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An Approach to Optimize a Regional Trauma Network

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Abstract

Trauma continues to be the leading cause of mortality and morbidity among US citizens aged <44 years. Literature suggests that geographical maldistribution of trauma centers (TCs) is associated with increasing fatality rate. Existing models for TC network design do not address the question often raised by trauma decision makers: *how many TCs are required to achieve acceptable levels of mistriages?* We propose a model to optimize the network of TCs under mistriage constraints. We propose a notional field triage protocol to estimate mistriages (under and over), based on existing guidelines in the trauma literature. Due to the complexity of the underlying model, we propose a Particle Swarm Optimization based solution approach. We use 2012 data from the State of Ohio, and model both ground and air transportation modes. Our results show that, for 2012 mistriage levels, it is possible to reduce the number of TCs from 21 to 10 by distributing them appropriately across urban and rural areas. Further, redistributing these 21 TCs can help satisfy the recommendation of under-triage ≤0.05 by the American College of Surgeons. In general, our study provides trauma decision makers an ability to determine a network that could improve care and/or reduce cost.

Keywords
Facility location; trauma network; patient safety; mistriage

1. Trauma Care in the United States

Trauma is a body wound or shock occurred due to a physical injury, as from accident or violence. It is the leading cause in the U.S. for disability, mortality, and morbidity for those under the age of 44, and results in millions of hospital admissions and hundreds of thousands of deaths per year, with an economic burden of $671 billion annually [1].

In the U.S., Level I and II trauma facilities provide the highest level of services (including orthopedic, neurology, and even burn) to patients suffering from traumatic injuries. All other lower level trauma facilities (Level III-V) are intermediate facilities that help in stabilizing the patient before a transfer to a TC. In this study, we refer to Level I and II facilities as trauma centers (TCs); all other facilities are referred to as non-trauma centers (NTCs).

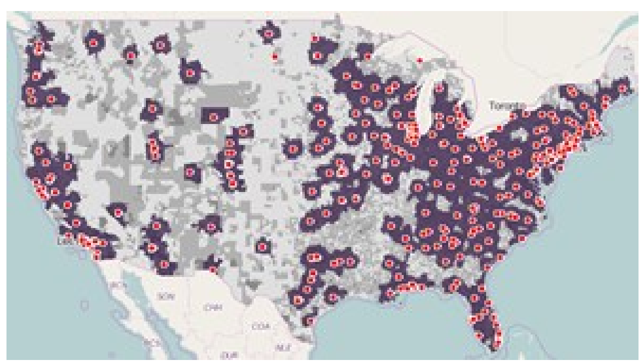

Figure 1: Network of 520 L1/L2 TCs in U.S. Red dots=TCs, dark shade = 60-minute coverage via ground and air, and light = U.S. population

If severely injured patients are able to receive care at TC rather than at an NTC, there could a 25% reduction in mortality [2]. Although trauma is a time-sensitive condition requiring rapid access to a TC for improved outcomes (mortality and morbidity), there is no access to a TC within 60 minutes (aka golden hour) for nearly 10% of the total U.S. population [1]. Brown et al. suggest that the reason for this is geographical misdistribution of TCs; 9 states had a clustered pattern, 22 had a dispersed pattern, and 10 had a random pattern of TC distribution [3]; see Figure 1.

To evaluate the quality of care delivered by a trauma system, mistriages by the Emergency Medical Service (EMS) providers at the incidence site has been used as a surrogate. A mistriage is referred to as transporting a trauma patient to a hospital that is not appropriate per the underlying injuries. In that sense, under-triage (UT) refers to transporting a severely injured patient to a non-trauma center, which could result in inimical conclusion (such as death and disability) due to delayed definitive care. On the other hand, over-triage (OT) refers to assigning a less severe injured patient to a trauma center, resulting in overcrowding of emergency department and increased cost of medical care for the patient [4]. UT and OT may occur either due to controllable (e.g., network of TCs, injury assessment protocols of EMS, mode of transportation) or uncontrollable (e.g., weather, law enforcement) factors.

It has been studied that distribution of and, thus, access to trauma centers could lead to higher injury mortality and unnecessary transfers [5, 6]. Thus, in the past decades, a few tools have been proposed for determining the optimal configuration of trauma care system. Branas et al. proposed a linear programming model that simultaneously locates trauma centers and medical helicopters with an aim of maximizing the coverage of severely injured patients using Maryland as a test region [7]. Jansen et al. proposed a data-driven approach that jointly considers minimizing the total travel time and the number of exception or system-related UT using Scotland and Colorado (US) as test regions [8, 9]. Even the American College of Surgeons (ACS) proposed a tool, Needs-Based Assessment of Trauma System (NBATS), to suggest the number of TCs in a specified geographical region based on population, transport time, community support, and alike; however, NBATS does not identify the location of these TCs [10].

Even though patient safety in terms of coverage and access times were included in these tools, they do not address the question that is often discussed among trauma decisions makers: *how many TCs do we need to ensure UT and OT are within acceptable range?* There is an underlying assumption here – upgrading an NTC to a TC is expensive, let alone maintaining that status. It requires recruiting full-time specialized physicians and associate staff, equipment, infrastructure, and education/training. However, from a community welfare standpoint, the local government would lean towards improving safety (i.e., lower UT).

We address this precise gap through our study by introducing an optimization model to determine the number and location of the TCs under UT and OT constraints, besides the standard coverage constraints. We not only characterize UT based on the injury type and on-scene decision making process of the EMS (extending prior work), we do the same to characterize OT (never done before). We now present this model, related details, and illustrate its use on a sample data set collected from the State of Ohio.

2. A Model for Locating TCs

Our model assumes that a geographically defined region, known as the Trauma Service Area (by the ACS), is known. This region could be a county, a region in the state, or the state itself. Further, the candidate sites for locating a TC are known and finite, which typically are the locations of existing TCs and NTCs. The Injury Severity Score (ISS) is used as a proxy to estimate, retrospectively, the severity of the injury of a patient at the incidence scene. The availability of ground ambulance for the transportation of patients from scene to a TC or NTC is assumed to be unlimited. Finally, to estimate coverage, a TC is assumed to cover the population of all adjacent zip-codes in the radius of 60 minutes using distances between the centroids using the Haversine formula.

Table 1: Parameters in the model

Notation	Definition
UT^{max}	Allowable UT rate for TSA
OT^{max}	Allowable OT rate for TSA
α, β	Threshold for UT and OT (minutes)
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
δ	Coverage parameter
V^{min}	Minimum trauma volume at location i
ISS_k	Injury severity score for incident k

Table 2: Decision variables in the model

Notation	Definition
x_i	$\begin{cases} 1, & \text{if TC is established at candidate location} \\ 0, & \text{otherwise} \end{cases}$
y_{ij}	$\begin{cases} 1, & \text{if zip code } j \text{ is covered by facility } i \\ 0, & \text{otherwise} \end{cases}$
γ_{ik}	$\begin{cases} 1, & \text{if incident } k \text{ is covered by facility } i \\ 0, & \text{otherwise} \end{cases}$
z_j	$\begin{cases} 1, & \text{if zip code } j \text{ is covered by any location } i \\ 0, & \text{otherwise} \end{cases}$
UT, OT	Estimated UT and OT rates for the TSA
X	Vector representing the network (TCs & NTCs)

In the proposed optimization model for the entire state as the TSA, i=index for the candidate location for TC, j=index for zip-code, and k=index for trauma incidence. Tables 1 and 2 list the model parameters and decision variables. Constraint (1) specify that the overall population covered by the network of TCs exceeds a predefined proportion (δ) of the total population in the TSA. Constraints (2) ensure that the population of a zip-code is only counted once. Constraint (3) limits on the lower bound on the trauma cases to be handled by a location i if it is a TC. Constraints (4) specify the permissible UT rate for the TSA, while constraints (5) defines the permissible OT rate for the TSA. Constraints (6) is the bounding constraint on the variables.

The above model is a classical combinatorial multi-facility location-allocation model and is *NP*-hard. As discussed later, for the test data we have, there are 161 potential sites, resulting in 2^{161} potential combinations to evaluate. We, therefore, propose a Particle Swarm Optimization (PSO) metaheuristic approach to derive high-quality solutions. PSO is a nature-inspired population-based metaheuristic introduced by Eberhart & Kennedy [11], which mimics the social behavior of fish schooling or bird flocking. It is easy to understand and implement, makes few assumptions about the structure of the problem, and runs efficiently.

Minimize: $\sum_i x_i$

Subject to:

$$\sum_j z_j P_j \geq \delta(TP) \quad (1)$$
$$z_j \leq \sum_i (y_{ij} A_{ij}) \quad \forall j \quad (2)$$
$$\sum_k \gamma_{ik} \geq x_i V^{min} \quad \forall i \quad (3)$$
$$UT = \sum_k f(X, ISS_k, \alpha) \leq UT^{max} \quad \forall i, k \quad (4)$$
$$OT = \sum_k f(X, ISS_k, \beta) \leq OT^{max} \quad \forall i, k \quad (5)$$
$$x_i, y_{ij}, \gamma_{ik}, z_j \in \{0, 1\} \; \forall i, j, k \; ; UT, OT \in [0, 1] \quad (6)$$

Further, in the above model, it is difficult to express UT and OT rates in closed form. For a given network of TCs, these rates depend upon the determination of the most appropriate closest TC or NTC for each incidence's injury severity score. Because this determination will change with modifications to the network, thus impacting resulting UT and OT rates, a notional field triage protocol is proposed. Below we discuss the PSO-based solution approach and then provide details of this notional field triage protocol.

3. A Particle Swarm Optimization Solution Approach

The PSO algorithm iteratively tries to improve a set of candidate solutions (particles) over a given measure of quality (fitness function) and moving these particles in a predefined search space using a mathematical operator in regard to particle's position and velocity. Flying through the search space, each particle gathers historical information and gets influenced by its local best-known position (*pbest*) and is directed toward the best position (*gbest*) known so far.

Binary PSO (BPSO) is a variant of continuous PSO, in which each particle position is represented in binary values, and the particle velocity is defined as the probability that might change it to either zero or one. In our proposed BPSO, a swarm of 10 initial feasible particles is considered. An example of a solution represented by a particle is as follows: $P_1 = \{0, 1, \ldots, 0\}$; where $|P_1|$ is the total number of candidate sites (i.e., existing hospitals in the TSA); 1 and 0 represents TC and NTC, respectively. The particle positions and velocities are updated per (7) and (8):

$$v_{id}^t = K(v_{id}^{t-1} + c_1 r_1(pbest_{id} - x_{id}^{t-1}) + c_2 r_2(gbest_d - x_{id}^{t-1})) \quad (7)$$
$$if\ (rand() < S(v_{id})), then\ x_{id} = 1; else\ x_{id} = 0 \quad (8)$$

where the *i*th particle in the *d*-dimensional search space is represented as $x_i = (x_{i1}, x_{i2}, \ldots, x_{id})$ with the velocity as $v_i = (v_{i1}, v_{i2}, \ldots, v_{id})$. In expression (7), the particle's previous best position is denoted as $pbest_i = (pbest_{i1}, pbest_{i2}, \ldots, pbest_{id})$ and the global best position as $gbest = (gbest_1, gbest_2, \ldots, gbest_d)$. Acceleration constant, c_1 and c_2, are set at 2.05 with constriction coefficient, $K = 0.7298$, and r_1 and r_2 are two uniformly distributed random numbers in [0,1]. In expression (8), *rand()* follows Uniform [0, 1] and $S(v_{id}) = 1/(1 + e^{-v_{id}})$ is the sigmoid limiting transformation function; see Eberhard & Kennedy [12] for further details. We now discuss how these UT and OT rates were estimated using the notional field triage protocol.

3.1 A Notional Field Triage Protocol: In practice, field triage is conducted by the EMS personnel on scene to transport a trauma patient to the most suitable level of care (TC or NTC) depending on the underlying injuries. The decision-making process is highly variable in nature and depends on many factors. Instead of modeling each factor, we introduce a notional field triage protocol, similar in concept to Jansen et al. [8]. The protocol assigns the patient to an appropriate level of trauma care based on ISS, trauma network, and the threshold values.

Trauma literature recommends that a patient with ISS>15 (severe injuries) should be assigned to the nearest TC, while a patient with ISS≤15 (non-severe injuries) should be assigned to the nearest NTC bypassing the nearest TC. However, mistriages occur when such recommendations are difficult to follow in practice due to access times; i.e., if the TC is too far, then the EMS may have no other choice but to take the patient to an NTC (a case of UT).

To model how EMS providers in practice use access time (via both ground and air) during their decision making, we introduce two threshold values; (i) access threshold for TC transport and (ii) bypass threshold for NTC transport. Figure 2 illustrates the entire protocol. For instance, for a patient with ISS>15, if the actual time from the scene to the nearest TC via ground is lower than the access threshold, then the protocol assigns the patient to that TC (a case of appropriate triage, AT-1). If no, then the availability of an air ambulance (helicopter) is checked and, if available then the total fly time (i.e., helipad to scene, patient loading, and scene to TC) is compared to the access threshold. If the fly time is lower, then this the case of AT-1 (via air), otherwise the helicopter is not used, and the case is considered UT (i.e., transport to NTC via ground).

On the other hand, for a patient with ISS≤15, the protocol considers the time difference between nearest TC and nearest NTC. If this time difference is lower than the predefined time (bypass road threshold), then the patient is taken to NTC (via ground) and this case is recorded as AT-2 (appropriately triage to NTC), else the protocol assigns it to the nearest TC (because the NTC is too far) and records it as OT.

As is evident, the field triage decision is a binary classification problem, which renders results in a contingency matrix with AT-1 as true positive, AT-2 as true negative, and UT and OT as Type 1 and 2 errors. We estimate UT rate as (1-sensitivity) and OT rate as (1-specificity) [4].

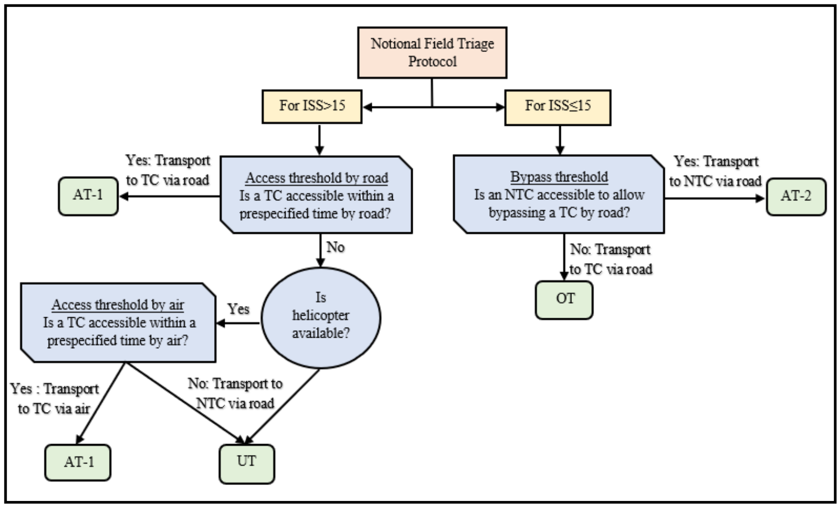

Figure 2: Notional Field Triage Protocol

3.2 Solution Implementation: We used Python programming platform to implement our proposed PSO and the notional field triage protocol on a Windows 7 desktop computer with 16 GB of memory running at 3.40 GHz on an Intel processor. We now discuss how we tested our proposed approached using the actual data from OH.

5. Ohio as the Test Region

The trauma network in OH serves over 11.7 million citizens. The Ohio Department of Public Safety (ODPS) had divided the state into 8 regions; this means, a TSA in our testing could either be the entire state or each of these 8 regions. We obtained deidentified records of 6,242 trauma incidences for 2012 from the ODPS; this is about a 1/6th of the actual occurrences, and we adjust the V^{min} accordingly. We also determined the location of the 21 designated TCs in OH during 2012 and the remaining 140 NTCs; see the GIS plot in Figure 3.

We used Google Distance Matrix API to derive actual ground times from each incidence location to all hospital sites and used the Haversine formula for air travel times (assuming helicopter speed of 150 mph). In modeling total air transport time, we also add helipad-to-scene (10 minutes) and preparing and loading of the patient (5 minutes). The available data indicated that air transport was used for 12.2% of the patients with ISS>15 (severely injured for whom air transportation may be required) and was kept constant in our testing. The resulting time matrices, one each for ground and air (6242 × 161 cells each), served as a look up table for later use in the estimation of UT and OT rates.

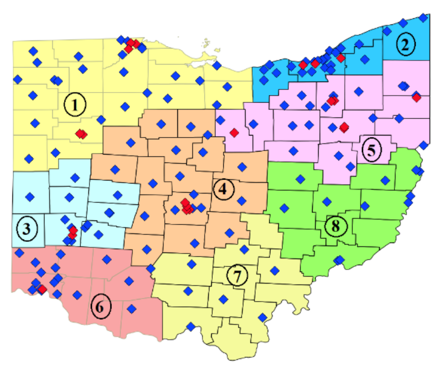

Figure 3: Trauma Care in OH for 8 regions. Red and Blue diamonds are TCs and NTCs, respectively.

To model coverage of a TC to its nearby population, distances between the candidate TC sites and 1,447 zip-codes in OH were calculated using the Haversine formula and converted into time. The coverage matrix (A_{ij}) was estimated a priori based on zip-code information. Population information was obtained from the United States Census Bureau.

We used an Access Threshold of 35 minutes and a Bypass Threshold of 8 minutes. Both these values resulted in UT and OT rates of 0.18 and 0.48, respectively, which closely matched the actual rates (UT_{actual}=0.2 and OT_{actual}=0.5) derived using the 2012 data using ISS and destination hospital type. Note that the recommended access threshold for EMS transport of ISS>15 patients is typically between 30 [13] and 45 [9] minutes per trauma literature, which adds credibility to the Access Threshold. We then derived two networks with varying EMS transportation capabilities; (i) unlimited ground transportation and (ii) unlimited ground and limited air transportation.

We test our approach against three problems instances with coverage parameter set at 0.85 and Access Threshold for UT as 35 minutes (ground and air), and Bypass Threshold for OT as 8 minutes (ground). Table 3 summarizes the problem instances, and the corresponding results, across ground-only (G), and combined ground and air (G+A).

Table 3: Problem instances & results summary

Prob #	*TSA*	Constraints			# of TCs		UT rate		OT rate	
		UT	OT	V^{min}	G	G+A	G	G+A	G	G+A
1	State	≤0.2	≤0.5	≥100	10	10	0.19	0.18	0.44	0.40
2	8 regions	≤0.2	≤0.5	-	17	14	0.11	0.15	0.49	0.36
3	State	≤0.05	≤0.6	-	23	21	0.049	0.047	0.58	0.52

For Problem 1, with only ground transportation, the best network resulted in 10 TCs instead of the 2012 network with 21 TCs. Similar to the 2012 network, the TCs in the PSO-generated solution were also located in the major cities of Toledo, Lima, Cleveland, Dayton, Columbus, Mansfield, Akron, Canton, Youngstown, and Cincinnati, but in lower numbers. While the addition of air transport did not reduce the number of TCs, it led to a slight decrease in both UT and OT rates. Severely injured patients (ISS>15) who were not able to access the nearest TC via ground in 35 minutes were now able to access this TC via air, resulting in a decrease in the UT rate. In both G and G+A scenarios, the coverage was over 96%. These results indicate that the State of OH can achieve a slightly better level of trauma care (state-wide UT of 0.18 instead of 0.2, and state-wide OT of 0.40 instead of 0.5) with only 10 TCs (G+A) instead of 21 in the 2012 network.

Both solutions to Problem 1 (G and G+A) revealed that there could be wide variation in the UT rates among the 8 regions (range 0.04 – 1.00) even if the state-wide total UT rate was within 0.2. This could cause differential care among state's citizen (some receiving better and some worse). To resolve this, in Problem 2, we included 8 additional UT≤0.2 constraints, one for each region. Solving this problem resulted in a network with 17 TCs (G), instead of 21.

Figure 4 shows the difference in the heat map for UT and OT rate for both these network). Five NTCs were upgraded to TCs in region 1, 7 and 8 and nine TCs were degraded to NTCs in region 1, 2, 3, 4, and 5. This decreased both the UT rate (from 0.20 to 0.11) and the OT rate slightly (from 0.50 to 0.49).

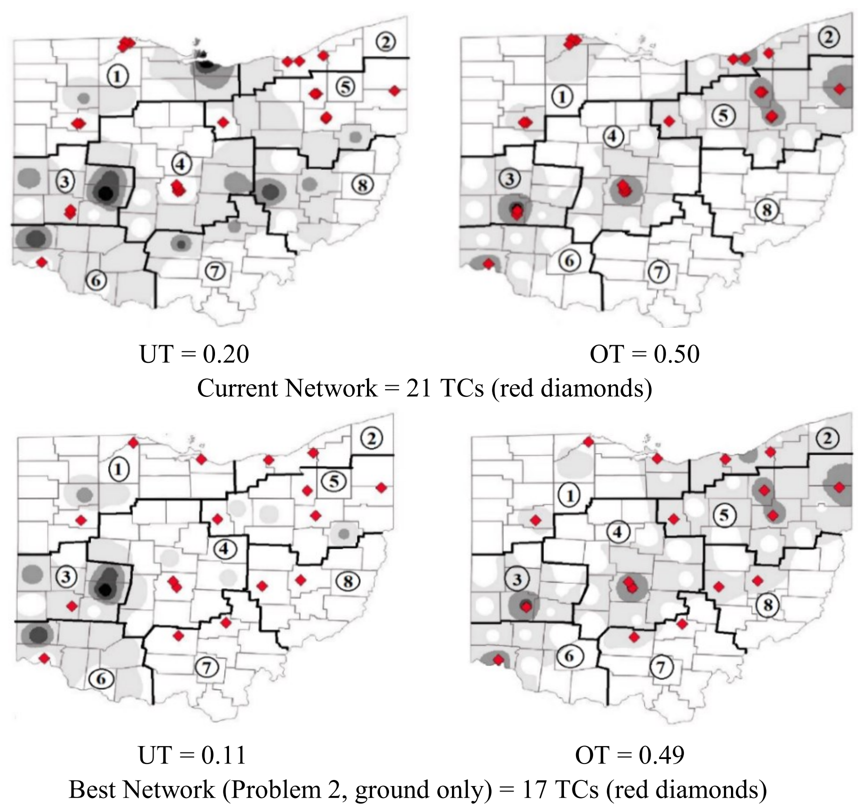

Figure 4: Heat maps of Mistriages.
(Note: Darker shades indicate higher values; red diamonds indicate TCs.)

The inclusion of air transportation in Problem 2 decreased the number of TCs from 17 to 14 with a downgrade of TC to NTC in region 2, 4 and 5. The model was able to trade this decrease off with a slight increase in the UT rate (from 0.11 to 0.15), which still satisfying the regional UT constraint of 0.2. In contrast, the OT rate decreased as now there are 3 more NTCs (as TCs have decreased from 17 to 14) resulting in easy access for less-severely injured patients (ISS≤15) to the nearest NTC. Both the approaches covered over 99% of the population.

The collective outcome of Problems 1 and 2 suggest that the State of Ohio could employ a total of 14 TCs (3 in Regions 1 and 5, 2 in Regions 7 and 8, and 1 in Regions 2, 3, 4, and 6) without exceeding the current levels of UT and OT in each of the 8 regions, providing uniform care across them.

Problem 3 attempted to address the suggestion by the ACS to achieve UT rates of 5%. To model this, we set UT rate at 5%, state-wide. The best solution derived via PSO resulted in a network with 23 TCs (G) and 21 TCs (G+A). Naturally, to decrease the UT rate, more TCs are required, but that induces a higher OT rate (similar to the tradeoff between Type 1 and Type 2 errors in a binary classification problem). It, however, is interesting that the 2012 network in OH also had 21 TCs, but with a UT rate of 0.2. These results suggest that un-clustering the TCs in urban areas and upgrading NTCs to TCs in a few strategic rural areas can achieve the ACS-suggested UT rate, with the same number of TCs (i.e., 21). Specifically, TCs by each region (vs. 2012 network) could be as follows: Region 1 – 3 (vs. 5), Region 2 – 2 (vs. 3), Region 3 – 3 (vs. 2), Region 4 – 3 (vs. 4), Region 5 – 5 (vs. 6), Region 6 – 3 (vs. 1), Region 7 – 1 (vs. 0), and Region 8 – 1 (vs. 0).

6. Conclusion

Trauma centers (TCs) are facilities that provide the highest level of emergency medical and trauma care to severely injured patients. Evidence in the trauma literature suggests maldistribution of TCs in the US affects patient care. Given the limitation of existing models for TC network design and aid trauma decision makers in making better decisions, we propose a model to determine the optimal number and location of TCs under prespecified UT and OT constraints. We propose a notional field triage protocol to estimate UT and OT based on the location of trauma incidences, underlying injury, location of TCs and NTCs, and mode of transportation. We tested our approach on 2012 data available from the State of Ohio and show that the TCs within the state could be redistributed reducing the number of TCs from 21 to 10. Results also show that it is possible that each of the 8 regions meet the UT constraints with a lower number of TCs (17 vs. 21). Meeting the ACS suggested UT rate of ≤ 0.05 is possible if the 21 TCs were reconfigured appropriately; un-clustered and some set up in rural areas.

Future work in this area could consider evaluating the sensitivity of the PSO-based solutions to input parameters (e.g., UT and OT thresholds, and minimum TC volume). If several years' worth of data were made available, then it would be possible to design a network that is robust to changes in trauma patterns across years.

Acknowledgements

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