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CASUALTY EVACUATION OPTIMIZATION IN A CONFLICTED ENVIRONMENT

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THESIS

CASUALTY EVACUATION OPTIMIZATION IN A CONFLICTED ENVIRONMENT

by

Stephen W. Cone

September 2022

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13. ABSTRACT (maximum 200 words)

Servicemembers who are injured, particularly in combat, often require rapid evacuation and transport through contested environments. Using unmanned autonomous vehicles (UAV) may help reduce the personnel required to move patients to points of care, thereby reducing the potential for further casualties. However, the UAV and the original patient may still be subject to detection by enemy agents in the area. Safely transporting a casualty in as little time as possible greatly improves survivability. Current treatment of the problem of moving casualties involves manned medical evacuation (MEDEVAC) missions, often with armed escorts. Autonomous evacuation will likely involve simple shortest path solutions to move from one point to another; however, this will not help protect from adversaries. Our model uses network flow optimization to best determine a safe path for autonomous casualty evacuation to follow, while avoiding adversaries and their attacks, and delivering a patient in a timely fashion. This model synchronizes departure and travel times of two echelons of vehicles to effect patient transfer for extraction to definitive care. With two scenarios, our results prove the concept of this model, successfully delivering patients with synchronized efforts, within time limits, and solving the problem in little computational time.

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ABSTRACT

Servicemembers who are injured, particularly in combat, often require rapid evacuation and transport through contested environments. Using unmanned autonomous vehicles (UAV) may help reduce the personnel required to move patients to points of care, thereby reducing the potential for further casualties. However, the UAV and the original patient may still be subject to detection by enemy agents in the area. Safely transporting a casualty in as little time as possible greatly improves survivability. Current treatment of the problem of moving casualties involves manned medical evacuation (MEDEVAC) missions, often with armed escorts. Autonomous evacuation will likely involve simple shortest path solutions to move from one point to another; however, this will not help protect from adversaries. Our model uses network flow optimization to best determine a safe path for autonomous casualty evacuation to follow, while avoiding adversaries and their attacks, and delivering a patient in a timely fashion. This model synchronizes departure and travel times of two echelons of vehicles to effect patient transfer for extraction to definitive care. With two scenarios, our results prove the concept of this model, successfully delivering patients with synchronized efforts, within time limits, and solving the problem in little computational time.

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List of Acronyms and Abbreviations

CASEVAC casualty evacuation

CCP casualty collection point

CTOPTWS capacitated team orienteering problem with time windows and synchronization

DOD Department of Defense

JMPT Joint Medical Planning Tool

KP knapsack problem

MEDEVAC medical evacuation

MTF medical treatment facility

NPS Naval Postgraduate School

OP orienteering problem

POI point of injury

PTP Profitable Tour Problem

TOP team orienteering problem

TSP travelling salesperson problem

VRP vehicle routing problem

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Executive Summary

With a shift in U.S. Navy and Department of Defense focus to distributed operations in contested environments, all logistics considerations, including the movement of injured members, need to adjust to the realities of the newer environment. For patient evacuation, time constraints and safety remain top concerns, and seeking a shortest route through uncontested areas would allow better chances for patient and vehicle survivability. As we continue to make improvements in autonomous vehicles, the opportunity to use these vehicles for logistics and casualty/medical evacuation (CASEVAC/MEDEVAC) reduces the number of additional personnel placed in harm's way. Successful CASEVAC/MEDEVAC requires multiple echelons of care and multiple modes of travel to move between them.

Our model proposes to link the echelons of vehicles, optimizing a shortest path for each, to effect transfer of patients. Borrowing elements from classical versions of traveling salesperson problems, we essentially propose a capacitated team orienteering problem with time windows and synchronization (CTOPTWS) as a mixed integer linear program using network flows. Our objective is to maximize the number of patients transferred while constraints restrict routes, times, and vehicles used. Outputs recommend routes and arrival and departure times for vehicles.

Testing on multiple networks of increasing complexity, we prove the concept of this model to properly match the echelons of vehicles required to transport patients. In all cases, vehicles from both sides synchronize at the collection point (node) to transfer patients within the time window determined. The model is able to solve these problems in negligible time.

This work opens a path for further exploration and elaboration of this field of optimization with respect to MEDEVACs. The first step could be extending the network for further proof of concept, followed by testing of real-world data with continued evaluation of the possible improvements in the model.

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CHAPTER 1: Introduction

Current strategic guidance and Department of Defense (DOD) focus has shifted to lines of effort in geographic areas that differ from recent experiences in Iraq and Afghanistan. Today's focus is on distributed operations in contested environments, changing the total logistics considerations, including the evacuation of injured or ill members by dedicated medical evacuation (MEDEVAC) or non-medical casualty evacuation (CASEVAC) vehicles (Jensen 2015; Department of the Army 2019). To assist with these changes, the DOD is examining ways in which autonomous systems can be employed to support our distributed units (Bornstein 2015). In this thesis, we examine the ramifications of these evolving strategic considerations with respect to successfully identifying routes to coordinate multiple vehicles involved in moving patients from point of injury (POI) to increasing levels of care, with eventual delivery to a medical treatment facility (MTF).

1.1 Problem Statement

Service members in the U.S. military routinely engage in activities that, by their nature, may be dangerous; whether training, travelling, or performing kinetic exercises. One aspect that helps enable service members to continue these activities is the surety that they receive the required clinical care necessary for whatever may befall them. The medical care promised to our service members begins with the level of self-care and/or buddy aid (Role 1 care), which happens at the POI. From that point, the patient is evacuated to increasing levels of care (Role 1 - Role 4), as indicated by the clinical situation, with the ultimate hope that the patient can be returned to duty from the lowest level possible, as in Figure 1.1.

Capability	Health Care	Example*	Comparable Roles of Medical Care*
First Responder	Medical care rendered at the point of initial injury or illness	Self Aid/Buddy Aid Hospital Corpsman Marine Corps Combat Lifesavers	Role 1
Forward Resuscitative Care	Forward advanced emergency medical treatment performed close to the point of injury (POI)/illness	Ship's Medical Department Battalion/Wing Aid Station	
		Shock Trauma Platoon Forward Resuscitative Surgery System Surgical Company Casualty Receiving and Treatment Ship Aircraft Carrier	Role 2
Theater Hospitalization	Modular theater hospitals with medical and surgical capabilities required to support the theater	Hospital Ship Expeditionary Medical Facility	Role 3
Definitive Care	Full range of acute, convalescent, restorative, and rehabilitative care	OCONUS Medical Treatment Facility CONUS Medical Treatment Facility Veterans Administration Hospital National Disaster Medical System	Role 4
En Route Care	Medical treatment during movement between roles of care	USN/USMC En Route Care system** USAF Critical Care Air Transport (CCAT)	

* This is not an all-inclusive list of medical resources.
** En route care can be used throughout all capabilities of care.

Figure 1.1. Display of different levels of care (Roles) in military medicine with example theater-level locations and capabilities available. Source: Department of the Navy (2013).

At each level of care, more service are available for the patient; in the worst cases the focus would be on stabilizing the patient sufficiently to be transported to the next level. A typical diagram of movement through the different levels of care is shown in Figure 1.2. Some of the key issues with this method, as illustrated in the diagram, is that each of the vehicles, as well as the multiple litter bearer teams involved, place more service members in harm's way, while removing multiple war-fighters from the fight. Autonomous systems could help reduce the human capital involved, but will require some measure to ensure vehicle actions are properly synchronized for patient transfer.

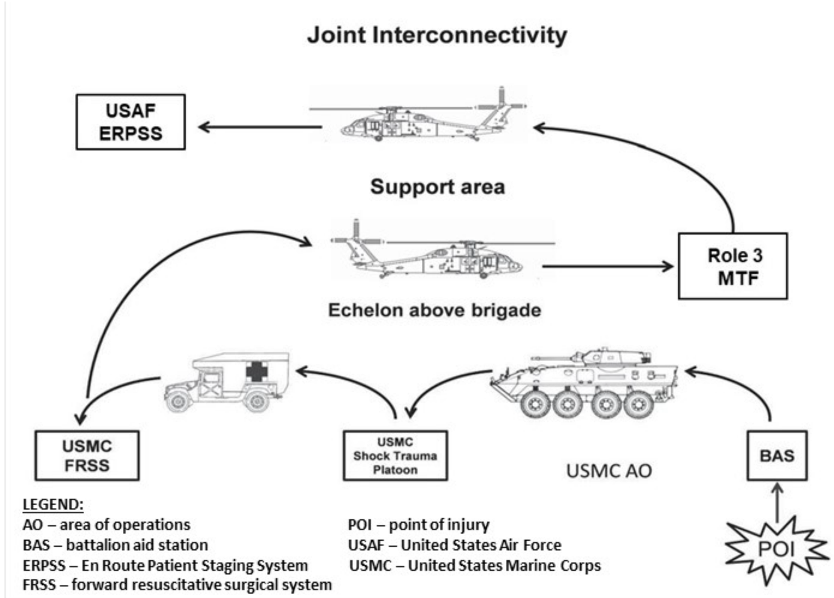

Figure 1.2. Diagram of patient movement from point of injury through successive levels of care, making use of multiple types of air and ground ambulances. Source: Department of the Army (2019).

The Joint Medical Planning Tool (JMPT) already provides all services with a planning tool for locating needed resources at appropriate locations (POC 2013). Through its suite of software, JMPT models casualty estimates along with locations for services and supplies/personnel needed at those locations, simulating the interactions of these pieces for a commander's view of outcomes of various decisions. However, this robust tool does not address the optimal routing of vehicles from point to point to effect these movements, a shortfall we address in this work.

1.2 Case Scenario

Our experiment envisions three (3) casualties at our POI. They require first-echelon transportation from POI to the casualty collection point (CCP), which we assume to be ground transportation by human litter bearers or autonomous vehicle. The CCP is located sufficiently distant from the POI for us to assume security of the location from adversary action. The second echelon transportation is located at a location intermediate between the CCP and the MTF. We assume the second echelon transport to be an aerial vehicle (human piloted or autonomous), and significantly faster than the ground transport. For the purposes of our initial experiments, the different echelons of vehicles may have different or identical capacities for carrying casualties. We assume that the total carrying capacities are sufficient for each echelon to meet the demand.

1.3 Proposed Solution

Our model proposes to link the two echelons of vehicles, after optimizing the path of each to synchronize in time at an optimal CCP, for effective transfer of the patient(s) and eventual transport to an MTF. It is likely that any particular planner is only responsible for a very limited number of potential CCPs. As network complexity increases, computational time is expected to increase and optimality may not be possible. However, this is a relatively small network problem to solve, with potentially many transshipment nodes, so an exact algorithm may be sufficient to reach optimality.

In essence, we propose a capacitated team orienteering problem with time windows and synchronization (CTOPTWS). We use a relatively small network for proof of concept purposes, increase to moderate complexity with limited adversary interdiction and propose future work to further evaluate this field.

CHAPTER 2:
Background

In this Background chapter, we present a brief overview of the field of optimization, with some focus given to specific network routing problems known as Traveling Salesperson, Vehicle Routing and Orienteering.

2.1 The Traveling Salesperson Problem

Within the realm of routing problems in network flows, one of the most famous and foundational examples is the travelling salesperson problem (TSP) (Ahuja et al. 1993). At its core, this family of problems involves routing a salesperson from an origin to all of the identified customers in the network, returning to the point of origin. The objective is to find the shortest route while visiting each customer exactly once during the course.

This can be represented according to the work of Miller et al. (1960), one of several formulations for the TSP, with a graph, G, consisting of $i, j \in V$ vertices/nodes and $(i, j) \in E$ edges, with x_{ij} as the decision variable and c_{ij} as the cost (or distance) parameter for travel from i to j. The objective is to minimize the total cost of travel on the network, as in Equation (2.1).

$$\min \sum_{i=1}^{n} \sum_{j \neq i; j=1}^{n} c_{ij} x_{ij}. \tag{2.1}$$

Constraints ensure that each city is only visited once, and that sub-tours do not exist (Miller et al. 1960). Figure 2.1 displays the results of the simple network considered in Miller et al. (1960), with the origin city indicated by node 1 and only the distances of the chosen route displayed.

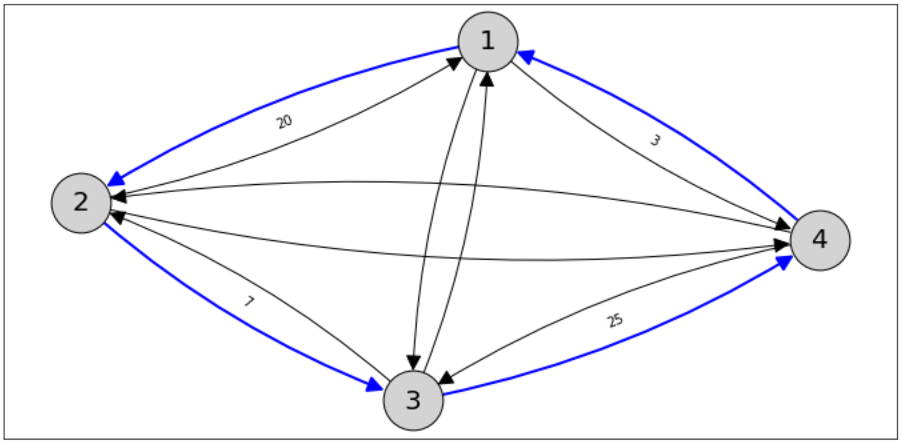

Figure 2.1. Graphic representation of solution to classic TSP. Adapted from Miller et al. (1960).

At this point, we begin to see some of the complexity issues with these types of problems. As Dantzig and Ramser (1959) point out, on a symmetric network, "the total number of different routes through n points is $\frac{1}{2}n!$." For $n = 10$, a relatively small network, the possible number of routes would equal $1,814,400$, and computational time for total enumeration would increase exponentially with larger networks.

Dantzig and Ramser (1959) go on to describe variants or generalizations of the TSP, in which a fleet of trucks is sent to deliver gasoline to customers, meeting all demand while minimizing travel distance. Ilavarasi and Joseph (2014) provide a good survey of TSPs over the years and describe variants of the TSP involving profit-seeking and time windows. These would then lead to further generalizations.

2.2 The Vehicle Routing Problem

Considered a generalization of the TSP, the vehicle routing problem (VRP) considers routing a fleet of multiple vehicles, $m \in M$, with certain capacities, to every customer (node) in the network (Ahuja et al. 1993). Customers are assigned to the vehicles in the fleet, and each vehicle is then assigned to the shortest route to reach all of its customers. The first big change from the TSP is the additional index of the fleet of vehicles, such that the objective function would become like that in Equation (2.2).

$$\min \sum_{i=1}^{n} \sum_{j \neq i; j=1}^{n} \sum_{m \in M} c_{ij} x_{ij}^{m} \tag{2.2}$$

Constraints for the VRP, like the TSP, ensure that customers are only visited once, by one vehicle, and that sub-tours are eliminated (Ahuja et al. 1993; Magnanti 1981). Additional constraints lead to some of the common variants encountered in VRPs. Toth and Vigo (2014) describe several variants within the family of VRP interesting to our endeavors, including the capacitated VRP, in which vehicles are limited in carrying capacity, in turn restricting which nodes can be visited; Dial-a-Ride, in which passengers are picked up and delivered from/to sites other than the depot; VRP with time windows, in which nodes must be serviced within certain time frames; prize-collecting VRP, in which one constraint ensures at least a minimum prize is collected; distance constrained VRP, in which the total route cannot exceed a distance/time; and the synchronized VRP, in which routing of multiple vehicles needs to be coordinated for arrival at the same place and time. An extension of interest in this work is the two-echelon VRP, in which one echelon of vehicle connects the depot to an intermediate/satellite and the second echelon vehicle connects the satellite to the customer (Crainic et al. 2009; Perboli et al. 2011). More recently, the problem has found new scientific interest from applications that involve operations of autonomous vehicles and drones (see, e.g., Faiz et al. (2020), Faiz et al. (2022), among others for operations in humanitarian logistics). Finally, Brown et al. (2013) describe a very unique VRP with aspects of prize-collecting, multiple depots, multiple cargoes, and fleet of vehicles with different characteristics.

2.3 The Orienteering Problem

Vansteenwegen et al. (2011) describe the orienteering problem (OP) as another significant generalization of the TSP and VRP, combined with aspects of the knapsack problem (KP). The KP involves optimizing (maximizing) the *profit* to be earned by placing objects of different values (and different weights/volumes) into a container with a limited total capacity (weight/volume) (Assi and Haraty 2018). The orienteering problem, then, combines this with the routing concerns of the VRP family to formulate a situation in which the goal is to maximize the reward, P_i, collected by one or more vehicles visiting selected (but not necessarily all) nodes in a network, with the general objective as in Equation (2.3).

$$\max \sum_{i=2}^{n-1} \sum_{j=2}^{n} P_i x_{ij} \tag{2.3}$$

General constraints in the OP mirror constraints from the TSP and VRP. However, the objective is markedly different, and the issue of minimizing distance (from the objective function in the previous models) is dealt with as a constraint in the OP family.

Variants of the orienteering problem include many of the same seen in VRP and several that are of interest in our pursuit (Vansteenwegen and Gunawan 2019). The Profitable Tour Problem seeks to maximize the reward earned minus the travel cost, in the objective function. The team orienteering problem (TOP) uses multiple people/vehicles to maximize rewards gained from multiple routes. The OP with time windows restricts the reward collection to certain time limits at given nodes. The Capacitated OP, as expected, limits how much a particular vehicle can carry/collect during its route.

We formulate a model using aspects of many of these variants to move patients from POI to definitive care. We need to have multi-echelon, capacitated fleets of vehicles, operating on distance-constrained routes, and synchronizing their efforts to arrive within specific time windows.

CHAPTER 3:
Formulation

3.1 Introduction and Description

We present a mixed integer linear program with similarities to two-echelon vehicle routing problems and team orienteering problems. Like the team orienteering type of problem, we seek to maximize the reward earned by transporting as many patients as possible. Like the two-echelon vehicle routing problem, we use echelons of vehicles to accomplish this.

3.2 Complete Formulation

Sets and Indices:

$i, j \in V = \{1, 2, \ldots, n\}$		Nodes
$(i, j) \in E$		Edges
$m \in \mathcal{M} = \{1, 2, \ldots, m\}$		MEDEVAC vehicles
$p \in P = \{1, 2, \ldots, p\}$		Patients
$k \in K = \{g, a\}$		Class
$V^k \subset V,$	$\forall k \in K$	Ground and Air Nodes
$V^c \subset V$		CCP Nodes
$E^k \subset E,$	$\forall k \in K$	Ground and Air edges
$\mathcal{M}^k \subset M,$	$\forall k \in K$	Ground and Air vehicles

Data:

O_m = Origin node for vehicle m

D_m = Destination node for vehicle m

Q_m = Carrying capacity for vehicle m [# of patients]

α_i = Service time at node $i \in V$ [minutes]

τ_{ij} = Travel time from node $i \in V$ to node $j \in V$ [minutes]

r_p = Reward for transporting patient $p \in P$ [unitless]

$T_{\max}$ = Travel time limit for vehicle $m \in M$ [minutes]

$[b_i, l_i]$ = Time window for synchronization and transfer at CCP node $i \in V^c$[minutes].

Decision Variables:

$$x_{mij}^k = \begin{cases} 1 & \text{if } k \in K \text{ class asset } m \in \mathcal{M}^k \text{ is routed using arc } (i,j) \in E, \\ 0 & \text{otherwise.} \end{cases}$$

$$v_m^k = \begin{cases} 1 & \text{if } k \in K \text{ class asset } m \in \mathcal{M}^k \text{ is used in operation,} \\ 0 & \text{otherwise.} \end{cases}$$

$$u_{mp}^k = \begin{cases} 1 & \text{if } k \in K \text{ class asset } m \in \mathcal{M}^k \text{ transports patient } p \in P, \\ 0 & \text{otherwise.} \end{cases}$$

$$w_{pi} = \begin{cases} 1 & \text{if patient } p \in P \text{ is assigned to CCP node } i \in V^c \text{ for transfer,} \\ 0 & \text{otherwise.} \end{cases}$$

$$y_{mi}^k = \begin{cases} 1 & \text{if } k \in K \text{ class asset } m \in \mathcal{M}^k \text{ is assigned to CCP node } i \in V^c \text{ for patient transfer,} \\ 0 & \text{otherwise.} \end{cases}$$

$s_{mi}^k, e_{mi}^k \in \mathbb{R}_{\geq 0}$: arrival and departure times for $k \in K$ type asset $m \in \mathcal{M}^g$ at CCP node $i \in V$.

$$\max \quad \sum_{m \in \mathcal{M}^a} \sum_{p \in P} r_p u_{mp}^a \tag{3.1}$$

$$s.t. \quad \sum_{i \in V^c} w_{pi} \leq 1, \qquad \forall p \in P, \tag{3.2}$$

$$\sum_{m \in \mathcal{M}^k} u_{mp}^k \leq 1, \qquad \forall p \in P, \forall k \in K, \tag{3.3}$$

$$\sum_{i \in V^c} y_{mi}^k \leq 1, \qquad \forall m \in \mathcal{M}^k, \forall k \in K, \tag{3.4}$$

$$\sum_{p \in P} u_{mp}^k \leq Q_m \cdot v_m^k, \qquad \forall m \in \mathcal{M}^k, \forall k \in K, \tag{3.5}$$

$$\sum_{m \in \mathcal{M}^k} u_{mp}^k = \sum_{i \in V^c} w_{pi}, \qquad \forall p \in P, \forall k \in K, \tag{3.6}$$

$$v_m^k \leq \sum_{p \in P} u_{mp}^k, \qquad \forall m \in \mathcal{M}^k, \forall k \in K, \tag{3.7}$$

$$v_m^k \leq \sum_{i \in V^c} y_{mi}^k, \qquad \forall m \in \mathcal{M}^k, \forall k \in K, \tag{3.8}$$

$$\sum_{p \in P} w_{pi} \leq \sum_{m \in \mathcal{M}^k} y_{mi}^k \cdot Q_m, \qquad \forall i \in V^c, \forall k \in K, \tag{3.9}$$

$$\sum_{j:(O_k, j) \in E} x_{mij}^k = v_m^k, \qquad \forall m \in \mathcal{M}^k, \forall k \in K, \tag{3.10}$$

$$\sum_{i:(i, D_k) \in E} x_{mij}^k = v_m^k, \qquad \forall m \in \mathcal{M}^k, \forall k \in K, \tag{3.11}$$

$$\sum_{(i,j) \in E} x_{mij}^k = \sum_{(j,i) \in E} x_{mji}^k, \qquad \forall m \in \mathcal{M}^k, \forall k \in K, \tag{3.12}$$

$$\sum_{j:(j,i) \in E} x_{mji}^k = y_{mi}^k, \qquad \forall m \in \mathcal{M}^k, \forall i \in V^c, \forall k \in K, \tag{3.13}$$

$$y_{mi}^k \leq \sum_{p \in P} u_{mp}^k \cdot w_{pi}, \qquad \forall m \in \mathcal{M}^k, \forall i \in V^c, \forall k \in K, \tag{3.14}$$

$$s_{mO_k}^k = 0, \qquad \forall m \in \mathcal{M}^k, \forall k \in K, \tag{3.15}$$

$$s_{mj}^k \geq e_{mi}^k + \tau_{ij} \cdot x_{mij}^k, \qquad \forall m \in \mathcal{M}^k, \forall (i,j) \in E, \forall k \in K, \tag{3.16}$$

$$e_{mi}^k \geq s_{mi}^k, \qquad \forall m \in \mathcal{M}^k, \forall i \in V^k, \forall k \in K, \tag{3.17}$$

$$e_{mi}^k \geq s_{mi}^k + \alpha_i \cdot y_{mi}^k, \qquad \forall m \in \mathcal{M}^k, \forall i \in V^c, \forall k \in K, \tag{3.18}$$

$$e^k_{m_2 i} \geq s^{k'}_{m_i i} + \alpha_i \cdot u^{k'}_{pm_1} u^k_{pm_2}, \quad \forall m_1 \in \mathcal{M}^{k'}, m_2 \in \mathcal{M}^k, k, k' \in K, \forall i \in V, \forall p \in P, \tag{3.19}$$

$$s^k_{mi} \leq T_{\max}, \quad \forall m \in \mathcal{M}^k, \forall i \in V^k \cup V^c, \forall k \in K, \tag{3.20}$$

$$b_i \cdot y^k_{mi} \leq s^k_{mi} \leq l_i \cdot y^k_{mi}, \quad \forall m \in \mathcal{M}^k, \forall i \in V^c, \forall k \in K, \tag{3.21}$$

$$x^k_{mij}, v^k_m, u^k_{mp} \in \{0, 1\}, \quad \forall m \in M, \forall (i, j) \in E, \forall p \in P, \forall k \in K, \tag{3.22}$$

$$w_{pi}, y^k_{mi} \in \{0, 1\} \quad \forall m \in M, \forall i \in V^c, \forall p \in P, \forall k \in K, \tag{3.23}$$

$$s^k_{mi}, e^k_{mi} \in \mathbb{R}_{\geq 0}, \quad \forall m \in M, \forall i \in V, \forall k \in K. \tag{3.24}$$

3.2.1 Sets and Indices

We consider a graph $G(V, E)$, in which V represents the vertices/nodes and E represents the edges. We have a set of vehicles and patients. We introduce a class for ground and air elements. Node subsets divide the nodes into ground, air, and CCP, with remaining nodes being reserved for transshipment nodes. Likewise, edges and vehicles are partitioned into classes for air and ground.

3.2.2 Data and Parameters

The key data for the model consists primarily of characteristics of the MEDEVAC assets being used and time data related to nodes and edges. Origin and destination nodes for the vehicles are represented by O_m and D_m, respectively. In general, ground vehicles begin and end at their origin, while air vehicles terminate at a hospital location (to return to origin at a later time). Each vehicle also has a specific carrying capacity, Q_m, which may be different for different types of vehicles, or even within types of vehicles.

The next set of data in the model reflect times used throughout. The value of α_i reflects the service time, in minutes, for transferring patients from one vehicle to another at the i CCP node. The travel time from node i to node j is represented by $\tau_{i,j}$, with time windows for service at a node depicted by $[b_i, l_i]$, all in minutes. The total time a vehicle may travel is determined by its operating radius and depicted by $T_{\max}$ in minutes.

Finally, reward values for patients, r_p, are fixed in our experiment without units; however, indexing by patient can determine different values for different patients.

3.2.3 Objective Function

The objective of our model (3.1) is to maximize the rewards gained by transporting and transferring patients from one vehicle to another, with ultimate successful transport to definitive care at a higher role hospital.

Of note, the reward values can be specified based on patient indexing, and the reward is dependent upon patient transfer to an air vehicle. In our model, the reward for patient transfer is one, and the model seeks to maximize the number of patients transferred.

3.2.4 Constraints

Patient Constraints

Constraints 3.2 ensure that patients can be assigned to one CCP node, at most.

Vehicle Constraints

1. Constraints 3.3 ensure that each patient can only be assigned to one ground and one air vehicle, at most.
2. Constraints 3.4 ensure that each vehicle can only be assigned to one CCP, at most.
3. Constraints 3.5 ensure that total patients carried by any vehicle (ground or air) cannot exceed the vehicle's carrying capacity.
4. Constraints 3.6 ensure any patient assigned to a CCP node must also be assigned to a ground and an air vehicle.
5. Constraints 3.7 ensure that a ground or air vehicle is not assigned to operation unless patient(s) are assigned to the vehicle.
6. Constraints 3.8 require that a vehicle selected for operations must go to at least one CCP node.

7. Constraints 3.9 ensure adequate carrying capacities of both types of vehicles for patients assigned to CCP.

Routing Constraints

1. Constraints 3.10 ensure that any vehicles selected for operations must leave their respective origins, while constraints 3.11 ensure they enter their respective destinations.
2. Constraints 3.12 ensure flow balance for each vehicle at each node.
3. Constraints 3.13 ensure that any vehicle routed to a CCP node must enter the CCP node.
4. Constraints 3.14 ensure that a vehicle goes only to a CCP node if patient(s) are assigned to the vehicle and the node.

Time Constraints

1. Constraints 3.15 ensure that vehicles arrive at their origins at time 0.
2. Constraints 3.16 ensure that a vehicle only arrives at a node after leaving the previous node, plus sufficient time to travel between the two.
3. Constraints 3.17 ensure that the departure times from any node should be later than the arrival time of that vehicle, while 3.18 do the same for CCP nodes with the addition of service times to transfer patients.
4. Constraints 3.19 ensure that a vehicle on one class cannot leave a CCP node before a vehicle of the other class has arrived.
5. Constraints 3.20 ensure that vehicles must arrive at all nodes visited before the max operating time of the vehicle.
6. Constraints 3.21 ensure vehicles arrive within a CCP node's time window.

Constraints 3.22-3.24 apply variable restrictions.

CHAPTER 4:
Results

For this experiment, we use a simple network with six (6) nodes with some duplication of nodes, following this with networks of increasing size and complexity, again with some duplication of nodes. In this chapter, we discuss the networks used, the need for duplicated nodes, and the results gained from our formulation.

Our formulation is modelled in Pyomo, an open-source optimization software based in Python (Bynum et al. 2021; Python Software Foundation 1995). Incorporation of quadratic function requires the use of a specialized solver in Pyomo, such as CPLEX solver (Cplex 2009). Our model used CPLEX, version 20.1, with all parameters set to their default values.

4.1 Introduction and Simple Problem

We imagine a simple network consisting of a POI on one side, with a MEDEVAC depot and hospital on the other side, separated by a CCP, at which patients are transferred between vehicles. POI is considered to be at node 1, with node 2 as a duplicate to enforce the constraint that every node can only be entered once. Origins and destinations are data fed to the program, CCP is user-entered, along with number of patients and $T_{\max}$ for the vehicles. Ground vehicles travel from node 1 to node 3, back to node 2. The air vehicle depot is at node 4, with node 5 as its duplicate, and node 6 as the ultimate destination. This relationship is displayed with associated distances in kilometers, in Table 4.1.

The distance data is used to determine the travel times for each type of vehicle. The travel times are used to determine the shortest route for each type of vehicle in the network, with the associated times being compared, and the maximum of these minima being used to determine the time windows for service at the CCP. The time windows are used to determine when each vehicle should leave its origin, and are used to synchronize their activities at the CCP.

Table 4.1. Sparse example network displaying distances along arcs that can be travelled. This dataset is used to test the first iterations of the formulation, to ensure functionality.

Arc	Distance (km)
(1,3)	7.5
(3,2)	7.5
(3,5)	95
(4,3)	95
(5,6)	80

When the data from Table 4.1 has been read into the formulation, we get the results displayed in Figure 4.1. Green nodes and edges/arcs represent ground vehicle travel, while blue nodes and edges/arcs represent air vehicle travel, with node 3 being the CCP and used by both types of vehicle. Success is indicated by a path from each vehicle's respective origin, through the CCP and to a respective destination node. The ground vehicles return to the origin site, to be ready to accept any new casualties. The air vehicles have a hospital as the final destination, rather than the origin, and return to the origin at a later time, perhaps after refueling.

For this experiment, three (3) patients are transferred, which is within the capacity of the ground and air vehicles. Additionally, the distances traveled are well within the assigned $T_{\max}$ of each of the vehicles. Adversarial interdiction is not considered at this point.

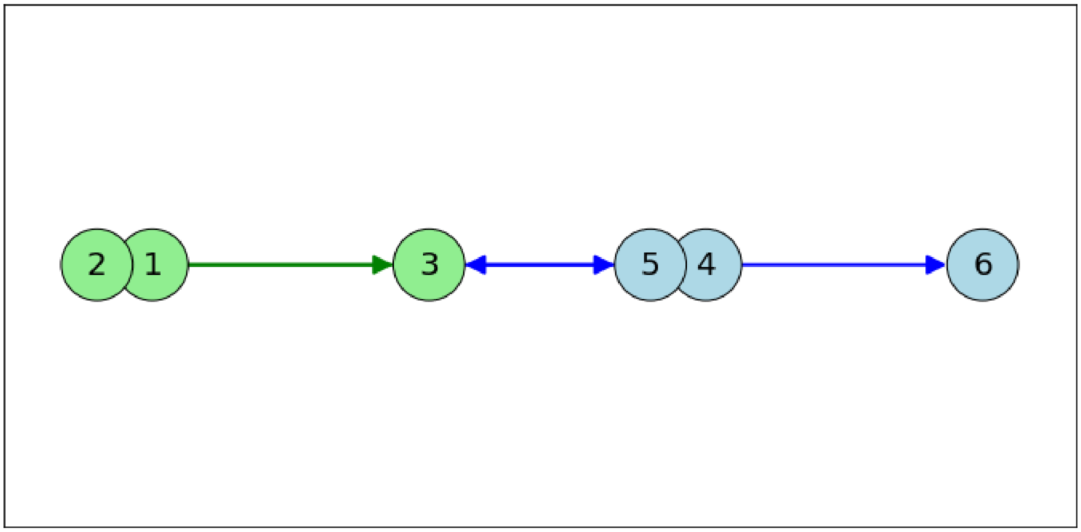

Figure 4.1. Solution to the data presented in Table 4.1, green edges and nodes indicate the route of ground units originating from node 1, travelling to node 3 and returning to node 2 (duplicate of node 1). Blue edges and nodes indicate the route of air vehicles. Numbers on the edges represent distances given.

Additional output from the model verifies this graphical result, displaying number of patients transferred, and the route of each vehicle used in the instance, as in Table 4.2. Duplicated nodes at the origins allow for routing back to the same coordinates, though with different index values.

Table 4.2. Simple example results. Output from the program includes the number of patients successfully transferred in the first row, and the route taken by those vehicles used (in the remaining rows).

Patients:	3.0
Vehicle	Route (nodes)
1	[1,3,2]
3	[4,3,5,6]

With respect to time windows and synchronization, Table 4.3 provides the program output of arrival and departure times at nodes visited by each vehicle. Service times at the CCP, α_i, are fixed for our purposes, and reflect the time required to move the patient from one vehicle to another. Service times do not reflect reality, and are not additive for multiple patients, nor do they change with respect to patient categories or monitoring equipment. In this simple experiment, service time is fixed at four (4) minutes.

Table 4.3. Arrival and departure times for vehicles from nodes visited. Times are all in minutes, with a fixed service time at the CCP of 4 minutes. Bold rows indicate synchronization of vehicle action at the CCP. Final destinations do not have departure times, as vehicle need not depart final destinations for this experiment.

Vehicle	Node	Arrival Time (minutes)	Departure Time (minutes)
1	1	0.0	0.0
1	**3**	**30.0**	**34.0**
1	2	64.0	–
3	4	0.0	0.0
3	**3**	**30.0**	**34.0**
3	5	57.0	57.0
3	6	76.2	–

A solution for this model is completed in 0.14 seconds, evaluating 33 variables, 44 linear constraints and 8 quadratic constraints.

4.2 Additional CCPs for Consideration

Having seen that the model works with a very simple network and data set, we move to a slightly more complicated model, with multiple potential CCP nodes, and variations in the vehicle carrying capacities. Table 4.4 displays the new arc and distance data. Notice that patients can be routed to either CCP node 3 or 4. Air vehicles, in this experiment, are reduced to carrying capacity of two (2), as opposed to three (3) previously. Ground carrying capacities remain at three (3).

Table 4.4. Second sparse network displaying distances along arcs that can be travelled. In this network, two CCPs are available for consideration, at nodes 3 & 4.

Arc	Distance (km)
(1,3)	7.5
(1,4)	5
(3,2)	7.5
(3,6)	95
(4,2)	10
(4,8)	90
(5,3)	95
(6,9)	80
(7,4)	90
(8,9)	80

In this case, the problem is solved in 0.01 seconds, evaluating 95 variables, 98 linear constraints and 56 quadratic constraints. Figure 4.2 shows the routes taken by the respective vehicles, with patient transfer occurring at node 3, while Table 4.5 lists the routes taken by each of the vehicles.

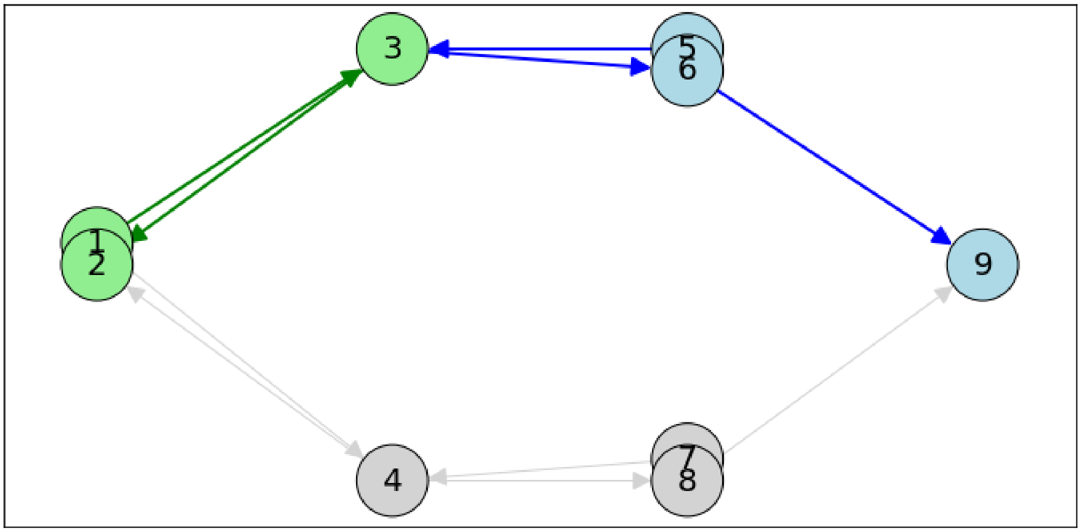

Figure 4.2. Solution to the data presented in Table 4.4, green edges and nodes indicate the route of ground units originating from node 1, travelling to node 3 and returning to node 2; blue edges and nodes indicate the route of air vehicles from node 5 to nodes 3,6 & 9. Numbers on the edges represent distances given.

Table 4.5. Multiple CCP outcome. Output from the program includes the number of patients successfully transferred in the first row, and the route taken by those vehicles used (in the remaining rows). Note: one ground vehicle required (with capacity of 3) while two air vehicles were required (with capacity of 2, each).

Patients:	3.0
Vehicle	Route (nodes)
2	[1,3,2]
3	[5,3,6,9]
4	[5,3,6,9]

As displayed in Table 4.6, ground vehicle 2 rendezvouses with air vehicles 3 & 4 at node 3 at a time of 30 minutes. Again, the service time is assigned before the vehicles depart the

CCP, and subsequent times reflect arrival at succeeding nodes until destination is reached.

Table 4.6. Arrival and departure times for vehicles from nodes visited. Times are all in minutes, with a fixed service time at the CCP of 4 minutes. Bold rows indicate synchronization of vehicle action at the CCP. Final destinations do not have departure times, as vehicle need not depart final destinations for this experiment.

Vehicle	Node	Arrival Time (minutes)	Departure Time (minutes)
2	1	0.0	0.0
2	**3**	**30.0**	**34.0**
2	2	64.0	–
3	5	0.0	0.0
3	**3**	**30.0**	**34.0**
3	6	57.0	57.0
3	9	77.0	–
4	5	0.0	0.0
4	**3**	**30.0**	**34.0**
4	6	57.0	57.0
4	9	77.0	–

4.3 Adding Complexity

Adding complexity to the network, we next test functionality with 21 nodes, with CCP nodes at 9 & 10, as in Table 4.7. We test the model with various numbers of patients, and with various combinations of transport vehicles/capacities.

Table 4.7. Complex network displaying distances along arcs that can be travelled. In this network, two CCPs are available for consideration, at nodes 9 & 10.

Arc	Distance (km)	Arc	Distance (km)
(1,5)	5.0	(10,12)	50
(1,7)	7.0	(10,14)	75
(3,5)	6.0	(10,16)	50
(3,7)	4.0	(11,9)	50
(5,9)	5.0	(11,10)	50
(5,10)	7.0	(12,18)	35
(6,2)	5.0	(12,20)	55
(6,4)	6.0	(13,9)	50
(7,9)	6.0	(13,10)	75
(7,10)	9.0	(14,20)	25
(8,2)	7.0	(15,9)	75
(8,4)	4.0	(15,10)	50
(9,6)	5.0	(16,18)	50
(9,8)	6.0	(17,11)	35
(9,12)	50	(17,15)	50
(9,14)	50	(18,21)	35
(9,16)	75	(19,11)	55
(10,6)	7.0	(19,13)	25
(10,8)	9.0	(20,21)	40

Using six patients and vehicles with sufficient capacity, the problem is solved in 0.23 seconds, evaluating 274 variables, 352 linear constraints and 34 quadratic constraints. Table 4.8 lists the routes taken by the respective vehicles, with patient transfer occurring at node 9.

Table 4.8. Complex network outcome. Output from the program includes the number of patients successfully transferred in the first row, and the route taken by those vehicles used (in the remaining rows). Note: two ground vehicles required (each with capacity of 3) while three air vehicles were required (with capacities of 2, 2, and 3).

Patients:	6.0
Vehicle	Route (nodes)
1	[1,5,9,6,2]
2	[1,5,9,6,2]
3	[17,11,9,14,20,21]
4	[17,11,9,14,20,21]
5	[19,13,9,14,20,21]

Table 4.9 displays ground vehicles 1 & 2 rendezvousing with air vehicles 3 & 4 & 5 at node 9 at a time of 40 minutes. Again, the service time is assigned before the vehicles depart the CCP, and subsequent times reflect arrival at succeeding nodes until destination is reached. Figure 4.3 displays these results graphically, with ground routes in green, air routes in light blue and CCP nodes represented in blue. For these results routes displayed indicate route for ground vehicle 2 and air vehicle 5.

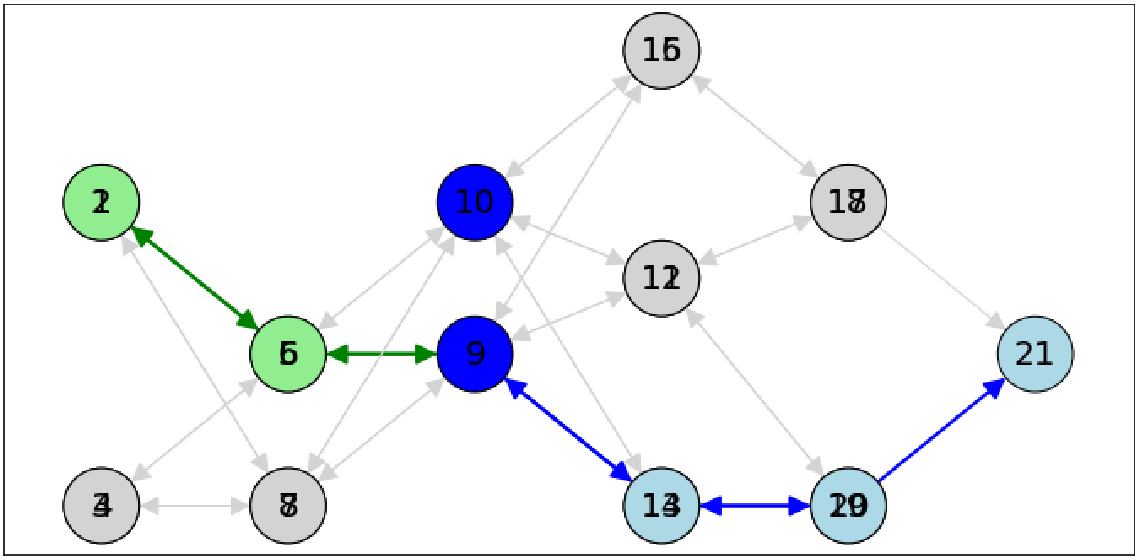

Figure 4.3. Solution to complex network presented in Table 4.8, green edges and nodes indicate the route of ground units originating from node 1, travelling to CCP node and returning to destination node; blue edges and nodes indicate the route of air vehicles from origin to CCP and destination. Blue nodes represent CCP nodes available.

Table 4.9. Arrival and departure times for vehicles from nodes visited. Times are all in minutes, with a fixed service time at the CCP of 4 minutes. Bold rows indicate synchronization of vehicle action at the CCP. Final destinations do not have departure times, as vehicle need not depart final destinations for this experiment.

Vehicle	Node	Arrival Time (minutes)	Departure Time (minutes)
1	1	0.0	0.0
1	5	20.0	20.0
1	**9**	**40.0**	**47.0**
1	6	67.0	67.0
1	2	87.0	–
2	1	0.0	0.0
2	5	20.0	20.0
2	**9**	**40.0**	**47.0**
2	6	67.0	67.0
2	2	87.0	–
3	17	0.0	0.0
3	11	8.4	8.4
3	**9**	**40.0**	**44.0**
3	14	71.4	71.4
3	20	77.4	77.4
3	21	87.0	–
4	17	0.0	0.0
4	11	8.4	8.4
4	**9**	**40.0**	**44.0**
4	14	71.4	71.4
4	20	77.4	77.4
4	21	87.0	–
5	19	0.0	0.0
5	13	6.0	6.0
5	**9**	**40.0**	**44.0**
5	14	71.4	71.4
5	20	77.4	77.4
5	21	87.0	–

Variations in the number of patients can affect the results in numerous ways. In Table 4.10, we see that reducing the patients carried changes the air vehicles routed as well as the route chosen for those vehicles, while maintaining the synchronization.

Table 4.10. Comparison of results from 6 versus 4 patients. With 4 patients for transfer, note that: only vehicles 4 & 5 used for air and that the air routes have changed.

Patients:	6.0	4.0
Vehicle	Route (nodes)	Route (nodes)
1	[1,5,9,6,2]	[1,5,9,6,2]
2	[1,5,9,6,2]	[1,5,9,6,2]
3	[17,11,9,14,20,21]	[]
4	[17,11,19,14,20,21]	[17,15,9,12,18,21]
5	[19,13,9,14,20,21]	[19,13,9,12,18,21]

To explore the effect of adversary action in the area, we apply a simple (time/distance) penalty to an affected arc in the network, forcing the air vehicles to reroute for a shorter path. In Table 4.11, we display the effect of adversary action on the indicated arcs, with the resulting route change for vehicles 3 and 4.

Table 4.11. Influence of adversary action on network and route chosen. With adversary action affecting the arc from node 17 to node 11, vehicles 3 & 4 seek a route through node 15.

Patients:	4.0	4.0
Adversary action:	None	Arc (17,11)/(12,18)
Vehicle	Route (nodes)	Route (nodes)
1	[1,5,9,6,2]	[1,5,9,6,2]
2	[1,5,9,6,2]	[1,5,9,6,2]
3	[17,11,9,12,20,21]	[17,15,9,16,18,21]
4	[17,11,9,12,20,21]	[17,15,9,16,18,21]

In a variety of circumstances, from simple to complex networks, with varying requirements and capacities, the model delivers a feasible solution in a reasonable time. We introduce the effects of adversary actions in the network, with a reasonable result produced.

4.4 Computational Complexity

The complexity of our problem is NP-hard, since this problem is an extension of the TOP and TOP is a NP-hard problem (Laporte and Martello 1990; Vansteenwegen and Gunawan 2019). Note that with multiple vehicles without vehicle capacity, synchronization and time window constraints on an unchanged underlying network, our problem becomes TOP. Even though the problem is NP-hard, we observe that Pyomo with Cplex solves this problem efficiently for our small and medium sized networks.

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CHAPTER 5: Conclusion

In this section, we discuss any restrictions or shortfalls of the formulation described in previous chapters and explore what we consider to be future directions to correct shortfalls or to expand the work.

5.1 Introduction and Description

Considering our initial results as proof of concept, our work can help to direct future work, perhaps providing methods to improve life-saving efforts for patient evacuation.

There is a fundamental difference between VRP and TOP models, particularly in the way they make us think about optimizing either distances/times or prizes. For our problem, there are benefits for each type of model, and also detractors for each type of model. We must make a decision about whether we want to use a VRP-type problem to minimize the total distance travelled, by all vehicles, while transferring a minimal number of patients (as a constraint in the model), while potentially not considering any additional patients that may also need transport. Alternatively, we could focus efforts on the prize collection, as we do with the OP-type problems, but we do not have as great control on minimizing the distance/time travelled, as this is treated as a constraint. For our experiments in this thesis, we choose to focus on the OP formulation to maximize the patient transfers, though it would be interesting to consider a Profitable Tour Problem (PTP) approach as an alternative, in which travel distances are subtracted from rewards (Vansteenwegen and Gunawan 2019).

In our initial computational experiments with one origin for ground, one origin for air, one vehicle of each type, with equal capacities, and simple linear connections from origin to target, the model was able to synchronize efforts to successfully move patients from POI to hospital care at the final node.

As we noticed in our second experiment, with extended CCP choices for the ground side, the model is still able to synchronize the two sides to effect transfer of patients as intended, despite the fact that there is a shorter path available for the ground vehicles. That route is not shorter for the air side, and not shorter overall, so the model makes the correct choice.

Throughout the course of the experiments we experience some of the formulation restrictions that can be expected with this family of problems, such as subtours and infeasibility. Often the subtour complications can be addressed with subtour elimination constraints following the Miller-Tucker-Zemlin model (Miller et al. 1960). However, time window constraints also successfully address this issue, as in our model. Our model also relies heavily on duplicated nodes to allow for reverse direction flow on the network, which helps us eliminate some of the infeasible solutions we experience otherwise, as flow balance constraints often enforce one visit per node.

5.2 Assumptions & Limitations

The formulation quickly becomes infeasible when vehicle capacity cannot accommodate all patients requiring evacuation. In our work, we assumed that vehicle capacities would be adequate for all patients transfers. Future work could consider relaxing constraints that require these capacities.

Since the OP family of models uses constraints to control distances travelled, we witness the maximum time constraint leading to later arrival times at destination nodes than anticipated. Seemingly, the vehicles loiter en route from the CCP to the destination. Further exploration, perhaps with a PTP-type formulation could help address this.

5.3 Extensions & Future Work Considerations

Our model serves as proof of concept of a basic framework for further exploring a form of OP and TOP that we have not previously seen, and could benefit MEDEVAC planners in successfully routing vehicles for delivery of patients to definitive care. Next steps should consider further expanding the network to ensure continued functionality while fully stressing the system, and evaluating computational time requirements. Whereas our model uses a simple penalty assignment to a single arc to represent adversary action, a full consideration of randomized adversary interdiction should be applied to ensure the model functions in this environment.

Finally, although we use a TOP approach to the model, there could be some benefits in considering other approaches. For instance, a VRP approach could ensure that the routes used are truly the shortest routes; with carefully constructed prize-collecting constraints to ensure patients are not abandoned, or a PTP approach could be considered. Alternatively, a multi-objective method could provide a means of addressing both the movement of patients while minimizing distance. Exploring online optimization or other algorithms for larger networks are additional considerations for future work.

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