [31], location and dispatching decisions for an ambulance system [32, 33], and shelter location in humanitarian logistics [34, 35]. Similarly, objective (ii) has been preferred in general healthcare facility planning [36, 37]; e.g., optimizing the location of ambulances [38], distribution centers in a relief network [39], and emergency response facility during an earthquake [40], as well as the relocation of ambulance stations [41].

A few approaches have been proposed in the IE/OR literature for multi-facility and multi-customer problems. Marianov and Taborga [42] presented a hierarchical p-covering type model to locate public health centers providing non-vital services in the presence of competing private centers to maximize low-income coverage. Yasenovskiy and Hodgson [43] proposed a hierarchical location-allocation model that allows for by-passing to maximize patron's benefits. Teixeira and Antunes [44] presented a hierarchical location model with two different types of assignment constraints: closest-assignment constraint and path-assignment constraint. Recently, Nasrabadi et. al. [45] proposed a bi-hierarchy multi-service capacitated facility location-allocation problem with the bi-objective of minimizing total weighted travel time, and the fixed and operating cost of facilities. These studies, however, do not account for the time-sensitive nature of the assignment and only consider ground transport mode.

Patient safety has been an important criterion in trauma facility location literature. Branas et al. [46] propose a linear programming model, namely the Trauma Resource Allocation Model for Ambulance and Hospitals (TRAMAH), to simultaneously locate trauma centers and air ambulance with an objective of maximizing coverage of severely injured patients using Maryland as a test region. TRAMAH, first of its kind, considers Rand-McNally TripMaker Version 1.0 to calculate the shortest driving time and Euclidean distance for air time and is solved using CPLEX Version 1.2. The model, however, uses a proxy for incident location, lacking geographical granularity and does not account for less severely injured patients. Cho et al. [1] present a model that simultaneously locates trauma centers and medical helicopters with the objective of maximizing the expected number of patients transported to a TC within 60 minutes. The authors not only incorporate busy fraction for medical helicopters, but also develop the Shifting Quadratic Envelopes algorithm to optimize the problem. However, the model only considers severely injured patients (ISS>15), employed Euclidean distance between the demand region and each TC, and did not consider the aspect of mistriages that occur for both severely and less severely injured patients.

Jansen et al. [6] propose a novel data-driven approach with a bi-objective of minimizing the total access time and the number of exceptions or system-related UT (srUT) for Scotland. The authors extend the model formulation in Handing et al. [47] and solve the extended formulation with a multi-fidelity surrogate-management strategy via NSGA-II. They demonstrate the viability of their approach using real data from the state of Colorado's trauma system [48]. In contrast, the model is computationally complex requiring considerable processing time and also fails explicitly in considering the over-triage cases, an important factor of a patient-safety metric. The ACS Committee on Trauma suggested tool, Needs-Based Assessment of Trauma System (NBATS), helps determine the required number of TCs in a specified geographical region by allocating points based on population, transport time, community support, where are severely injured patients transported (TCs and NTCs), and the total number of TCs [49]. However, the tool does not determine the location of the TCs.

Our review of the above literature reveals the following gaps. *First*, the derivation of OT rates, based on injury score and its on-field operational decision-making process, has never been explicitly considered and accounted in the optimization models. *Second*, none of the prior approaches consider the fact that the determination of medically-appropriate time to access a suitable hospital (TC or NTC) varies by the type and volume of the injuries. For a severely injured patient, the proposed transportation times to the TC are as low as 30 and as high as 60 minutes (depending on the region/state), but for a less-severely injured patient, there is no such reasonable transport time to the NTC proposed in the literature. *Third*, the sensitivity of the 'access' and 'bypass' thresholds for a patient to reach their designated level of care, used for determining the srUT and srOT rates, has not been explored. *Finally*, we know of no literature that jointly considers the metrics of mistriages (i.e., srUT and srOT) to determine the optimal number and location of TCs.

To fill the gap as mentioned above, we propose a bi-objective trauma facility location optimization model to determine the optimal number and location of trauma centers with the aim of minimizing the weighted sum of mistriages. The key feature of our model is the inclusion of patient level decision-making related to destination selection, which is in turn based on patient's severity of injuries and estimated drive times to each candidate location (TC or NTC). Our proposed notional tasking algorithm helps to estimate the resulting srUT and srOT rates. Several practical insights are presented based on the sensitivity analysis conducted by varying minimum trauma case volume, weights of mistriages, and threshold values for the srUT and srOT rates. We now present our proposed model.

3 A bi-objective model for TCLP

We define the Trauma Center Location Problem (TCLP) as determining the optimal location of TCs that minimizes the weighted sum of mistriages (srUT and srOT) in the entire trauma care network. The model assumes that a geographically defined area, typically known in the trauma literature as the Trauma Service Area (TSA), is known. This defined region could be a county, a region in the state, or the state itself.

Before we present the model, it is important to effectively capture the EMS decision making around destination determination. Based on the existing trauma literature [48] and our discussions with EMS providers in our region, this process requires both clinical and resource considerations. To mimic this decision-making process, we propose two thresholds: (i) 'access' and (ii) 'bypass.' Here the 'access' threshold is a clinically-driven value that prespecifies the time to reach a hospital for a severely injured patient; this time is specified by the American College of Surgeons or state regulations. On the other hand, the 'bypass' threshold is a resource-driven value that prespecifies the maximum additional minutes (compared to a nearby TC) the EMS can dedicate towards a non-severely injured patient in order to transport them to an NTC.

Further, in line with the existing trauma literature, we use Injury Severity Score (ISS) as a surrogate for the severity of injuries on the field; ISS is a post-hoc metric evaluated after the patient arrives at the hospital. For a severely injured patient (ISS>15), the EMS providers often first check if a TC (the appropriate hospital) is accessible within the 'access' threshold time. If yes, then the patient is transported to that TC, resulting in a system-related appropriate triage positive ($srAT^P$). If no, then they check if an air ambulance can be called in to transport the patient to the nearest TC ($srAT^P$ via air). However, if the sum of the inbound-to-field, loading, and transport-to-TC times for the air ambulance is higher than the 'access' threshold, then the EMS would most likely transport the patient to a nearby NTC, resulting in a srUT.

In contrast, the case of a srOT is a bit more complicated. A TC may be located close to the trauma incidence site compared to an NTC. In this case, if for a less severely injured patient (with ISS $\leq$ 15) the additional time (beyond the time to TC) to reach an NTC (the appropriate hospital for this patient) is within the 'bypass' threshold, then the EMS will likely take the patient to the NTC; this would be deemed as system-related appropriate triage negative ($srAT^N$). Otherwise, the EMS would likely take the patient to the nearby TC; this would be deemed as srOT. Anecdotally, such situations may arise due to EMS perception of a nearby TC's reputation to be higher (i.e., the bigger the hospital the better the care), patient/family choice, insurance situation, and even negotiated contracts between the EMS and TC.

Both srUT and srOT are estimated based on, and as indicated earlier, the EMS decision making process for 'destination determination' which is similar to a binary classification problem. Accordingly, we can generate a confusion matrix with $srAT^P$ (true positive), $srAT^N$ (true negative), srUT (type-1 error), or srOT (type-2 error); see Table 1. The notional tasking algorithm provides a means to classify each patient into these 4 categories in the confusion matrix; as explained above (see Appendix 1 for examples); corresponding analytical expressions are in the optimization model below. If there are multiple patients at the incidence site (say, during a multi-vehicle crash), then each patient will be evaluated individually (as suggested by the EMS providers and specified in the data).

The srUT rate is then calculated as (1-sensitivity), where the true positive value is the count of total system-related appropriate triages (via ground or air), and the false negative value or type-1 error is the total number of system-related under-triage cases for incidents with ISS > 15 and for a given configuration. Similarly, the srOT rate is calculated as (1-specificity), where the true negative value is the count of total system-related appropriate triages, and the false positive value or type-2 error is the total number of system-related over-triage cases for incidents with ISS ≤ 15 and for a given configuration. The two rates can be determined by $\text{srUT} = 1-\text{sensitivity} = 1-\left(\frac{srAT^P}{srAT^P+srUT}\right)$ and $\text{srOT} = 1-\text{specificity} = 1-\left(\frac{srAT^N}{srAT^N+srOT}\right)$ [13].

Given this background, we now present our model under the following assumptions:

- The candidate locations for the TCs and NTCs are known and finite.
- Injury Severity Score (ISS) is used as a surrogate to estimate a patient's injury severity at the field.
- While ground ambulance services are available without constraints, the availability of air ambulance was restricted to 6.6% based on historical available data.
- In line with the existing trauma literature, air ambulance is only allowed for severely injured patients.

Tables 2 and 3 summarize the parameters and decision variables, respectively, used in our model.

$$\text{Minimize}: \quad \omega_1\left(1-\frac{\sum_{i:s_i=1}\sum_j\left(y_{ij}^1+y_{ij}^2\right)}{\sum_i s_i}\right) + \omega_2\left(1-\frac{\sum_{i:s_i=0}\sum_j y_{ij}^1}{\sum_i(1-s_i)}\right)$$

Subject to:

Determining the nearest TC via *ground*

$$z_{ij}^1 \le x_j;\ \forall i\in I, \forall j\in J \tag{1}$$

$$\sum_j z_{ij}^1 = 1;\ \forall i\in I \tag{2}$$

$$x_j + \sum_{l\in SG_{ij}} z_{il}^1 \le 1;\ \forall i\in I, \forall j\in J \tag{3}$$

Determining the nearest NTC via *ground*

$$z_{ij}^0 \le \left(1-x_j\right);\ \forall i\in I: S_i = 0, \forall j\in J \tag{4}$$

$$\sum_j z_{ij}^0 = 1;\ \forall i\in I: S_i = 0 \tag{5}$$

$$\left(1-x_j\right) + \sum_{l\in SG_{ij}} z_{il}^0 \le 1;\ \forall i\in I: S_i = 0, \forall j\in J \tag{6}$$

Each severely injured case is assigned to only one category (to TC via *ground, to TC* via *air, or srUT)*

$$\sum_j\left(y_{ij}^1+y_{ij}^2+y_{ij}^3\right) = 1;\ \forall i\in I: S_i = 1 \tag{7}$$

Assign severely injured cases to nearest TC that is within 'access' time threshold via *ground*

$$y_{ij}^1 = 0;\ \forall i\in I: S_i = 1, \forall j\in J, TG_{ij} > \alpha \tag{8}$$

$$y_{ij}^1 = z_{ij}^1;\ \forall i\in I: S_i = 1, \forall j\in J, TG_{ij} \le \alpha \tag{9}$$

Table 1 Confusion matrix

		Injury Severity Score (ISS)	
		ISS > 15	*ISS ≤ 15*
Destination	*To TC*	System-related appropriate-triage ($srAT^P$)	System-related over-triage (srOT)
	To NTC	System-related under-triage (srUT)	System-related appropriate-triage ($srAT^N$)

Table 2 Parameters in the model

Notation	Definition
i	Index for trauma incidence (case); $i=1, 2, \ldots, I$
j	Index for candidate location for TC and NTC; $j=1, 2, \ldots, J$
α	'Access' time threshold for srUT (in minutes)
β	'Bypass' time threshold for srOT (in minutes)
S_i	Injury severity of case i, 1 if severely injured (ISS>15); 0, otherwise
T_{in}	Inbound time for an air ambulance from its base to field (in minutes)
T_{load}	Loading time of a patient to an air ambulance (in minutes)
Z	Maximum allowable air ambulance use
V^{min}, V^{max}	Minimum and maximum volume of a severely-injured patient if TC is located at j
C	Maximum number of allowable TCs in the TSA
ω_1, ω_2	Weights for the srUT and srOT terms in the objective function; $\omega_1 + \omega_2=1$
TG_{ij}	Travel time from the location of case i to any candidate location j via ground
TA_{ij}	Travel time from the location of case i to any candidate location j via air
SG_{ij}	$\{l \in J: TG_{ij} < TG_{il}\}$, $i \in I, j \in J$, that is the subset of candidate locations with higher time from case i than candidate location j via ground
SA_{ij}	$\{l \in J: TA_{ij} < TA_{il}\}$, $i \in I, j \in J$, that is the subset of candidate locations with higher time from case i than candidate location j via air
M	Big number

Table 3 Decision variables in the model

Notation	Definition
x_j	1, if a candidate location j is designated to be a TC; 0, otherwise
z_{ij}^1	1, if location j is marked as TC and is the nearest TC for case i via ground; 0, otherwise
z_{ij}^0	1, if location j is marked as NTC and is the nearest NTC for case i via ground; 0, otherwise
y_{ij}^1	1, if case i is transported to location j via ground transport; 0, otherwise (i.e., if j is a TC, then case i is srAT^{P} and if j is an NTC, then case i is srAT^{N})
y_{ij}^2	1, if a severely injured case i is transported to location j (that is marked as TC) via air transport; 0, otherwise (i.e., this case is considered srAT^{P} via air)
y_{ij}^3	1, if case i is transported to location j that is marked as TC via ground transport; 0, otherwise (i.e., this case is considered srUT)

Assign severely injured cases to nearest TC that is within 'access' time threshold via *air*

$$y_{ij}^2 = 0; \forall i \in I: S_i = 1, \forall j \in J, TA_{ij} + T_{in} + T_{load} > \alpha \tag{10}$$

$$x_j + \sum_{l \in SA_{ij}} y_{il}^2 \le 1; \forall i \in I: S_i = 1, \forall j \in J \tag{11}$$

$$\sum_i \sum_j y_{ij}^2 \le Z \tag{12}$$

Assign severely injured cases to nearest TC located outside 'access' time threshold via *ground (transfer srUT cases to TC from NTC)*

$$y_{ij}^3 \le z_{ij}^1; \forall i \in I: S_i = 1, \forall j \in J, TG_{ij} > \alpha \tag{13}$$

Assign non-severely injured cases to nearest NTC if 'bypass' time criteria met

$$\sum_j \left(z_{ij}^0 TG_{ij}\right) - \sum_j \left(z_{ij}^1 TG_{ij}\right) - \beta \le M\left(1 - \sum_j y_{ij}^1\right); \forall i \in I: S_i = 0 \tag{14}$$

$$y_{ij}^1 \le z_{ij}^0; \forall i \in I: S_i = 0, \forall j \in J \tag{15}$$

Allowable number of TCs, and their minimum and maximum volume

$$\sum_j x_j \le C \tag{16}$$

$$\sum_{i:S_i=1} \left(y_{ij}^1 + y_{ij}^2 + y_{ij}^3\right) \le x_j V^{max}; \forall j \in J \tag{17}$$

$$\sum_{i:S_i=1} \left(y_{ij}^1 + y_{ij}^2 + y_{ij}^3\right) \ge x_j V^{min}; \forall j \in J \tag{18}$$

Bounds on decision variables

$$x_j, z_{ij}^1, z_{ij}^0, y_{ij}^1, y_{ij}^2, y_{ij}^3 \in \{0,1\}; \forall i \in I, \forall j \in J \tag{19}$$

The objective of the TCLP is to minimize the weighted sum of total srUT and srOT rates (referred to as WSM from now on) for the TSA. In the above objective function, the first term in bracket represents srUT rate = 1 – sensitivity $= 1-\frac{appropriately\ triaged\ cases\ to\ a\ TC}{cases\ with\ ISS>15} = 1-\frac{\sum_{i:s_i=1}\sum_j\left(y_{ij}^1+y_{ij}^2\right)}{\sum_i S_i}$ and the second term represents srOT rate = 1–specificity = 1 $-\frac{appropriately\ triaged\ cases\ to\ a\ NTC}{cases\ with\ ISS\le 15} = 1-\frac{\sum_{i:s_i=0}\sum_j y_{ij}^1}{\sum_i(1-S_i)}$.

Note that a severely injured case i is classified as srUT if it is not accessible to any TC (within the 'access' time threshold) via air or ground $\left(\sum_j\left(y_{ij}^1+y_{ij}^2=0\right)\right)$. On the other hand, a non-severely injured case i is classified as srOT if the difference between nearest NTC and TC time (via ground) exceeds the 'bypass' time threshold $\left(\sum_j y_{ij}^1=0\right)$; i.e., this case would likely be transported to a TC via ground as the NTC (correct hospital) is much further from the nearest TC (which mimics the practice among EMS). The values of srUT and srOT rates in the above objective function are weighted by multipliers ω_1 and ω_2, respectively.

Constraints (1)-(3) determine the nearest TC. While Constraints (1) ensure that candidate location j must be a TC to be considered as the nearest TC, Constraints (2) ensure that for every case i, only one TC should be considered as the nearest TC. For any pair of case i and candidate location j, if candidate location j is marked as TC, then Constraints (3) rule out the assignment of case i to candidate location(s) l that are located further (in terms of time) than j (the nearest TC for case i). Constraints (4)-(6) serve the same purpose as (1)-(3), respectively, for the nearest NTC via ground.

Constraints (7) ensure that each severely injured case is either assigned to a TC within the 'access' time threshold via air or ground (resulting in $srAT^P$) or transferred to a TC located outside of the 'access' time threshold after the case i has been stabilized at a nearby NTC (resulting in srUT). Constraints (8) rule out the assignment of severely injured cases to candidate locations that are not accessible within 'access' threshold via ground. Constraints (9) enforce the assignment to the nearest TC when a nearest TC exists within the 'access' threshold for a severely injured case i.

Constraints (7), (10), and (11) assign the remaining severely injured patients (unassigned via ground) to the TC via air if the total time to the TC is within the 'access' threshold. Constraints (10) rule out an assignment of severely injured cases to candidate locations that require total transport time more than the 'access' threshold via air. Constraints (11) rule out an assignment of severely injured cases to further located candidate location(s) via air if a given candidate location j marked as TC. Constraint (12) makes sure that the air transport usage does not exceed their availability $Z = \lfloor \mu \sum_i S_i \rfloor$, where μ = availability of air ambulance; $0 \le \mu \le 1$.

As mentioned earlier, every srUT case (originally transported from the scene to an NTC) is eventually transferred to a TC to receive definitive care. Constraints (13) capture such transferred srUT cases to the nearest TC (considered from the incidence location) for eventual volume estimation at this TC. Here we assume that the reason a severely injured patient is transported to a NTC (srUT case) is because there is no nearby TC (say TC-1) within 'access' threshold from the incidence. Our analysis of real data from a US midwestern state (see Section 5.1) indicated that the ratio of NTC to TC was 6.57 in 2012; i.e., there are a lot more NTCs than TCs. That is, there is a fairly low likelihood that another TC (say TC-2) is closer to the NTC than TC-1 (which was the closest from the incidence, but outside of the 'access' threshold). We use this low likelihood as the basis of assigning a srUT case to a TC that was closer to the incidence (i.e., TC-1, which was already identified as part of the constraints), instead of adding new constraints to locate a nearby TC from the NTC.

Further, an NTC is not designed to provide definitive care for severely injured patients. A srUT patient is only resuscitated/stabilized at an NTC before an eventual transfer to a TC. This would typically happen within 24 hours of arrival to the NTC. Because of that, NTCs do not have any capacity requirements associated with treating severely injured patients, and hence we do not need such constraints on NTC.

For each non-severely injured case i, Constraints (14) rule out the assignment of non-severely injured case i to an NTC if the 'bypass' threshold criterion is not met for that case; this case is marked as srOT. That is, it captures the situation when the nearest TC is located closer to the incidence site than the nearest NTC. Given that we have already categorized such a case as srOT, we do not need to explicitly assign srOT to a TC as they are not counted towards trauma volume; these are non-severely injured cases and are often discharged from the ED of a TC (without admission to the inpatient trauma unit). For non-severely injured cases where the 'bypass' time threshold is met, Constraints (15) assign those cases to the nearest NTC and mark them as $srAT^N$.

Constraint (16) ensures that the total number of TCs must be less than or equal to the maximum allowable TC. Constraints (17) and (18) calculate the volume of severely injured cases at each candidate location j that is designated as a TC location and ensures that the volume is within the allowable bound. As mentioned before, besides the $srAT^P$, srUT cases are also counted in TC volume. The minimum bound essentially reflects the recommendations from the American College of Surgeons to ensure the financial viability of a TC; each TC must be able to offset the high cost of trauma readiness (physician, staff, equipment, and infrastructure).

Clearly, TCLP is a specific case of the discrete multi-facility location optimization problem with specific focus on patient-level safety measures. Such problem is combinatorial in nature and has been shown to be NP-hard [50]. TCLP exhibits the same characteristic where the decision to open TC or NTC at each of the n candidate locations. For n = 159, this results in $2^{159} = 7.3\text{x}10^{47}$ solutions. A commercial solver such as CPLEX 12.10 and Gurobi were not able to obtain an optimal solution to our original problem due to the large problem size and resulting out-of-memory issues. We noticed that runtime increased exponentially with an increase in the number of candidate locations (x_j). For problem sizes with more than 47 candidate locations, we encountered out-of-memory issues with commercial solvers; see Fig. 3.

Considering this limitation of solving TCLP exactly, we explored the use of a heuristic-based approach via Particle Swarm Optimization (PSO) to derive near-optimal solutions within a reasonable amount of time. We now discuss our proposed PSO algorithm.

4 Binary particle swarm optimization

PSO is a nature-inspired population-based metaheuristic algorithm that optimizes continuous nonlinear function [51]. The approach mimics the social behavior of birds flocking and fish schooling. It is easy to implement, makes fewer assumptions about the problem, is flexible and robust, and can be applied in a parallel manner. It has been implemented in a wide range of research areas such as facility location [52, 53], network design [54, 55], and scheduling [56, 57].

The algorithm starts with a randomly distributed set of particles (potential solutions). With mathematical operators, the algorithm tries to progress to a solution with quality measure (fitness function). As the swarm of particles searches over time, they tend to fly towards better search regions, resulting in the convergence to a global optimum solution [58]. Each particle keeps track of its position which associates with the best solution it has achieved so far, known as particle best (*pbest*). On the other hand, global best (*gbest*) keeps track of the overall best value obtained thus far by any particle in the swarm.

For example, the ith particle is represented as $x_i = (x_{i1}, x_{i2}, \ldots, x_{id})$ in a d-dimensional search space. The previous best position of the ith particle is represented as $pbest_i = (pbest_{i1}, pbest_{i2}, \ldots, pbest_{id})$. The location of the best particle in the swarm is designated as $gbest = (gbest_1, gbest_2, \ldots, gbest_d)$. The rate of position change (velocity) for the particle is represented as $v_i = (v_{i1}, v_{i2}, \ldots, v_{id})$. The velocity v_{id} and particle x_{id} used to update the dth dimension of the ith particle for the tth iteration are given by:

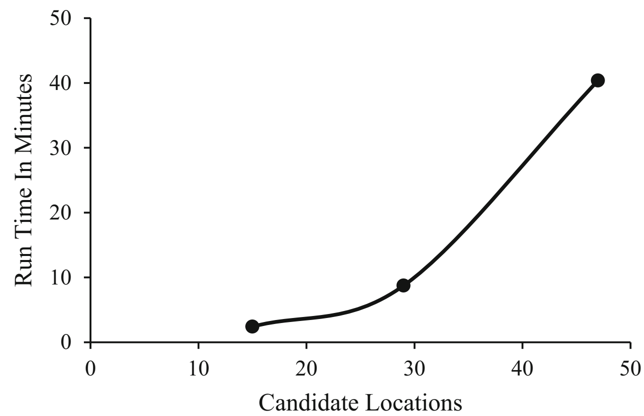


Fig. 3 Number of candidate locations vs runtime using commercial solver

$$x_{id}^{t} = x_{id}^{t-1} + v_{id}^{t}, \tag{20}$$

$$v_{id}^{t} = K\left(v_{id}^{t-1} + c_1 r_1 \left(pbest_{id} - x_{id}^{t-1}\right) + c_2 r_2 \left(gbest_d - x_{id}^{t-1}\right)\right), \tag{21}$$

where c_1 and c_2 are acceleration constants; c_1 = 2.05 [58], while c_2 is initially set to $c_1/5$ and gradually increase by 0.41 for every 25 iterations to allow particles to move slowly toward the global best solution. Further, r_1 and r_2 are two uniformly distributed random numbers in [0,1]. Constriction coefficient, K, aids in the convergence of the particle swarm algorithm; K=0.7298 [58]. The particle velocity given in equation (21) is composed of three primary parts: velocity from the previous iterations, cognitive or selfish influence (which uses the particle's personal best to improve the individual particle), and social influence (which represents alliance among the particle in the swarm using global best).

Recall that the decision variables in the TCLP are binary. We, therefore, use the binary version of the PSO, referred to as the BPSO [59]. Accordingly, each particle represents its position in binary values, and the velocity of a particle is defined as the probability that might change the particle to either zero or one. The behavior and meaning of the velocity clamping and the inertia weight in the BPSO differ considerably from the real-valued PSO [60]. However, the velocity update equation (21) remains unchanged, except that now the positions are binary and particle update equation (20) is replaced by:

$$if\left(rand\ () < S(v_{id})\right), then\ x_{id} = 1; \text{else } x_{id} = 0, \tag{22}$$

where function $S(v)$ is a sigmoid limiting transformation function, $S(v_{id}) = 1/\left(1 + e^{-v_{id}}\right)$, and $rand\ () \sim$ Uniform [0, 1].

The likelihood of a change in a bit-value depends on $S(v)$. Furthermore, the probability that a bit will be 1 equals $S(v_{id})$, and that a bit will be 0 equals 1 - $S(v_{id})$ [59]. The high-level structure of the PSO is as follows:

Initialize a population of particle with positions and velocities
Do
  For each particle:
    Evaluate fitness function using the notional tasking algorithm
    Evaluate constraints
    If feasible:
      If the fitness value is better than the particle best:
        Set the current solution as particle best
      If the fitness value is better than the global best:
        Set the current solution as global best
    Else:
      Reject the solution
  End
  For each particle:
    Update the particle velocity
    Update the particle position
  End
Until the termination criterion is met

In our proposed BPSO, we consider a swarm of 40 initial feasible particles, each representing a network of TCs, with the following representation: $H = \{0, 1, 0, 1, 1, 0, ..., 0, 1\}$; where 1 represents TC and 0 represents NTC, and $|H|$ represents the total number of existing hospitals. As the optimization model aims to minimize the objective function, the value given to an infeasible solution is set much higher. Hence, keeping them out of the loop. Equation (21) and (22) are applied to updating the velocity and particle, respectively.

We used *R* to implement our proposed BPSO and the notional tasking algorithm on a computer with 2 nodes, each node had 12 cores and each core had 2 threads (i.e., a total of 48 parallel processing options). Each core had a 3 gigahertz processor. The total RAM across all 12 cores was 256 GB. We also implemented parallel processing in *R* to allow for faster evaluation of each particle, which helped reduce the computation time to about 8 hours. Preliminary experiments suggested that 40 particles sufficiently balanced solution quality and solution time. Further, we implemented a dynamic change in the value of acceleration constant c_2, which gradually increased the attraction to the global best (compared to personal best). This allowed the particles sufficient time to explore the search space around their personal best instead of speedy attraction to the global best position. We used two termination criteria based on preliminary experiments: maximum iterations (set to 1,000) and less than 0.1% improvement in the global best solution within 100 iterations.

5 Experimental setting

To generate managerial insights, we conducted a series of experiments using a sample dataset made available for Ohio state by the Ohio Department of Public Safety (ODPS). The Wright State University's Institutional Review Board approved this study as not involving human subjects (IRB#06027). We first summarize the characteristics of this dataset and then present our insights.

5.1 Data collection

We considered the 2012 network of hospital locations (TCs and NTCs) made available to us by the ODPS. The 2012 data corresponded to a network of a total of 159 hospital sites; 21 TCs and 138 NTCs. We were able to obtain the (latitude, longitude) information for each of these sites. We were also able to derive a sample of 6,002 de-identified trauma incidences from the data provided by the ODPS for that year. This sample was about $1/11^{\text{th}}$ of the typical number of trauma incidences occurring in the state; 67,542 cases in 2018 [61]; the correlation of a number of cases in each county between them was 0.84 suggesting that the 2012 data sample is a good enough representation of the spatial distribution of incidences. Figure 4 illustrates the heat map of 6,002 incidents, and the location of TCs and NTCs in 2012.

We used the Google Distance Matrix API to estimate drive time based on the quickest route from each incident to a hospital site. We used the Haversine formula for the corresponding air travel time (assuming the helicopter speed of 120 mph).

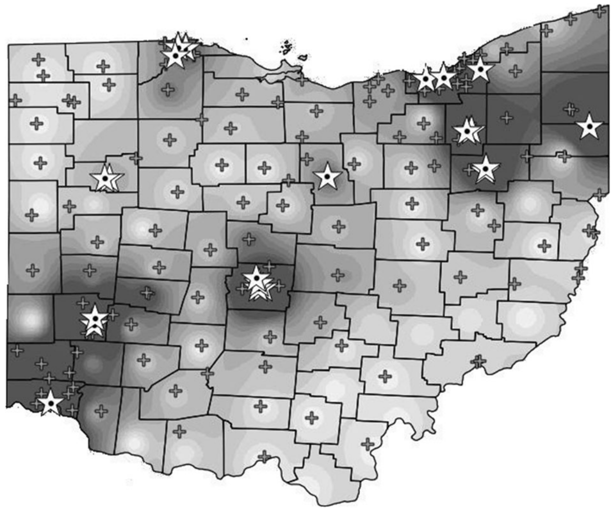


Fig. 4 Trauma Care in OH for 8 regions; stars indicate TCs and crosses indicate NTCs. Darker shades of grey indicate higher values of incidences

The resulting time matrix for ground and air (each 159 × 6002 in size) served as a look-up table to the notional tasking algorithm in order to estimate srUT and srOT rates. Because helipad locations were not available, we let the time from helicopter depot to the field be 10 minutes; in a similar vein, the loading of the patient was set to 5 minutes. Aggregating these two with the airtime from field to the nearest TC calculated using the Haversine formula, we estimated the total air transport time.

5.2 Experimental study and insights

Based on preliminary experiments, we noticed that the solutions were sensitive to four key factors, which are summarized in Table 4 along with their levels and values. Further, the American College of Surgeons recommends having at least 240 trauma cases per year for a TC to be viable; i.e., V^{min} = 240 cases with severe injuries estimated as ISS>15 [4]. Hence, to correspond with the sample of 6,002, we scaled V^{min} to 22 (=⌈240/11⌉).

We set our 'base case' with $V^{min} = 22$ and $\alpha = 45$, and $\beta = 0$ to mimic the current protocols in most states in the US. We set $(\omega_1, \omega_2) = (0.8, 0.2)$ to allow for more focus on patient safety; again, attempting to mimic how state governments try to locate TCs. We set $V^{max} = 91$ (equivalent to 1,000 cases) as the upper bound on a TC volume and $C = 159$ in all our experiments. Maximum air ambulance usage for severely injured patients was bounded; i.e., $Z = 61$ to match with sample 2012 data. Below we summarize the results and insights from the sensitivity analysis.

Insight 1: A higher emphasis on reducing the srUT rate means a corresponding increase in the number of TCs, but this can lead to a higher srOT rate

The selection of the weights plays a vital role in determining the optimal number and location of TCs. We varied both weights (ω_1, ω_2) between 0 and 1 in steps of 0.2 such that $\omega_1 + \omega_2 = 1$. Note that when $\omega_1 \gg \omega_2$, the emphasis is towards reducing the srUT rate (likely resulting in more TCs); while for $\omega_1 \ll \omega_2$, the emphasis is towards reducing the srOT rate (likely resulting in less TCs).

Figure 5 represents the trend in srUT and srOT rates, and WSM value over the weights. The figure shows that as ω_1 decreased the srUT rate increased and as ω_2 increased the srOT rate decreased, resulting in a drop in the number of TCs. Although a solution with (1.0, 0.0) may be attractive in terms of the lowest WSM, it comes at a cost. First, the corresponding network has the highest number of TCs, which puts a financial burden on the state and the hospital system. Second, a higher corresponding srOT rate (0.14) means a higher number of less severely injured patients at a TC, which is much more expensive than treating such patients at an NTC. Because such costs are difficult to estimate, we expect that this analysis will allow the trauma decision makers to make an informed judgement on the most appropriate network suitable for their region. From what we have learnt first-hand from trauma network designers, srUT is given a much higher emphasis compared to srOT. We would expect trauma decision makers to use our tools and start with a high ω_1 and then gradually lower it until a tolerable srUT is achieved to effectively trade-off srUT and srOT.

Insight 2: An increase in the minimum required volume of severely injured patients at a TC reduces the number of TCs in the network, but substantially increases srUT

We varied V^{min} between 0 and 33 in increments of 11 to evaluate the impact of the minimum trauma volume on the TC

Table 4 Summary of the parameters, levels, and values in the sensitivity analysis

Parameter	Levels	Values
Weights (ω_1,ω_2)	5	(1,0), (0.8,0.2), (0.6,0.4), (0.4,0.6), (0.2,0.8)
V^{min}	4	0, 11, 22, 33
Access threshold (α)	3	15, 30, 45 min
Bypass threshold (β)	3	−10, 0, 10 min

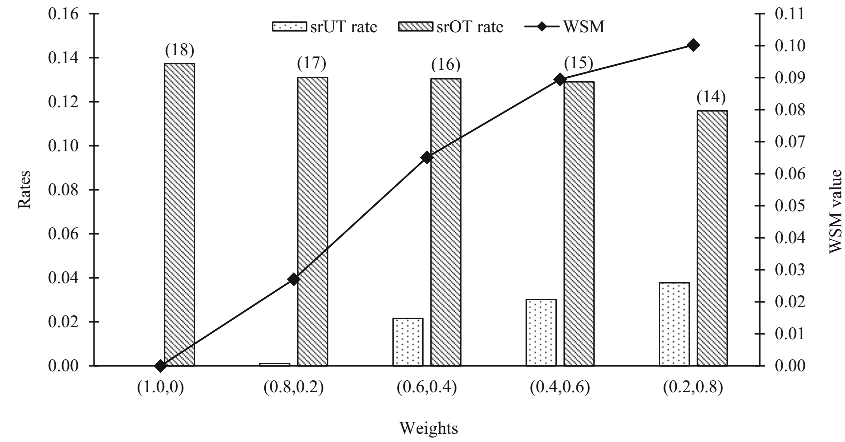


Fig. 5 Representation of the srUT rate, srOT rate and WSM value over the weights; TCs in parenthesis for each column

network. As mentioned earlier, the 240 cases (22 in our scaled down version) is a suggestion by the ACS based on empirical evidences, and, therefore, this sensitivity analysis provided a much-needed quantitative evaluation of the impact of changes in this value on the TC network and resulting srUT and srOT rates. Our results suggest that as minimum total trauma volume requirement at TC increased, the WSM value also increased. For a smaller value of the V^{min}, the network tends to have more TCs in order to minimize the srUT rate; recall, we used $\omega_1 = 0.8$ for srUT (base case). This is intuitive as an increase in the number of TCs would likely allow more severely injured patients to reach a TC, which results in a decrease in the srUT rate. However, it also means that less severely injured patients may now be transported to a TC (as there is likely a TC as close to the field as an NTC) resulting in an increase in the srOT rate. However, as the V^{min} increased, the number of TCs decreased in order to satisfy the V^{min} constraint. As a result, the srUT rate and the WSM value both increased. Figure 6 illustrates this trend.

Essentially, a lower volume requirement can result in higher TCs and better patient safety. The implication of this is that the trauma decision-maker must appropriately set the minimum volume requirement as a TC with a low volume may not be financially viable.

Insight 3: An increase in the ‘access’ threshold reduces the number of TCs

For this analysis, we considered the ‘access’ threshold (α) at 15, 30, and 45 minutes and a constant ‘bypass’ threshold of 0 minutes. Figure 7 illustrates the trend in the srUT and srOT rates, the WSM, and the number of TCs. Note that as the ‘access’ threshold (α) increased, the WSM (objective function) decreased. This is intuitive as, for the same network, an increase in α would mean that there is more allowable time for the EMS to transport a severely injured patient to a TC further away from the field (as compared to lower values of α). This means that the corresponding network will need fewer TCs to achieve lower levels of srUT rate. Fewer TCs also means a lower srOT rate. As both srUT and srOT rates decrease, the WSM will also experience a drop with an increase in α.

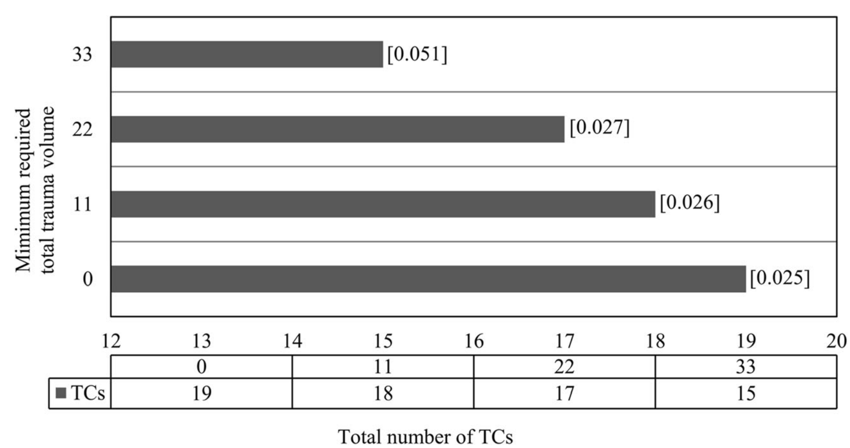


Fig. 6 Representation of V^{min} against the total number of TCs; WSM value in the []

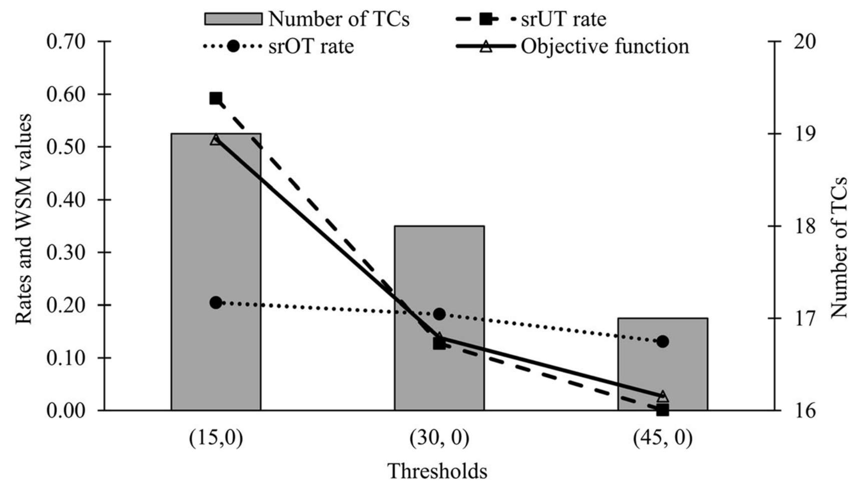


Fig. 7 Representation of trend in srUT rate, srOT rate, objective function, and number of TCs

Insight 4: An increase in the 'bypass' threshold has a slight impact on the number of TCs

For this analysis, we considered the 'bypass' threshold (β) at -10, 0, and 10 minutes and a constant 'access' threshold of 45 minutes. Table 5 summarizes the corresponding number of TCs and the resulting srUT, srOT, and WSM. Notice the increase in the number of TCs is only marginal. The reason is that as the 'bypass' threshold increases, the EMS providers now have more opportunities to skip the nearby TC and reach the appropriate NTC for a less severely injured patient. This, in turn, means that even if the number of TCs increases marginally (as seen in Table 5), the NTCs are still reachable from the incidence location, resulting in a reduction in srOT. Note that because of higher access threshold and reasonable number of TCs, srUT rates are fairly low and their effect on the WSM is negligible. Any further increase from 18 TCs, for the case of (45, 10), led to an increase in the srOT rate (as more TCs means an increased likelihood of srOT cases) causing WSM to increase.

5.3 Performance of the derived network with respect to unseen demand

As mentioned earlier, there is a significant cost associated with upgrading an NTC to a TC. Consequently, it is important to evaluate if the PSO-derived, near-optimal, TC network based on historical data would perform reasonably well with respect to the unseen, future demand. To do this, we used the Train-Test approach. Accordingly, we apportioned the 2012 data (6,002 cases) into Train (4,002) and Test (2,000) datasets, approximately a 2/3:1/3 split. To ensure that the spatial distribution of trauma incidences in each of these two datasets is similar to the Full dataset, we conducted the apportionment at the county level. The GIS-generated heatmaps in Fig. 8 indicate that the apportionment was reasonable. We ran our proposed solution approach on the 'base case' (i.e., access threshold = 45 min, bypass threshold = 0 min) and adjusted other parameters corresponding to the reduced train and test sets.

Table 5 Impact of 'bypass' threshold on srOT and the number of TCs

Thresholds	#TC	srOT	srUT	WSM
(45, −10)	16	0.492	0.002	0.100
(45, 0)	17	0.131	0.001	0.027
(45, 10)	18	0.018	0.000	0.004

The following are the key observations from this analysis; see Table 6 for a summary:

- The number of TCs found through the Train data set is identical to that found when using the full data set; WSMs are also similar.
- Test WSM on the same network (obtained through Train data) is very similar to Train WSM.

This analysis provides evidence that a near-optimal network obtained using 2012 (Full) data will work reasonably well with respect to unseen, future demand.

6 Case study based on OH's trauma network

We now illustrate how we used our proposed approach using the 2012 data from OH to derive (i) an optimal network (greenfield problem) and (ii) an optimal redistribution of existing TCs within that network (redistribution problem). Due to limited data fields in this data set, we used the overall UT and OT rates (that could also include clinical mistriages) for this case study; these were UT rate = 0.20 and OT rate = 0.515 (which we use as srUT and srOT rate, respectively, in our discussion below). Because we observed variations in

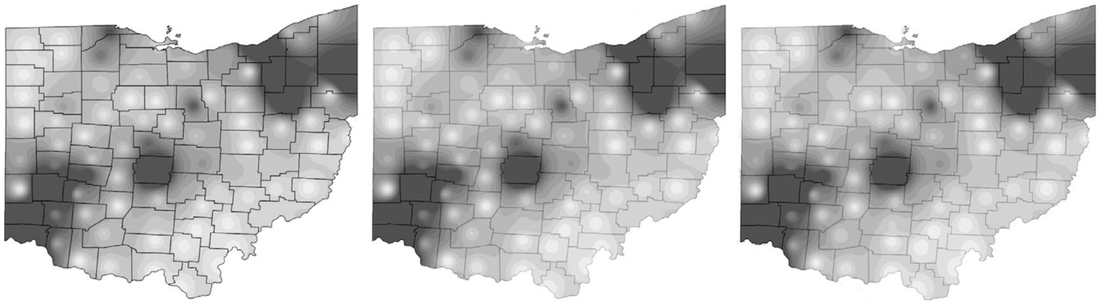


Fig. 8 Heatmap of incidences (darker area indicate higher values of incidences)

EMS practice on 'access (α)' and 'bypass (β)' thresholds in the state, and in order to conduct a fair comparison, we treated both thresholds as meta-parameters that encompass the existing variations in EMS-practice when it came to 'destination determination.' Subsequently, we empirically derived α = 30 minutes and β = -9 minutes ensuring that the resulting performance of the network met the 2012 srUT and srOT rates (0.20 and 0.515, respectively). Note that due to limited data fields, it was difficult for us to tease out the clinical mistriages; we, therefore, used these values of 0.2 and 0.515 as surrogate estimates for srUT and srOT rates, respectively.

Our analysis of the 2012 trauma network is shown in Fig. 4, which shows the distribution of the 21 TCs in the state. These TCs are generally located in areas with higher population density, resulting in a clustered pattern (also alluded in [12]); the resulting WSM at ω_1=0.8 and ω_2=0.2 was 0.270. Not surprisingly, Regions 7 and 8 with no TCs experienced the highest srUT rate (=1.00) and a zero srOT rate; in contrast, Regions 2 and 5 yielded a much lower srUT rate (0.078 and 0.084), but higher srOT rates of 0.527 and 0.772, respectively. On the other hand, Region 1 with 5 TCs still produced an unusually high srUT rate of 0.47, largely because of the clustering of 3 out of 5 TCs in a single urban area (Toledo), which result in high access times for incidences that occur outside of Toledo.

6.1 Greenfield design of OH's trauma network

To optimize the network, we used identical system parameters: (ω_1, ω_2) = (0.8, 0.2), α = 30, β = -9, V^{max} = 91, C = 159; we set V^{min} = 22 to meet the ACS guidelines. The best solution obtained by BPSO (with 40 particles) resulted in 22 TCs with WSM=0.185 (a 31.5% decrease from the 2012 estimate of 0.270). This optimized network reduced the srUT rate by 51.9% (i.e., 0.099 vs. 0.206 in 2012), with srOT rate increased by around 1% (i.e., 0.530 vs. 0.525 in 2012). Evaluation of the results depicted a rather dispersed pattern of TCs across the state (see Table 7). Specifically, Regions 7 and 8 (with TC in Region 8 near to the boundary of the Region 7) now experienced a lower srUT rate of 0.786 and 0.278, respectively. But the counter effect is that because of a TC in the region or near to the boundary of the region, the srOT rates increased in both Regions 7 and 8 (i.e., 0.229 and 0.324, respectively). Alternatively, a reduction from 5 TCs to 2 TCs in Region 1 resulted in the srUT rate dropping to 0.313 (compared to 0.47 in 2012) with a significant decrease in the srOT rate (0.252 compared to 0.41 in 2012). That is, while the state of OH may have a nearly optimal number of TCs, their suboptimal distribution leads to high WSM.

6.2 Redistribution of 21 TCs in OH

If a 'greenfield' design may not be possible, then *could a redistribution of the 21 TCs within the state reduce the mistriages rate?* To answer this question, we set C = 21 in Constraint (16) of the TCLP model and kept the rest of the parameters identical to Section 6.1. Figure 9 illustrates the differences in the heat maps for srUT and srOT across the 3 networks (2012, greenfield, and redistributed).

The results were quite interesting; the 21 TCs were distributed quite differently across the state (see Table 8 region-wise comparison). This redistribution likely allowed more trauma patients to access a TC within the 'access' threshold (via ground or air). This is evident from a substantial drop in the srUT rate (by 46.6% to 0.11); the srOT rate also decreased by 4.95% to 0.499; WSM reduced to 0.188 compared to 0.270 (a 30.4% decrease).

Table 6 Comparison of performance of network for full data and train data, and performance of test data for the network obtained through train data

	Full Data (6002 incidences)	Train Data (4002 incidences)	Test Data (2000 incidences)
WSM	0.0271	0.0291	0.0299
# TCs	17	17	–

Table 7 Comparison of 2012 network and optimized greenfield network

Region	# of TCs		srUT rate		srOT rate	
	2012 allocation	*TCLP allocation*	2012 allocation	*TCLP allocation*	2012 allocation	*TCLP allocation*
1	5	*2*	0.470	*0.313*	0.410	*0.252*
2	3	*3*	0.078	*0.000*	0.527	*0.525*
3	2	*4*	0.227	*0.061*	0.553	*0.668*
4	4	*4*	0.184	*0.143*	0.576	*0.588*
5	6	*5*	0.084	*0.036*	0.772	*0.515*
6	1	*3*	0.174	*0.062*	0.302	*0.553*
7	0	*0*	1.000	*0.786*	0.000	*0.229*
8	0	*1*	1.000	*0.278*	0.000	*0.324*
Overall	**21**	***22***	**0.206**	***0.099***	**0.525**	***0.530***

The above two illustrations of our approach (i.e., greenfield and redistribution) using an actual state-wide network of all hospitals (TCs and NTCs) not only demonstrate that opportunities exist in the state to substantially improve patient safety, but also that our proposed approach is able to unearth those by specifying better networks.

7 Summary and future research

Timely access of severely injured trauma victims to trauma centers can improve survival by 25%. Given the limitations of existing approaches in locating trauma facilities to address patient safety, we proposed the Trauma Center Location Problem (TCLP). The TCLP is to determine the optimal number and location of TCs in order to minimize the weighted sum of mistriages (srUT and srOT). This problem is an extension of multi-facility and multi-customer location models, which incorporates individual customer characteristics and individualized network-dependent allocation, along with multi-transportation modes.

We introduced an optimization model for TCLP that explicitly models patient safety via srUT and srOT rates, both estimated using our proposed notional tasking algorithm based on the standing guidelines in the trauma literature. To efficiently solve the resulting model, we proposed a Binary Particle Swarm Optimization (BPSO) approach and illustrated its use on 2012 data for the state of Ohio. The Train-Test approach provided further validity to our approach.

The key insights from our study include the following:

(i) While an increase in the number of TCs can reduce srUT, it can increase srOT; setting an appropriate emphasis on their reduction (via weights) in the objective function is critical.

(ii) There is an inverse relationship between TC volume requirement and the number of TCs in the network. As a minimum volume requirement increases, some of the TCs need to downgrade to NTC's because of infeasibility due to low volume. A downgrade of TC increases the srUT rate that eventually decreases patient safety.

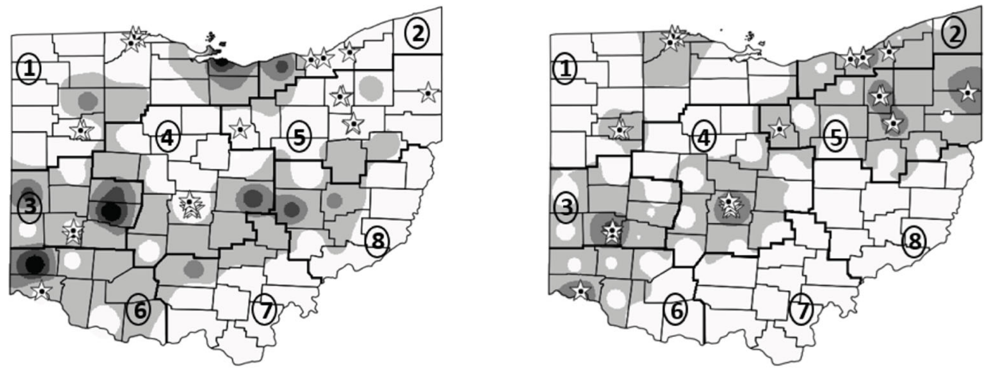
(iii) While requiring EMS to transport severely-injured patients to the nearest TC is desirable (reflected by a lower 'access' threshold), this can only be achieved through an increase in the number of TCs in the network (with the corresponding effect indicated in (i) above).

(iv) The illustration of our approach using real data from OH suggested that state has the nearly optimal solution in terms of the number of TC but significantly suboptimal objective value. A state can achieve up to 51.9% reduction in srUT at almost the same srOT rates can be realized with 1 additional TC; redistributing the same 21 TCs can still achieve the high reduction in srUT (46.6%) along with a 4.95% reduction in srOT.

We believe our proposed approach is effective and efficient in helping state trauma decision makers not only evaluate their current system, but also optimize it (either as a greenfield or redistribution problem). They can also conduct 'what-if' analysis by fixing certain TCs in their current locations and allowing the optimization approach to find the locations of other TCs in the state. This latter approach can be of particular interest to those states where a mass reallocation of TCs is not possible; instead, they are seeking a gradual change over a period of time, or evaluating the viability of a proposal by a healthcare system to upgrade an NTC to a TC or downgrade an existing TC to an NTC.

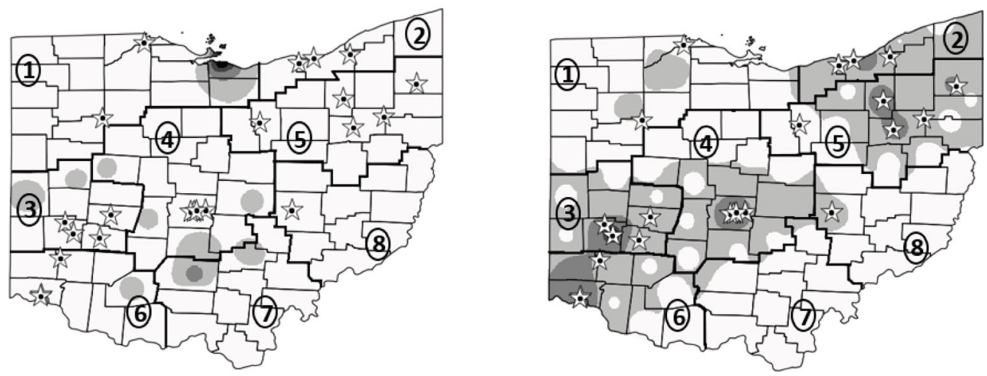
While the notional tasking algorithm closely matches with what ideally EMS providers are expected to do (per state EMS department), future work could include enhancing the tasking algorithm with additional features

Fig. 9 Heat maps of mistriage. (Note: Darker shades indicates higher values; Stars represents TCs)



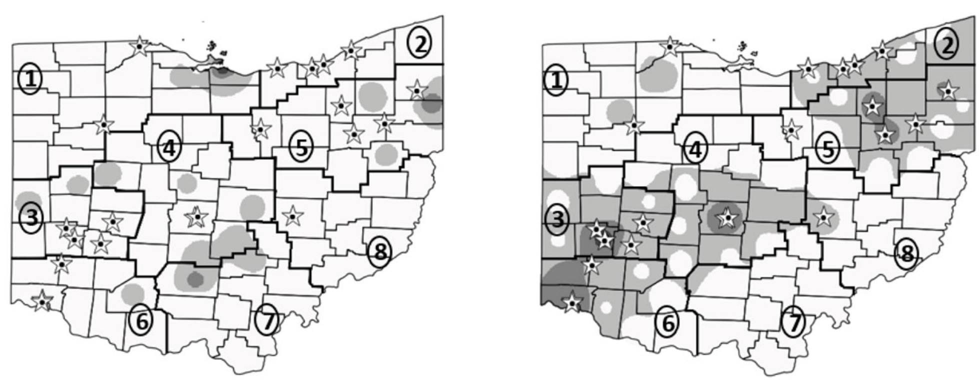
srUT = 0.206 srOT = 0.525

(a) 2012 Network = 21 TCs



srUT = 0.099 srOT = 0.530

(b) Greenfield Network = 22 TCs



srUT = 0.110 srOT = 0.499

(c) Redistributed Network = 21 TCs

such as patient/family choice and other operational criteria. The inclusion of the cost incurred in upgrading an NTC to a TC through a multi-criteria optimization model would allow trauma policy-makers to appropriately tradeoff cost vs. care in designing their network. Models to jointly optimizing the network of L1-L2 TCs and L3-L5 TCs (that provide intermediate care) could be devised based on this foundational work to help local and state government trauma officials to effectively tradeoff between patient safety and system cost.

Table 8 Comparison of 2012 network and redistributed network

Region	# of TCs		srUT rate		srOT rate	
	2012 allocation	TCLP allocation	TCLP allocation	2012 allocation	TCLP allocation	2012 allocation
1	5	*2*	0.470	*0.253*	0.410	*0.223*
2	3	*4*	0.078	*0.022*	0.527	*0.341*
3	2	*4*	0.227	*0.055*	0.553	*0.668*
4	4	*2*	0.184	*0.156*	0.576	*0.540*
5	6	*5*	0.084	*0.080*	0.772	*0.504*
6	1	*3*	0.174	*0.056*	0.302	*0.553*
7	0	*0*	1.000	*0.786*	0.000	*0.229*
8	0	*1*	1.000	*0.389*	0.000	*0.324*
Overall	**21**	***21***	**0.206**	***0.110***	**0.525**	***0.499***

Appendix 1. Notional Tasking Algorithm to estimate srUT and srOT

Figure 10 presents a schematic of the notional tasking algorithm. Accordingly, let $t_{TC\text{-}gnd}$ and $t_{TC\text{-}air}$ refer to the total time from field to the TC via ground and air, respectively, and t_{NTC} is the time from field to NTC via ground (i.e., road). While t_{in} and t_{load} refer inbound and loading time for the air ambulance, respectively. If t_{access} and t_{bypass} refer to the 'access' and 'bypass' thresholds, then

- If ISS > 15 (i.e., severe injuries), then
  - If $t_{TC\text{-}gnd} \leq t_{access}$, then transport to TC
  - Elseif (helicopter available), then
    - If $t_{TC\text{-}air} + t_{in} + t_{load} \leq t_{access}$, then transport to TC
    - Else transport to NTC (and mark the case as srUT)
  - Else transport to NTC (and mark the case as srUT)
- Elseif ISS ≤ 15 (i.e., less severe injuries), then
  - If $t_{NTC} - t_{TC\text{-}gnd} \leq t_{bypass}$, then transport to NTC
  - Else transport to TC (and mark the case as srOT)

Table 9 presents a few representative cases to illustrate how the tasking algorithm helps classify a specific trauma incidence as appropriately triaged (srAT^P for triaged to TC

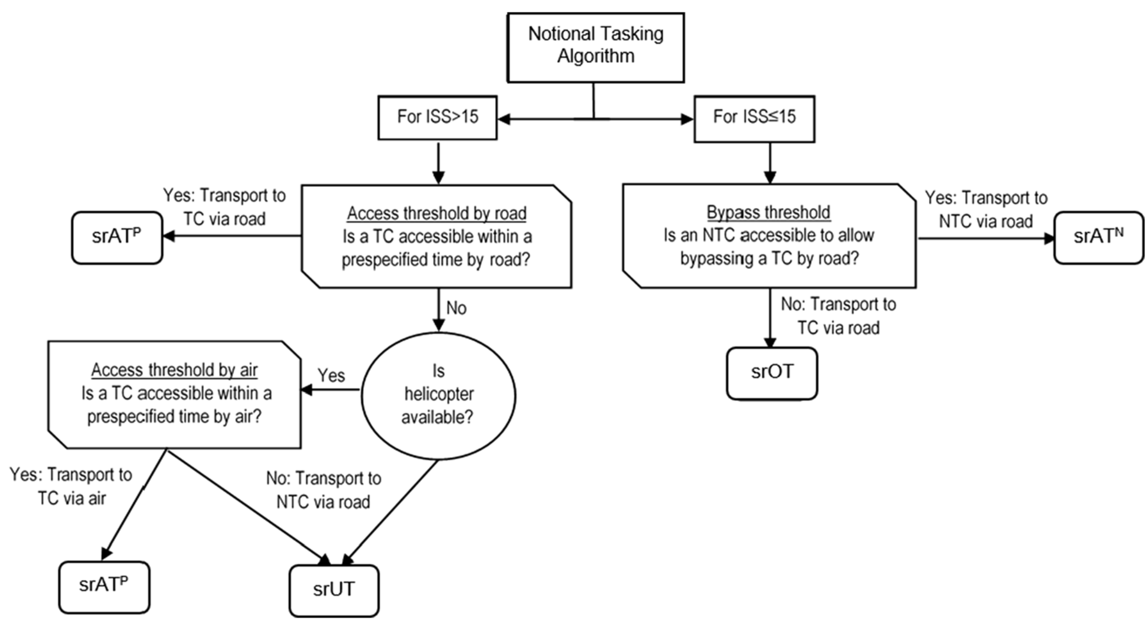


Fig. 10 Notional Tasking Algorithm

Table 9 Illustration of Triage Classification by the Notional Tasking Algorithm (t_{access} = 30 min and t_{bypass} = 15 min)

Instance	ISS	Ideal hospital	Time to nearest TC by road, $t_{TC\text{-}gnd}$ (mins)	Time to nearest TC by air, $t_{TC\text{-}air}$ (mins)	Time to nearest NTC by road, t_{NTC} (mins)	Likely EMS transport	Triage classification	Reason
1	18	TC	25	10	45	TC	$srAT^P$	$t_{TC\text{-}gnd} \le t_{access}$ TC is within access threshold by road
2	27	TC	40	15	55	TC	$srAT^P$	$t_{TC\text{-}air}+t_{in}+t_{load} \le t_{access}$ TC is within access threshold by air
3	24	TC	80	35	24	NTC	srUT	$t_{TC\text{-}gnd}$; $t_{TC\text{-}air}+t_{in}+t_{load} > t_{access}$ TC is not within threshold by road/air
4	10	NTC	30	–	16	NTC	$srAT^N$	$t_{NTC}- t_{TC\text{-}gnd} \le t_{bypass}$ NTC is within bypass threshold
5	14	NTC	25	–	8	TC	srOT	$t_{NTC}- t_{TC\text{-}gnd} > t_{bypass}$ NTC is not within bypass threshold

and $srAT^N$ for triaged to NTC) or mistriaged (srUT or srOT). In these cases, we assume t_{access} = 30 min and t_{bypass} = 15 min.

In Table 9 consider trauma incidence #1 with ISS > 15, suggesting the need to transport this patient to the nearest TC. The algorithm first finds the nearest TC from the incident field in a given network and compares the EMS ground transportation to this TC ($t_{TC\text{-}gnd}$) to the 'access' threshold. Because $t_{TC\text{-}Gnd} < t_{access} = 25 < 30$, driving to this TC is feasible, and so the case is categorized as $srAT^P$. However, for incidence #2 also with ISS > 15, $t_{TC\text{-}Gnd} > t_{access}$ (40 > 30), and so the possibility of air transportation is explored. The algorithm then compares the total flight time to this TC ($t_{TC\text{-}air}$), which accounts for inbound from the nearest helicopter base, patient loading, and outbound to the TC, with t_{access}. Assuming an inbound time of 5 min and a loading time of 5 min, the total air transportation time will result in 25 min. In this case, $t_{TC\text{-}air} < t_{access}$ (25 < 30), and thus this incidence is classified as transportation via air, also resulting in $srAT^P$. But the total air transportation time incorporating inbound and loading time may not be feasible, as in the case of incidence #3 where $t_{TC\text{-}air} > t_{access}$ (35 + 5 + 5 = 45 > 30), in which case the patient will be assigned to the nearest NTC by road, and the incidence will be classified as a srUT. Similarly, all the patients meeting the inclusion criteria are run through the tasking algorithm. A similar process is followed for patients with ISS ≤ 15; air transportation is not considered as the injuries are less severe, in line with the actual EMS practice.

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