A MODEL TO OPTIMIZE MAJOR TRAUMA CENTER NETWORK CONSIDERING PATIENT SAFETY

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I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY SUPERVISION BY Monit D. Vaishnav ENTITLED A Model to Optimize Major Trauma Center Network Considering Patient Safety BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Master of Science in Industrial and Human Factors Engineering.

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ABSTRACT

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Trauma is any physical injury that has the potential to cause prolonged disability and death if the appropriate level of care is not administered in a timely fashion. Existing approaches in the literature and by the American College of Surgeons (ACS) to optimize the network of trauma centers are limiting. To address this challenge, we introduce the Trauma Network Design Problem, a bi-objective mathematical model that aims at determining the optimal trauma network by minimizing the weighted sum of mistriages. We use the trauma network data from 2012 for the state of Ohio to illustrate the use of our approach and conduct sensitivity analysis. While substantial improvements in mistriages can be realized through our approach, the solutions are sensitivity of the weights in the objective terms, trauma volume, and threshold values. We also illustrate how our approach can be used to compare suggestions from the ACS's NBATS tool.

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1. INTRODUCTION

Trauma is a body wound caused by sudden physical injury, such as from motor-vehicle crash, gunshot, fall, or violence which requires immediate medical attention (Cho et al., 2014). It is #1 leading 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 (ACS, 2016). It is the most expensive, yet predictable and preventable public safety problem (Potter, J. D., 2011).

A trauma center is a type of hospital equipped and operated to provide a designated level of care for the patients suffering from major traumatic injuries (Cho et al., 2014). The American College of Surgeons (ACS) has verified, and categorized trauma centers based on their level of care, from Level I (L1) to Level V (L5). Both L1 and L2 are designated 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 (ATS). Because L1/L2 center are destinations for appropriate care of 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).

Because trauma is a time-sensitive disease condition, timely access to a TC is recognized as one of the critical components of key determinants of outcome in trauma care system (Branas et al., 2013; Jansen et al., 2015). It has been reported that if a severely injured trauma victim is able to receive care at a TC, then their survival improves by 25% relative to the care delivered at an NTC (MacKenzie et al., 2006). 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)" (ACS, 2016) . The reason for this is the geographic maldistribution of TCs in the US; 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. (Brown et al., 2016). Figure 1 shows the distribution of nearly 520 L1/L2 TCs in the U.S. with the 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 (14.09% land) (Branas et al., 2005; Carr & Branas, 2010).

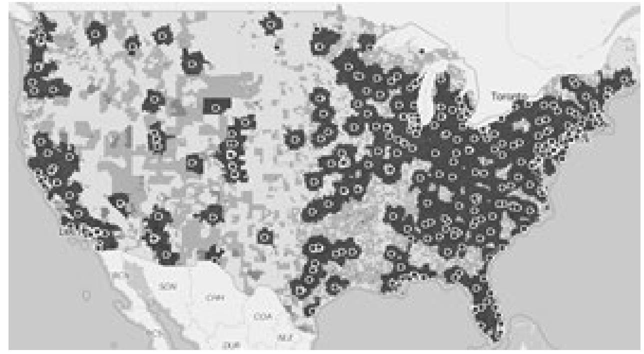


Figure 1: Network of L1/L2 TCs in U.S. Red dots=TCs, dark shade = 60-minute coverage via ground and air, and light = U.S. population

Trauma decision making starts from the moment the Emergency Medical Service (EMS) providers arrive at the scene of the incidents. EMS field triaging is the process of accessing a patient's severity of injury to determine the required level and promptness of care. The goal of the triage decision is to improve safety and reduce mortality, a primary safety metric. Literature suggests that errors in field triage, known as mistriages, can jeopardize patient safety, and is often used as surrogate, quantifiable, patient-safety measure (Sasser et al., 2012). A mistriage is referred to as an incorrect determination of the required level of care based on the patient's underlying injuries (Ciesla et al., 2015).

Several reasons contribute to mistriages: controllable (such as trauma network, injury assessment, EMS resources) or uncontrollable (such as weather condition, law and policy, traffic congestion) factors. While approaches to address some of the controllable factors such as accurate assessment of injury (Brown et al., 2016; Parikh et al., 2017), and EMS resources (Eastwood et al., 2015; Voskens et al., 2018) have been studied that may lead to mistriages, very little work has been done in assessing the implications of a suboptimal network of TCs (quite often a primary factor in the EMS decisions) on mistriages. A lack of a TC within a prespecified time (per clinical recommendations, say 45 minutes) from the scene can cause the EMS providers to take a severely injured patient to a nearby NTC, which is referred to as under-triage (UT). Similarly, an excess (or cluster per Brown et al., 2016) of TCs in the vicinity of a scene can prompt the EMS providers to take a less severely injured patient to one of those (instead of an NTC), which is referred to over-triage (OT) (Newgard et al., 2016). UT causes delay in the provision of definitive care and increases the likelihood of an adverse outcome (such as disability, morbidity, and even mortality) (Roland et al., 2014). In contrast, OT can cause overcrowding at emergency departments (Lerner, 2006), unnecessary trauma activation requiring trauma providers (physicians and nurses) to suspend their care of admitted trauma patients in the 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 (Frykberg, 2002; Armstrong et al., 2008). OT also has another side effect of higher cost of care due to clinical tests, trauma activation fee, trauma surgeon charges, etc. The American College of Surgeons (ACS) has suggested the acceptable range for UT to be less than 5% and OT rate to be around 25-35% for optimal triage and system utilization (Roland et al., 2014).

In the recent years, there has been an increased interest in developing approaches to analyze an existing network of TCs and potentially optimize it to meet the ACS recommendations. The ACS itself has developed a guideline, Needs Based Assessment of Trauma Systems (NBATS), that suggests the number of TCs in a region (but not their location), it is limited as the impact of these TCs on UT and OT cannot be estimated. A few studies have emerged that attempt to use optimization-based approaches (see Section 2) but they do not account for OT and discuss the sensitivity of their solutions to system parameter

The specific objective of this study is to address the questions that were posed to us by our collaborating trauma decisions 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., UT and OT)?;* (ii) *How sensitive is the network to changes in system parameter; and (iii) How does this solution compare to the current network in the state and recommended network using the ACS-NBATS tool?* To address these questions, we propose the Trauma Network Design Problem (TNDP) of determining the optimal number and location 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 explicitly include both UT and OT in the objective function; OT was not considered in prior work limiting the negative implications on patient safety if TCs in a region were in excess. Second, we propose an approach to estimate it using a notional field triage protocol, which uses actual drive times from the scene to all the candidate hospitals calculated using Google Distance Matrix API. Third, because UT and OT are not in closed analytical form lending the optimization model not amenable to be solved using state-of-the-art methods, we propose a heuristic-based solution approach using binary particle swarm optimization. Fourth, we also evaluate the sensitivity of our solutions to the minimum trauma volume required for a TC to exist, choices of weights in the bi-objective function, and threshold value for UT estimation. Finally, we compare our solutions to that of the current network in the state of OH and that proposed by the ACS-NBATS tool. We illustrate the use of our approach and conduct all the analysis using a representative sample of nearly 6000 de-identified trauma patient data from 2012 provided from the Ohio Department of Public Safety's EMS Division.

Our findings suggest that it is possible to achieve same or better performance on mistriages with 19 TCs versus 21 TCs in the state of OH in 2012; we observed a 26% reduction in WSM. Further, an increase in the minimum required total trauma volume results in a decrease in the total number of TCs. Solutions from our approach are also sensitive to the selection of weights; higher weight on UT increases the number of TCs, while higher weight on OT decreases this number. Furthermore, an increase in the ‘access’ threshold value in the notional triage protocol, which indicates a higher access time margin for the EMS to reach the appropriate TC, results in a decrease in the WSM. A comparison with the ACS-NBATS prediction, which projects a total of 12 TCs for the state but does not specify locations, demonstrate a 31% decrease in the WSM value (46.4% decrease in UT rate and 35% increase in OT rate. Similarly, just a re-distribution of the 2012 network for the same number of TCs (i.e., 21) led to a 26% reduction in WSM value (62.5% drop in the UT rate and 18.75% increase in the OT rate).

2. LITERATURE REVIEW

The literature in healthcare facility location is vast and includes locating long-term health care facilities (Cardoso et al., 2015), blood bank locations (Çetin & Sarul, 101), organ-transplant centers (Caruso & Daniele, 2018), tuberculosis testing laboratories (Saveh-Shemshaki et al., 2012), and mobile healthcare units (Doerner et al., 2007). See (Ahmadi-Javid et al., 2017) for a comprehensive review of similar healthcare facility location models. These models vary in their objectives, may it be cost-based or patient safety based. Several cost-based approaches have been proposed; e.g., location-allocation of organ-transplant center (Zahiri et al., 2014), design of medical service (Shishebori & Babadi, 2015), and health centers for traumatic brain injury(Côté et al., 2007; Syam & Côté, 2010). Because the focus of our work is on patient safety, we now summarize key approaches 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 with a fixed assess time. Objective (i) has been used to improve access to healthcare facilities (Cocking et al., 2012), optimizing the location of organ transplant centers (Beliën et al., 2013), solving location and dispatching problem for an ambulance system (Schmid, 2012; Toro-Díaz et al., 2013), and optimizing shelter location in humanitarian logistics (Bayram et al., 2015; Chen et al., 2013). Similarly, objective (ii) has been preferred in general healthcare facility planning (Kim & Kim, 2013; Shariff et al., 2012), optimizing ambulance location (Ingolfsson et al., 2008), and relocation of ambulance station (Cheng et al., 2011), and location of distribution centers in a relief network (Balcik & Beamon, 2008), and emergency response facility during an earthquake (Salman & Yücel, 2015).

Patient safety has been an important criterion in the trauma facility location literature. Branas et al., (2000), proposes a linear programming model, Trauma Resource Allocation Model for Ambulance and Hospitals (TRAMAH) that simultaneously locates 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 shortest driving time and Euclidean distance for air time and is solved using CPLEX Version 1.2. The model uses proxy for incident location, lacking the geographical granularity and does not account for the less severely injured patients. Lee et al., (2012), presents a model that simultaneously locates trauma centers and medical helicopters with an objective of maximizing the expected number of patients transported to a TC within 60 minutes and applies the model to nationwide trauma care system in Korea. The authors have not only incorporated busy fraction for medical helicopters, but also developed the Shifting Quadratic Envelopes algorithm to optimize the problem However, the model only considers severely injured patients and has incorporated Euclidean distance between demand region and a TC. Jansen et al., (2014), proposes a novel data-driven approach with a bi-objective of minimizing the total access time and the number of exceptions or system related UT for Scotland (Jansen et al., 2015). They extended the model formulation in (Handing et al., 2016) and solves it by proposing a multifidelity surrogate-management strategy for NSGA-II. They demonstrate the viability of their approach using real data from the state of Colorado's trauma system (Jansen et al., 2018). 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 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 were severely injured patients transported (TCs and NTCs), and total number of TCs (ACS-NBATS, 2015). However, the tool does not determine the location of these TCs.

Our review of the above literature reveals the following gaps. First, the derivation of OT rates based on injury score and its on-scene operational decision-making process has never been explicitly considered and accounted in the optimization models. Second, no studies 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 injury. For a severely injured patient, the proposed access time is 30, 45, or 60 minutes (depending on the region/state), but for a less-severely injured patient, there is no such access time proposed by the literature. Third, the sensitivity of the 'access' threshold values for a patient to reach its designated level of care, used for determining the UT based on the number and location of trauma centers has not been explored. Finally, we know of no literature that jointly considers the metrics of mistriages (UT and OT) to determine the optimal number and location of trauma centers.

To fill the gap as mentioned above, we propose a bi-objective non-linear mathematical model that determines the optimal number and location of trauma centers with the aim of minimizing the weighted sum of mistriages. The key features of this model are the inclusion of actual drive times from the scene to all the candidate hospital locations, a notional field triage protocol to determine UT and OT rates, and sensitivity on the minimum trauma case volume, weights of mistriages, and threshold value for UT rate. We now present our proposed model and solution approach.

3. A BI-OBJECTIVE MODEL FOR TNDP

We define the Trauma Network Design Problem (TNDP) as the determination of an optimal network that minimizes the weighted sum of mistriages (UT and OT). The model assumes that a geographically defined region, known as the Trauma Service Area (TSA), is known. This defined region could be a county, a region in the state, or the state itself. We make the following assumptions in developing our model:

- The candidate locations for the TCs in the TSA are known and finite.
- Injury Severity Score (ISS) is used as a surrogate to estimate the severity of injury at the scene.
- Ground ambulance services are available without constraints, but the availability of air ambulance is limited, but known.
- If a TC is located in a zip-code, the population of all adjacent zip-codes in the radius of 60 minutes are assumed to be covered to emulate the 'golden hour' coverage often reported in the trauma literature.

Tables 1 and 2 summarize the parameters and decision variables, respectively, used in our model.

Table 1. Parameters used in model

Notation	Definition
i	Index for candidate location for TC; i = 1, 2, …, I
j	Index for zip-code; j = 1, 2, …, J
k	Index for trauma incidence; k = 1, 2, …, K
TP	Total population in the region
P_j	Population in zip-code j
A_{ij}	1, if zip-code is covered by a TC; 0, otherwise
α	'Access' time threshold for UT (minutes)
β	'Bypass' time threshold for OT (minutes)
In-time	Inbound time for an air ambulance from its base to scene
Load-time	Loading time of a patient to an air ambulance
δ	Coverage parameter
μ	Availability of air ambulance; $0 \leq \mu \leq 1$
V^{min}	Minimum trauma volume at location i
ISS_k	Injury severity score for incident k
ω_1	Weight for under-triage (UT)
ω_2	Weight for over-triage (OT)

Table 2. Decision variables in the model

Notation	Definition
x_i	1, if a candidate location is designated to be a TC; 0, otherwise
y_{ij}	1, if a zip-code j is covered by a facility i; 0, otherwise
γ_{ik}	1, if an incident k is assigned to a facility i; 0, otherwise
z_j	1, if a zip-code j is covered by a facility i; 0, otherwise
UT	Estimated UT rate from the notional field triage algorithm
OT	Estimated OT rate from the notional field triage algorithm

Minimize: $\omega_1 \cdot \mathrm{UT} + \omega_2 \cdot \mathrm{OT}$

Subject to:

$$\mathrm{UT} = f\,(x_i, \alpha\ \mu, ISS_k; \forall i, k) \quad (1)$$

$$\mathrm{OT} = g\,(x_i, \beta, ISS_k; \forall i, k) \quad (2)$$

$$\textstyle\sum_j (z_j\ P_j) \ \geq\ \delta\ P \quad (3)$$

$$z_j\ \leq\ \textstyle\sum_i (y_{ij}\ A_{ij}) \qquad \forall\ j \quad (4)$$

$$\textstyle\sum_k \gamma_{ik}\ \geq\ x_i\ V^{min} \qquad \forall\ i \quad (5)$$

$$x_i, y_{ij}, \gamma_{ik}, z_j\ \in\ \{0, 1\} \qquad \forall\ i, j, k \quad (6)$$

$$UT,\ OT\ \in\ [0, 1] \quad (7)$$

$$\omega_1 + \omega_2 = 1 \quad (8)$$

The objective of the TNDP is to minimize the weighted sum of under-triage (*UT*) and over-triage (*OT*) rates. Both UT and OT are estimated via functions *f* and *g*, respectively, which depend on several system parameters (Constraints (1) and (2)). We estimate these functions through the notional field triage protocol (see Section 3.1).

Constraint (3) ensures that the total population covered across all zip-codes exceeds a pre-specified proportion (δ) of the total population in the State. Constraints (4) define the population covered by the network of TCs for each zip-code. We use z_j to ensure that a zip-code is only counted once. Constraint (5) specifies a lower bound on the trauma cases required to be handled by a location *i* if it is a TC. Constraints (6), (7), and (8) specify bounds on the decision variables and parameters.

Clearly, TNDP is specific case of a more general network design problem. Such problems are combinatorial in nature and have been shown to be NP-hard (Daskin, 2013). TNDP exhibits the same characteristic where the decision to upgrade or downgrade each of the *n* existing hospitals is binary. For n=150, this results in $2^{150} = 1.42x10^{45}$ solutions. To further add complexity to the TNDP, both UT and OT rates cannot be expressed in a closed analytical form. For a given trauma network, these rates depend upon the decision of the allocation to the most appropriate closest TC or NTC for each patient's injury severity score. That is, as the network of TCs changes, so do the UT and OT rates. Considering the limitations of existing approaches to solve TNDP optimally, we explore the use of a heuristic based approach using the Particle Swarm Optimization (PSO) framework to derive near-optimal solutions in a reasonable time. We now discuss how we estimate the UT and OT rates for a given network based on a notional field triage algorithm and then discuss the PSO algorithm.

3.1 A Notional Field Triage Protocol to estimate UT and OT rates

Our proposed notional field triage protocol, similar to (Jansen et al., 2018), attempts to mimic the decision-making process of the EMS providers on the field. To model the EMS decisions based on transport times, we introduce two threshold values; (i) 'access' threshold for transport to the TC (for UT) and (ii) 'bypass' threshold for transport to NTC (for OT). While (i) helps determine if a case would be an UT, (ii) helps to determine if the case may result in an OT. 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. Note that while (i) was used in (Jansen et al., 2018), (ii) has never been discussed in the literature before; in that sense, our notional protocol is more general than previous work. Figure 2 shows a schematic of the notional protocol.

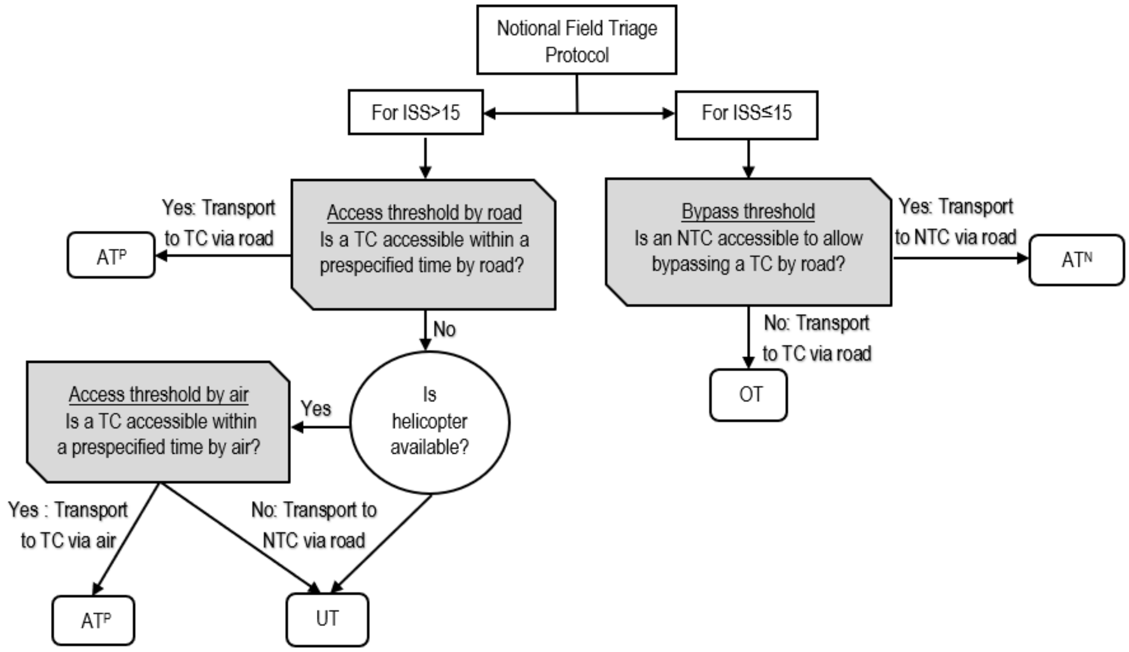


Figure. 2 Notional Field Triage Protocol

Our review of the literature and observations at a leading EMS agency in our region suggests that for severely injured patients, the EMS providers first check if a TC is accessible within the 'access' threshold time. If yes, then the patient is transported to the TC. If no, then they check if an air ambulance can be called in to transport the patient to the nearest TC. However, if the sum of the inbound-to-scene, loading, and transport-to-TC is higher than the 'access' threshold, then the EMS would most likely take the patient to a nearby NTC, resulting in a UT. In contrast, the case of an OT is a bit more complicated. While less severely injured patients should be taken to an NTC, if the additional time to reach a TC is within the 'bypass' threshold, then the EMS often take the patient to the TC, resulting in an OT. The reasons for such OT can vary; TC's reputation, the-bigger-the-hospital-the-better-the-care, patient/family choice, insurance situation, and even negotiated contracts between the EMS and TC.

Table 3 presents a few cases to illustrate how the protocol helps classify a specific trauma incidence as appropriately triaged (AT^P for triaged to TC and AT^N for triaged to NTC) or mistriaged (UT or OT). For these instances, we assume 'access' (t_{access}) and 'bypass' (t_{bypass}) thresholds as 30 minutes and 15 minutes, respectively. For example, consider the trauma incidence #1 with ISS>15, suggesting the need to transport this patient to the nearest TC. The algorithm first finds the nearest TC 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 AT^{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 the inbound time of 5 minutes and loading time of 5 minutes, the total air transportation time will result in 25 minutes. In this case, $t_{TC\text{-}air} < t_{access}$ (25<30), and hence this incidence is classified as transportation via air, also resulting in AT^{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 an UT. Similarly, all the patients meeting the inclusion criteria are run through the protocol. A similar process is followed for patients with ISS≤15; air transportation is not considered as the injuries are less severe, in line with actual EMS practice.

Table 3. Illustration of Triage Classification by the Notional Field Triage Protocol (t_{access} = 30 minutes and t_{bypass} = 15 minutes)

Trauma incidence	ISS	Should be allocated to	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 classifi-ation	Reason
1	18	TC	25	10	45	TC	AT^P	$t_{TC\text{-}gnd} < t_{access}$ TC is within access threshold by road
2	27	TC	40	15	55	TC	AT^P	$t_{TC\text{-}air} < t_{access}$ TC is within access threshold by air
3	24	TC	80	35	24	NTC	UT	$t_{TC\text{-}gnd}$; $t_{TC\text{-}air} > t_{access}$ TC is not within threshold by road/air
4	10	NTC	30	-	16	NTC	AT^N	$t_{NTC} - t_{TC\text{-}gnd} < t_{bypass}$ NTC is within bypass threshold
5	14	NTC	25	-	8	TC	OT	$t_{NTC} - t_{TC\text{-}gnd} > t_{bypass}$ NTC is not within bypass threshold

Table 4. Contingency matrix

		Injury Severity Score (ISS)	
		ISS>15	ISS≤15
Destination	To TC	Appropriate-triage (AT^P)	Over-triage (OT)
	To NTC	Under-triage (UT)	Appropriate-triage (AT^N)

Trauma literature suggests treating the EMS decision making process as similar to a binary classification problem. Accordingly, we can generate a contingency matrix with AT^P (true positive), AT^N (true negative), UT (Type 1 error), or OT (Type 2 error); see Table 4. In that case, UT is calculated as (1-sensitivity), where the true positive value is the count of total appropriate triages, and the false negative value or type-1 error is the total under-triage cases for incidents with ISS>15 for a given network. Similarly, *OT* rate is derived as (1-specificity), where the true negative value is the total appropriate triage, and false positive or type-2 error is the sum of total over-triage cases, for incidents with ISS≤15 for a given configuration and can be determined via the below expressions: UT = 1 – sensitivity $= 1 - \left(\frac{AT^P}{AT^P+UT}\right)$ and OT = 1 – specificity $= 1 - \left(\frac{AT^N}{AT^N+OT}\right)$ (Newgard et al., 2016) .

Note that the notional protocol provides a means to estimate UT and OT rates for a given network. We embed this protocol to provide these estimates for every candidate network of TCs generated by the BPSO algorithm, discussed next.

4. BINARY PARTICLE SWARM OPTIMIZATION

PSO is a nature-inspired population-based metaheuristic algorithm that optimizes continuous nonlinear function (Kennedy James & Eberhard Russell, 1995). PSO has been implemented in a wide range of research areas such as facility location (Yapicioglu et al., 2007; Latha et al., 2013), network design (Chia-Feng Juang, 2004; Izquierdo et al., 2008), and scheduling (Bo Liu et al., 2007; Liao, Chao-Tang & Luarn, 2007). It is not only used in engineering but also used in various applications, ranging from biological and medical applications to computer graphics and music composition (Sedighizadeh & Masehian, 2009). The PSO framework is easy to implement, makes fewer assumptions about the problem, is flexible and robust, and can be applied in a parallel manner (Ponnambalam et al., 2009).

The algorithm mimics the social behavior of birds flocking and fish schooling. It begins with a randomly distributed set of particles (potential solutions) and using mathematical operators the solution tries to progress to a 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 (Clerc & Kennedy, 2002). 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 the 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 among all the population 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} updates of the dth dimension of the ith particle for tth iteration are given by:

$$x_{id}^{t} = x_{id}^{t-1} + v_{id}^{t} \tag{9}$$

$$v_{id}^{t} = K(v_{id}^{t-1} + c_1 r_1 (pbest_{id} - x_{id}^{t-1}) + c_2 r_2 (gbest_d - x_{id}^{t-1})) \quad (10)$$

where c_1 and c_2 are acceleration constant set at 2.05, and r_1 and r_2 are two uniformly distributed random numbers in [0,1]. Constriction coefficient, *K,* aides in the convergence of the particle swarm algorithm; *K*=0.7298 (Clerc & Kennedy, 2002). The particle velocity given in equation (10) 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 TNDP are binary. We, therefore, use the discrete binary version of the PSO, the Binary PSO (BPSO) (Kennedy & Eberhart, 1997). Accordingly, each particle represents its position in binary values, and the velocity of a particle is defined as the probability that might change it to either zero or one. The behavior and meaning of the velocity clamping and the inertia weight differ considerably from the real-valued PSO (Khanesar et al., 2007). However, the velocity update equation (10) remains unchanged, except that now the positions are binary and particle update equation (9) is replaced by:

$$if\ (rand() < S(v_{id})), then\ x_{id} = 1;\ else\ x_{id} = 0, \quad (11)$$

where the function *S(v)* is a sigmoid limiting transformation function, $S(v_{id}) = 1/(1 + e^{-v_{id}})$, and *rand*()~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 equal $S(v_{id})$ and a bit will be 0 equals 1 - $S(v_{id})$. If it is already zero, then the probability that it will change is $S(v_{id})$, and if it is one, then the probability that it will change is 1 - $S(v_{id})$ (Kennedy & Eberhart, 1997). The high-level structure of the PSO is as follows:

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

In our proposed BPSO, we consider a swarm of 8 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. Solutions that are not feasible are not evaluated and not considered as either personal or global best. As the mathematical model aims to minimize the objective function, the value given to in-feasible solutions is much higher. Hence, keeping them out of the loop. Equation (10) and (11) are applied for the update of velocity and particle, respectively.

We have used Python programming to implement our proposed BPSO and the notional field triage protocol on a personal computer with 8-core, each 3.4 gigahertz processors, and a total of 16 GB RAM. We also implemented parallel processing in Python to allow for parallel evaluation of each particle, which reduced the computation time to about 4 hours, nearly 60% reduction from a standard sequential evaluation approach. We used 8 particles in the PSO to maximally utilize the 8 cores; preliminary experiments suggested that additional particles improved the solution quality minimally but increased the run time considerably.

5. EXPERIMENTAL SETTING

In this section, we apply our approach to the design of a state-wide trauma network for the state of Ohio. The state has plain topographic nature and is a manageable size in terms of geographical region. The Ohio trauma network serves over 11.6 million citizens over 44,825 mil^2 area. The Ohio Department of Public Safety (ODPS) divides the state into 8 regions. The ODPS provided us with sample of over 7,000 deidentified trauma incidences for the year of 2012. After removing records with missing data, we were left with 6,002 records, which is about a 1/10th of the typical trauma incidences occurring in the state. Accordingly, we scale the minimum trauma volume at a TC (V^{min}) to a tenth in our experiments; i.e., in the base case, we set V^{min}=50 trauma patients.

The 2012 data corresponded to a trauma network in the state with 21 TCs and 140 NTCs. That is, we considered a total of 161 potential candidate locations for TCs and geocoded them in terms of their latitudes and longitudes. Figure 3 illustrates the heat map of 6,002 incidents, and the location of TCs and NTCs during 2012.

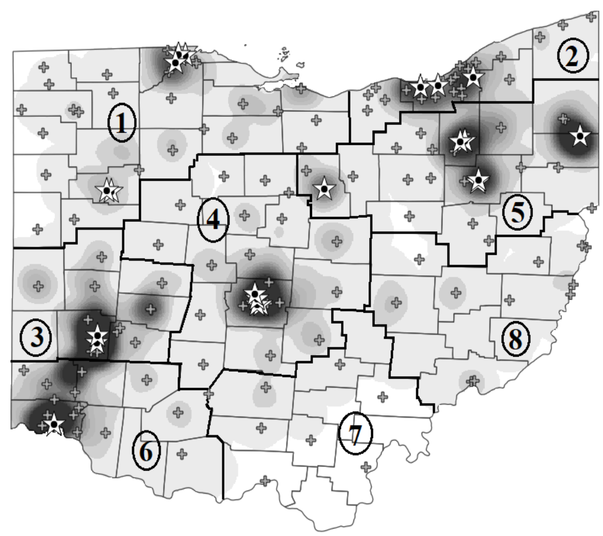


Figure 3: Trauma Care in OH for 8 regions; stars indicate TCs and 'plus' indicate NTCs. Darker shades of grey indicate higher values of incidences

We used Google Distance Matrix API to calculate the actual drive time based on the quickest route from each incidence location to all the potential destination facilities; we used the Haversine formula for air travel times (assuming the helicopter speed of 150 mph). The resulting time matrix for each ground and air (each 161 × 6002 in size) served as the look-up table for the notional triage protocol when estimating UT and OT rates for a given network of TCs. Analysis of the transport mode from the incident's scene to the hospital (TC or NTC) across 6,002 incidents indicated that air transport was used for 12.2% of severely injured patients. The evaluation of total air transport time was calculated by combining the time from helicopter depot to scene (10 minutes), loading of the patient (5 minutes) and air time from scene to nearest TC.

To estimate, the coverage of a TC to its nearby population, we used the Haversine formula to estimate the travel time between the candidate hospital sites and available 1,447 zip-codes in the state. This helped us derive the coverage matrix (A_{ij}). The zip-code level population was obtained from the United States Census Bureau. The coverage parameter was set at 0.90, which means that a network of TCs must cover at least 90% of zip-code-level population.

Further, for the base case, we used 35 minutes as the 'access' threshold and -8 minutes as the 'bypass' threshold. Both these thresholds resulted in the UT rate of 0.16 and OT rate of 0.49, which closely matched the actual rates (UT_{actual}=0.2 and OT_{actual}=0.5) derived from the original 2012 data. Even the trauma literature recommends the 'access' threshold for the transport of severely injured patients (ISS>15) to the nearest TC should typically be between 30 (Minnesota Department of Health, EMS triage and transport guidelines.) and 45 (Jansen et al., 2018) minutes, which lends credibility to the base value of 35 minutes. Considering that the trauma literature often suggests UT as more critical patient safety measure than OT, in the base case, we set the weights for UT and OT rate as 0.8 and 0.2, respectively. Given these foundations, we conducted our experiments to (i) optimize the 2012 network, (ii) evaluate the sensitivity of the solutions to system parameters, and (iii) evaluated the effect of redistributing a given number of TCs as with ACS-NBATS and the 2012 network.

5.1 Optimizing the State's Trauma Network

Because we have access to 2012 data, we focus our attention on analyzing the trauma network that existed in that year. Figure 3 shows the distribution of the 21 TCs in the state, generally located in the areas of the higher population density forming a clustered pattern, as also alluded in (Brown et al., 2016). With 6,002 de-identified trauma patients, we estimated the UT (=0.16) and OT (=0.49) rates using the notional field triage protocol (see Section 3.1); the resulting WSM at ω_1=0.8 and

ω_2=0.2 was 0.23. Not surprisingly, Regions 7 and 8 (with no TC) experienced higher UT rate (=1.00) and negligible OT rate; in contrast, Regions 2 and 5 yielded much lower UT rate (=0.04), but higher OT rates of 0.47 and 0.75, respectively. On the other hand, Region 1 with 5 TCs still produced an unusually high UT rate of 0.43, largely because of the clustering of 3 out of 5 TCs in a single urban area (Toledo), resulting in higher access times for incidents occurring outside of Toledo. This initial study raised an important question; *can we optimize this network to minimize the weighted sum of mistriages?*

To optimize the network, the values of the system parameter used were the same as mentioned above (i.e., the base case values). We manually generated 8 feasible particles inspired by the 2012 network. The best solution obtained by PSO resulted in 19 TCs with the WSM value of 0.17, a 26% decrease from the 2012 estimate of 0.23. This optimized network reduced the UT rate by 50% (i.e., 0.08 vs. 0.16 in 2012), with a slight (6.12%) increase in the OT rate (i.e., 0.52 vs. 0.49 in 2012). This network covers over 99.14% of the zip-code level population.

Evaluation of the results depict a rather dispersed pattern of TCs across the state. To be specific, the distribution of TCs by each region (vs. 2012 network) is as follows: Region 1 – 3 (vs. 5), Region 2 – 2 (vs. 3), Region 3 – 2 (vs. 2), Region 4 – 3 (vs. 4), Region 5 – 5 (vs. 6), Region 6 – 2 (vs. 1), Region 7 – 1 (vs. 0), and Region 8 – 1 (vs. 0). Regions 7 and 8 (with 1 TC each) have a lower UT rate of 0.07 and 0.33, respectively. But with a TC in the region, the OT value increases; the OT rates for Region 7 and 8 are 0.83 and 0.33, respectively. Alternatively, a reduction from 5 TCs to 3 TCs in Region 1 resulted in the UT rate dropping to 0.2 (compared to 0.43 in 2012). Figure 4 shows the difference in the heat map in the UT and OT rates for 2012 and optimized network for every eight regions, along with the location of TCs.

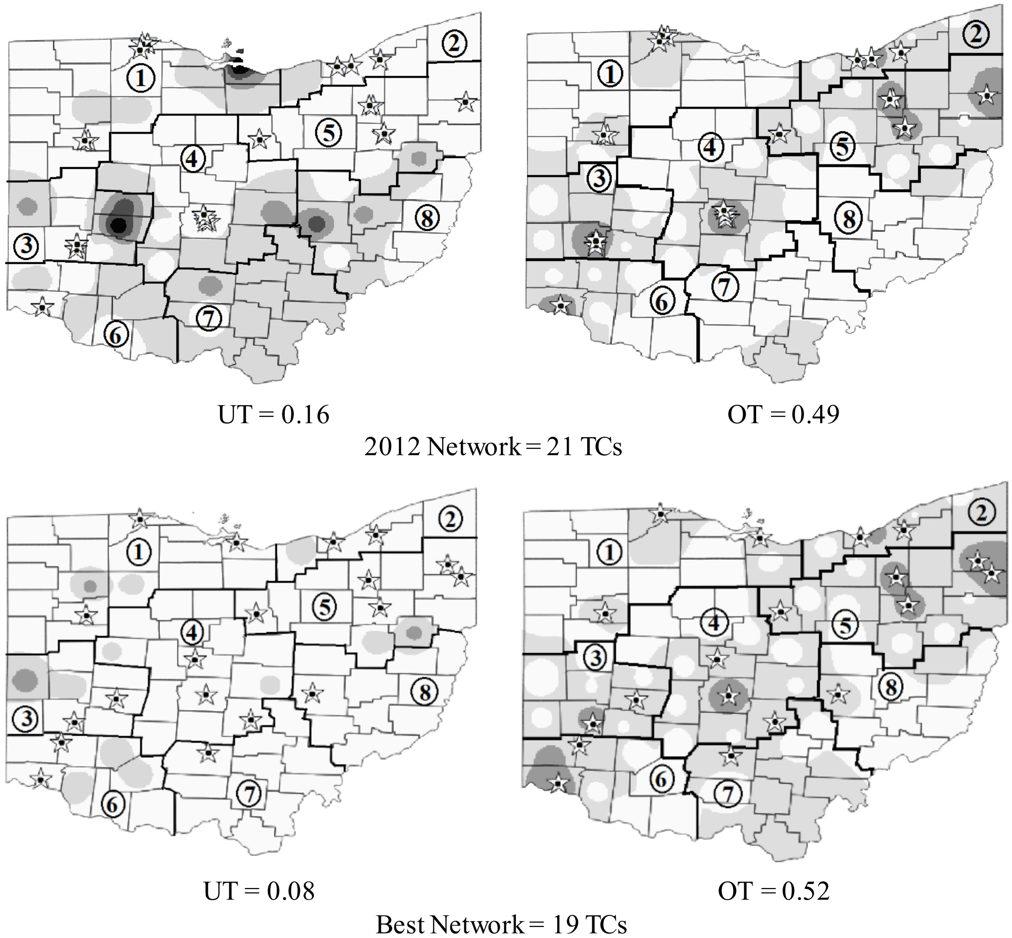


Figure 4: Heat maps of Mistriages.
(Note: Darker shades indicate higher values; Stars represents TCs

5.2 Sensitivity to System Parameters

We further evaluated the sensitivity of the best solution obtained via the PSO to system parameters. These parameters included (i) minimum required total trauma volume at a TC, (ii) weights for UT and OT in the objective function, and (iii) 'access' threshold for UT estimation. Note that we vary the system parameters from their base case value; i.e., V^{min}=50, ω_1=0.8, ω_2=0.2, α=35 minutes, and β=-8 minutes. We only vary one parameter at a time and keep the rest constant.

5.2.1 Sensitivity to Minimum Required Total Trauma Volume at a TC (V^{min})

We varied V^{min} between 0 and 100 in increments of 25; 0 meant a TC can have any number of cases assigned to it, while 100 referred to a more stringent requirement (double of the base case). We did this as there is no clear guideline from ACS or state of OH on how many trauma cases a TC must manage to be financially viable; trauma literature has used as low as 450 (which corresponds to 45 in our case), while anecdotal evidence suggests 1000 (which corresponds to 100 in our case)

Our results suggest that as total trauma volume 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 UT rate; recall, we use ω_1=0.8 for UT (base case). This is intuitive as an increase in the number of TCs would likely allow more severely-injured patients to reach a TC resulting in a decrease in the UT 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 scene as an NTC) resulting in an increase in OT rate. However, as the V^{min} increases, the number of TCs will decrease in order to satisfy the V^{min} constraint. This will increase the UT rate and, so the WSM value. Figure 5 illustrates this trend. With a reduction in the number of TCs (as V^{min} increased), the percentage of population covered at zip-code decreased slightly, from 99.66% to 96.15%.

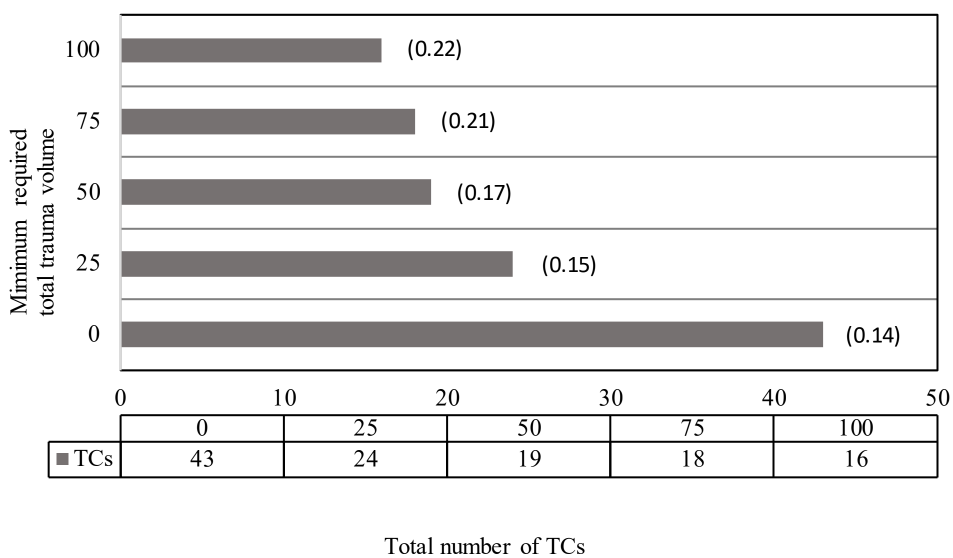


Figure 5: Representation of V^{min} against the total number of TCs with the WSM value in the parenthesis for each column.

5.2.2 Sensitivity to Weights Selection

We varied the weights (ω_1, ω_2) between (1.0, 0.0) and (0.0, 0.1) in steps of 0.2 ensuring that $\omega_1 + \omega_2 = 1$. The selection of the weights does play a vital role in determining the optimal number and location of TCs. When $\omega_1 >> \omega_2$, the emphasis is on reducing the UT rate by increasing the number of TCs; when $\omega_1 << \omega_2$, the emphasis is on reducing the OT rate by decreasing the number of TCs.

Figure 6 represents the trend in UT and OT rates, and WSM value over the weights; the coverage decreased from 99.14% to 91.4% as ω_1 decreased. The figure shows that as ω_1 decreased the UT rate increased and as ω_2 increased the OT 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 put a financial burden on the state and the hospital system. Second, a higher corresponding OT rate (0.56) means a higher number of less severely injured patients at a TC, which is much more expensive then treating such patients at an NTC. Because such costs are difficult to estimate, vary by geographical region and specific clinical conditions, 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.

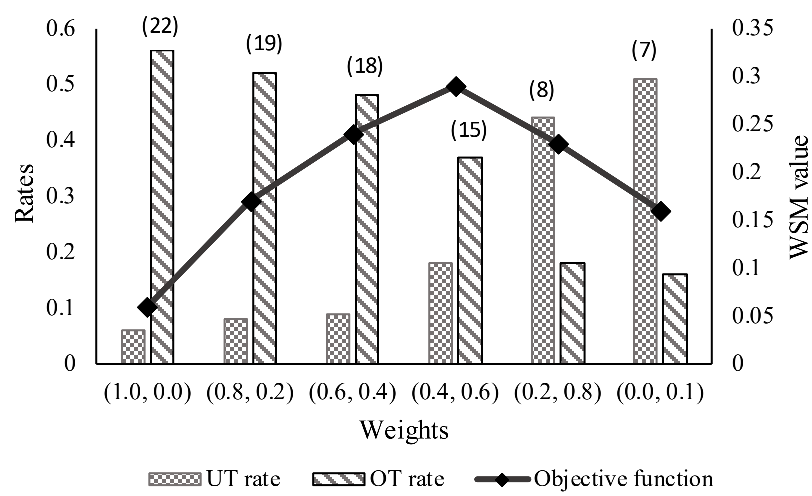


Figure 6: Representation of the UT rate, OT rate and WSM value over the weights; TCs in parenthesis for each column

5.2.3 Sensitivity to the 'Access' Threshold Value

For this analysis, we consider the 'access' threshold (α) at 30, 45, and 60 minutes and a constant 'bypass' threshold of -8 minutes. Figure 7 illustrates the trend in UT and OT rates, the objective value (WSM), and the number of TCs. Note that as the 'access' threshold (α) increases, the value of the objective function decreases. 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 scene, compared to lower values of α. Clearly, this will result in a decrease in the UT rate. This also means that the corresponding network will need fewer TCs, which will also decrease the OT rate. As both the UT and OT rates are falling, the WSM value would also observe a sudden drop. The population coverage ranged between 96.15% and 97.64%.

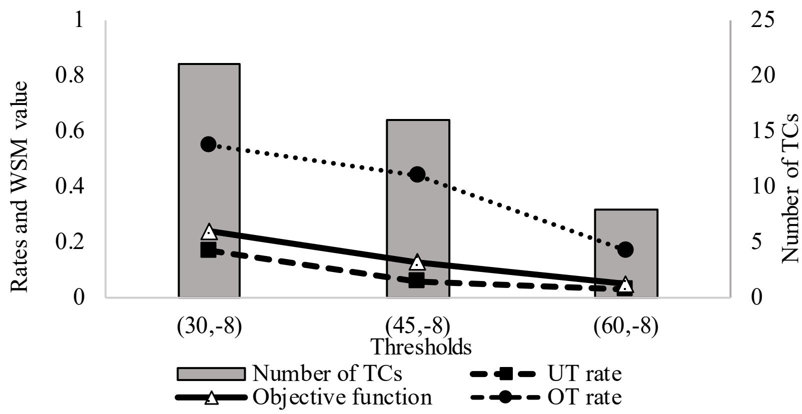


Figure 7: Representation of trend in UT rate, OT rate, objective function, and number of TCs

6. EXTENDING THE USE OF OUR APPROACH

While the analysis presented earlier focused on solving the greenfield design problem (i.e., identifying the best network -- number and location -- of TCs), we also wanted to extend our model to evaluate and optimize existing networks in which the number of TCs is already given. This may be useful in situations where the number of TCs cannot be increased or decreased in the region due to socio-economic-political reasons, but their location could be altered via upgrading some NTCs to TCs and downgrading a few TCs to NTCs. For instance, the ACS-NBATS tool only specifies the number of TCs, but not their location. Similarly, for the 2012 network in OH, we can evaluate if a redistribution of the same 21 TCs could have improved patient safety. To facilitate such analyses, we extended our model by adding an additional constraint that fixed the number of TCs to a prespecified value; the only decision then is their locations.

6.1 Comparison with the ACS-NBATS tool

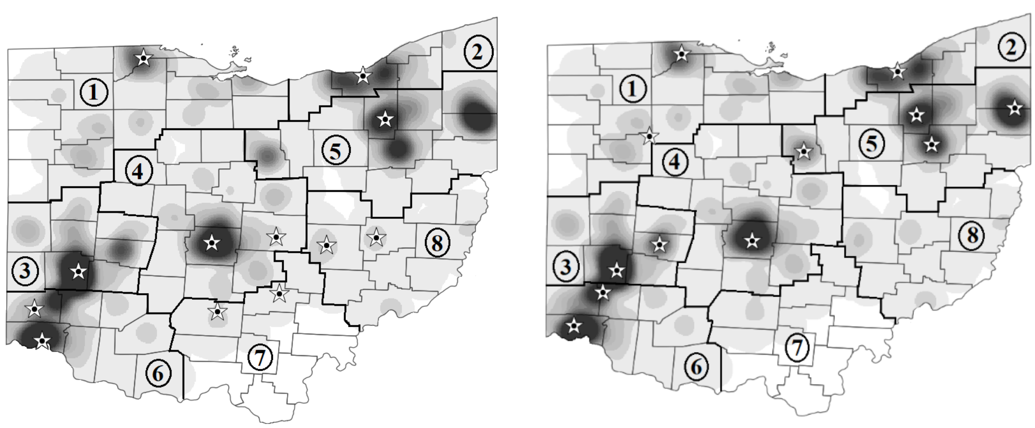
Recall that the ACS-NBATS tool provides a score based on 6 elements; population, transport times, agency support, where were severely injured transported (TCs and NTCs), and the current number of TCs. We used this tool to estimate the number of TCs for the state of Ohio based on the 2012 data. Following the approach in prior work done for the states of CA (Uribe-Leitz et al., 2017) and GA (Garlow & Johns, 2018), we first estimated the number of TCs in each of the 8 regions and used the total for the state. This analysis resulted in a total of 12 TCs. More precisely, the distribution by each region is as follows: Region 1 – 1, Region 2 – 1, Region 3 – 1, Region 4 – 2, Region 5 – 1, Region 6 – 2, Region 7 – 2, and Region 8 – 2.

Because the NBATS tool does not specify the locations of these TCs, we used the structure of the best solutions identified in prior sections to determine these locations for each region. Essentially, we tried to mimic how a trauma decision maker would use the NBATS tool; first find the number of TCs based on the tool and then manually locate them. This network of 12 TCs was then evaluated via the notional triage protocol to derive estimates of the resulting UT and OT rates;

these were 0.28 and 0.31, respectively. The corresponding WSM value is 0.29 and the network covers 97% of the total population. Our finding suggests that as tool prioritize rural region (also observed in CA and GA states, it leads to higher UT rate experienced in urban regions.

We then employed our approach (with the added constraint of 12 TCs) in order to optimize the location of these TCs in order to minimize the WSM. The remaining constraints were set at V^{min}=50 patients and δ=0.90. The resulting network reduced the WSM by 31%; UT=0.15 and OT=0.42. Figure 8 represents the difference in the location of manually-allocated configuration and the optimized network of 12 TCs. The location of these TCs by each region is as follows: Region 1 – 2, Region 2 – 1, Region 3 – 2, Region 4 – 1, Region 5 – 4, Region 6 – 2, Region 7 – 0, and Region 8 – 0. The analysis of the results shows that the now the TCs are largely allocated to the urban regions, resulting in the lower UT rate and WSM value. The coverage was over 96%.

Clearly, the NBATS tool is limited in its current state (no direct consideration for UT and OT, and no suggestions on the location of the TCs). Our approach not only alleviates both these limitations, but also potentially provides a quantitative evidence to the ACS in revising the NBATS tool in future iterations.



NBATS (manually-allocated) = 12 TCs NBATS (best-network by TNDP) = 12 TCs

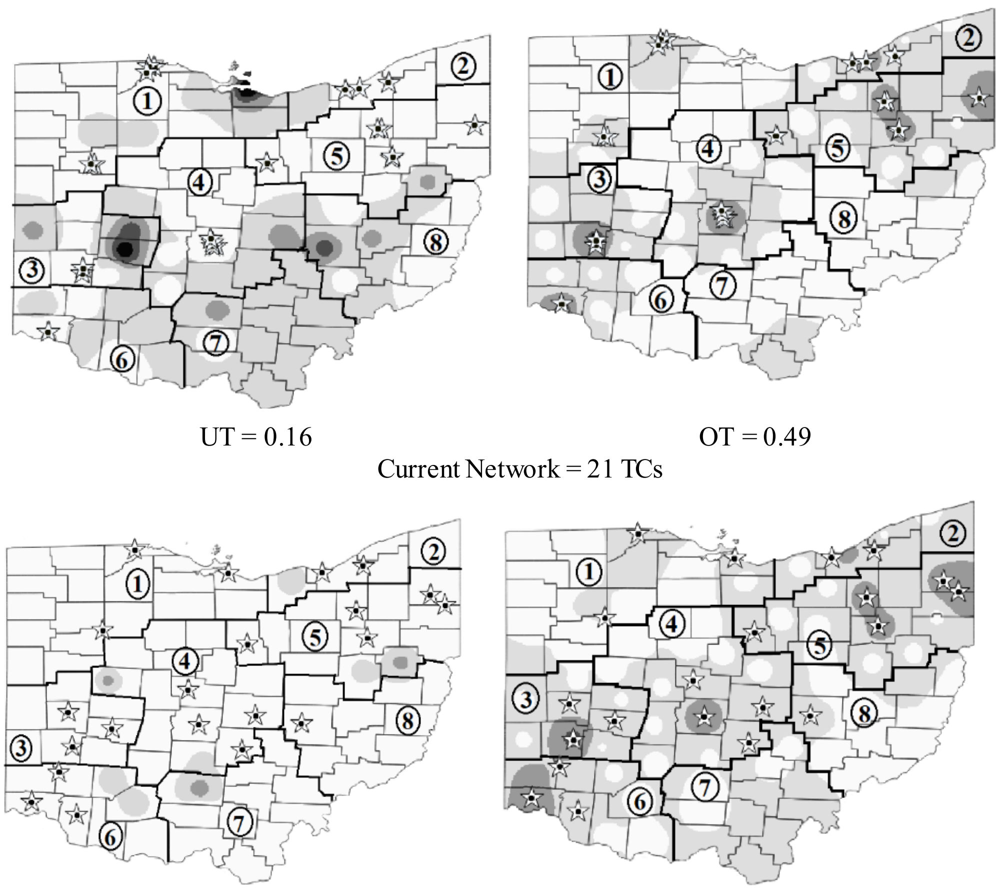
Figure 8: Heat maps of Incidents with location of TCs.
(Note: Darker shades indicate higher values of incidents; Stars represents TCs)

6.2 Re-Distribution of 2012 Network with 21 TCs

We posed a similar question to the 2012 network of TCs for OH: *could a redistribution of the 21 TCs within the state reduce the mistriages rate?* This question as a natural extension to a prior study by (Brown et al., 2016) which pointed at OH having a clustered pattern; this was also indicated as a concern by the Trauma decision makers at the state.

To analyze the impact of redistribution, we used the same approach as in Section 6.1. We used V^{min}=50 patients, δ=0.90, α=35 minutes, and β=-8 minutes. We had already evaluated this network, which resulted in WSM=0.23 (UT=0.16 and OT=0.49) with 21 TCs. We then used the PSO algorithm with the added constraint of maintaining a fixed number of 21 TCs and optimized their location to minimize WSM.

The results were quite interesting; the 21 TCs widely spread across the state. Figure 9 represents the difference in heat map for UT and OT rates for both these networks. The objective function (WSM) reduced to 0.17 compared to 0.23; UT=0.06 and OT=0.58. That is, the UT rate dropped by 62.5%, but the OT rate increased by 18.75%. The reason of the sudden drop in the UT rate is disperse pattern of TCs in the state, which allowed more trauma patients to access a TC within the 'access' threshold (via ground or air). Specifically, the distribution of TCs by each region (vs 2012 network) is as follows: Region 1 – 3 (vs. 5), Region 2 – 2 (vs. 3), Region 3 – 3 (vs. 2), Region 4 – 4 (vs. 4), Region 5 – 5 (vs. 6), Region 6 – 3 (vs. 1), Region 7 – 0 (vs. 0), and Region 8 – 1 (vs. 0). The network covered 98.36% of the total zip-code level population.



UT = 0.16 OT = 0.49

Current Network = 21 TCs

UT = 0.06 OT = 0.58

Best Network = 21 TCs

Figure 9: Heat maps of Mistriages.
(Note: Darker shades indicate higher values of mistriages; stars represent TCs)

7. CONCLUSION AND FUTURE RESEARCH

Timely access of a severely injured trauma victim to a trauma center (TC) can improve survival by 25%. Given the limitations of existing approaches in locating trauma facilities to address patient safety, we proposed the Trauma Network Design Problem (TNDP). The TNDP is to determine the optimal number and location of TCs in order to minimize the weight sum of mistriages (UT and OT). We introduced a notional field triage protocol to estimate the UT and OT based on the standing guidelines in the trauma literature. To efficiently solve the resulting model, we proposed a Particle Swarm Optimization (PSO) approach and illustrated its use on 2012 data for the state of Ohio.

The key findings of our study include the following. First, optimizing the 2012 network of TCs in the state resulted in a reduction of 2 TCs (19 vs. 21) with a 26% reduction in the objective value; UT rate was reduced by 50% (0.16 to 0.08) with a very slight increase in OT rate. This indicated that a (near) optimal distribution of TCs can improved patient safety with lesser number of TCs. Second, the solutions were sensitivity to the choice of weight; a higher weight on UT compared to OT increased the number of TC, and vice versa. Third, a higher requirement of trauma volume at a TC, partly due to financial viability of a trauma center, reduces the number of TCs in the network and negatively impacts patient safety.

To compare our model with the ACS-NBATS recommendation, we solved a specific case of the TNDP whereby the number of TCs is given a priori, but their locations need to be determined. Our findings suggested that there is 31% decrease in the objective value (46.4% decrease in UT rate and 35% increase in OT rate). This shows that it is critical to design a network of TCs not purely based on 'need' (as in ACS-NBATS) expressed through a limited set of questions, but by the 'performance' of such a network through a geospatial analysis and optimization approach. Similarly, the optimized location for the re-distribution of the 21 TCs (i.e., 2012 network) led to a drop in UT rate by 62.5% drop, but with an increase in the OT rate by 18.75%.

The successful application of the TNDP model to Ohio offers integrity and its potential application to the other regions in the U.S. Future work in this area could include enhancing the notional field triage protocol with additional features such as patient/family choice and additional EMS criteria. The inclusion of the cost incurred in upgrading an NTC to a TC through a multicriteria optimization model would allow trauma policy-maker to appropriately tradeoff cost vs. care in designing their network.

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