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Incorporating Armed Escorts to the Military Medical Evacuation Dispatching Problem via Stochastic Optimization and Reinforcement Learning

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INCORPORATING ARMED ESCORTS TO THE MILITARY MEDICAL EVACUATION DISPATCHING PROBLEM VIA STOCHASTIC OPTIMIZATION AND REINFORCEMENT LEARNING

THESIS

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Abstract

The military medical evacuation (MEDEVAC) dispatching problem seeks to determine high-quality dispatching policies to maximize the survivability of casualties within contingency operations. This research leverages applied operations research and machine learning techniques to solve the MEDEVAC dispatching problem and evaluate system performance. More specifically, we develop an infinite-horizon, continuous-time Markov decision process (MDP) model and approximate dynamic programming (ADP) solution approach to generate high-quality policies. The ADP solution approach utilizes an approximate value iteration algorithm strategy incorporating gradient descent Q-learning to approximate the value function. A notional, synthetically-generated scenario in Africa based around Niamey, the capital city of Niger, is developed and utilized to compare the ADP-generated policies with the closest-available dispatching (i.e., myopic policy) currently employed by military medical planners. This research also develops a custom OpenAI gym environment in Python to evaluate system performance and the efficacy of the ADP solution approach. Initial results from our computational experiments indicate a 10% increase in performance over the myopic policy. Further testing indicates which problem features have the most significant impact on the system performance gap between the myopic policy and the ADP-generated policies. The model, methodologies, and results from this research may be utilized to advise current and future military medical planning procedures, operations, and tactics.

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We dedicate this research to the servicemen and women who have dedicated their lives in service to our country. We hope this research can help improve the military medical evacuation system to improve the quality of care to our service members who risk their lives in defense of our country.

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Andrew Gelbard

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INCORPORATING ARMED ESCORTS TO THE MILITARY MEDICAL EVACUATION DISPATCHING PROBLEM VIA STOCHASTIC OPTIMIZATION AND REINFORCEMENT LEARNING

I. Introduction

This chapter provides motivation and background for the medical evacuation (MEDEVAC) dispatching problem related to military operations. We briefly outline the history of battlefield MEDEVAC and the essential problem features. We also discuss the variation of the problem this research examines and how it adds to the current literature.

1.1 Motivation

Military emergency medical service (EMS) response teams are responsible for evacuating injured personnel from the battlefield to a medical treatment facility (MTF) as quickly as possible to maximize patient survivability rates. The primary methods utilized to accomplish this are casualty evacuation (CASEVAC) and MEDEVAC. CASEVAC units do not come equipped with the medical supplies nor trained medical personnel, whereas MEDEVAC units do (Department of the Army, 2019). For this reason, military medical planners typically leverage MEDEVAC units to respond to severe casualties (i.e., casualties with life-threatening injuries) on the battlefield. MEDEVAC units typically employ HH-60M Black Hawk helicopters to evacuate battlefield casualties because they are better suited than ground platforms. For example, HH-60M Black Hawk helicopters can travel directly to casualty collection points (CCPs), unhindered by rough terrain or poorly constructed roads. The HH-60M

Black Hawk helicopter also comes equipped with the necessary medical resources (e.g., electrocardiogram (EKG) machine built in external hoist, oxygen generators, electronically controlled litters), which enable medical personnel to simultaneously treat the patients while in route to the MTF (Jenkins, 2017).

The military MEDEVAC dispatching problem refers to the sequential resource allocation and decision making within the MEDEVAC system to determine which MEDEVAC unit to dispatch when responding to a casualty event (Robbins et al. 2018). These decisions are highly complicated when considering the location of the casualty, location of the MTFs, triage level of the request, threat level of the request, service times, response times, and request arrival rate. This thesis seeks to solve a variation of the MEDEVAC dispatching problem that explicitly models and controls the use of armed escorts via a Markov decision process (MDP) model and approximate dynamic programming (ADP) solution approach. Improved performance of a MEDEVAC system leads to increased patient survivability rates and confidence in the service members.

1.2 Background

MEDEVAC system development typically considers the location of assets, dispatching policies, response times, and redeployment. Military medical planners typically base the determination of MEDEVAC system location on responding to a request as quickly as possible while also providing maximum coverage (Jenkins *et al.*, 2020c,b). Redeployment consideration is complex within the MEDEVAC system due to the potential for communication errors. The current dispatching policy employed is myopic, meaning dispatching the closest available unit to a service request. The myopic policy does not consider important system characteristics such as the priority level or threat level of requests. Response times are a critical consideration due to

the loss of blood being a leading cause of death in battlefield casualties (Shackelford *et al.*, 2017). Both MEDEVAC and CASEVAC operations have leveraged various vehicle types throughout histories such as helicopters, ships, trucks, and horse-drawn wagons. This thesis focuses on the utilization of aeromedical helicopter operations for MEDEVAC operations. Helicopters are well suited for MEDEVAC operations as they can land directly at the site of the casualty event and can move at relatively quick speeds as opposed to other MEDEVAC platforms. Dedicated MEDEVAC helicopters come equipped with medical supplies and trained medical personnel to help respond to various battlefield injuries.

From January 2010 to April 2012, approximately 31 percent of MEDEVAC missions required an armed escort (Garrett, 2013). Traditionally, the dispatching authority requests an armed escort from a separate unit when a MEDEVAC request is submitted with the appropriate threat level. This research seeks to study MEDEVAC system performance when the dispatching authority explicitly controls armed escort assets. Having this control allows the dispatching authority to manage the location of the armed escort assets throughout the duration of combat operations. For example, it may be beneficial for an armed escort to loiter in a particular combat zone based on the likelihood of future high-threat level MEDEVAC requests. Conversely, the dispatch authority may decide armed escort presence is better suited in a different combat zone.

This thesis develops a discounted, infinite-horizon, continuous-time MDP model that seeks to maximize the expected total discounted reward of the system. An ADP solution approach is also developed to solve the problem as the state space becomes too large to solve optimally with an exact solution procedure. The ADP solution approach utilizes an approximate value iteration (AVI) algorithm strategy incorporating gradient descent Q-learning to approximate the value function.We develop a

computational example to apply to a MEDEVAC system in western and central Africa during contingency operations. We compare the policies developed by our ADP algorithm with the myopic policy. We also perform sensitivity analysis and examine several excursion scenarios to obtain insights.

1.3 Document Overview

This document is organized as follows. Chapter II reviews the literature related to civilian and military EMS systems leveraging MDP and ADP techniques. Chapter III outlines the problem description and model formulation developed to solve for dispatching policies. Chapter IV covers the testing and results of the proposed methodology on a representative scenario, along with sensitivity analysis and excursions. Chapter V concludes this thesis and offers considerations for future research.

II. Literature Review

This chapter outlines the current research literature related to military and civilian emergency medical service (EMS) response systems. The literature review emphasizes research related to the dispatching policies of assets to service requests and the associated methodologies.

2.1 EMS response systems

EMS response systems commonly leverage various operation research techniques such as simulation modeling, queueing, and stochastic optimization due to their ability to develop quantitative, defensible, and rigorous results (Green & Kolesar, 2004). For example, dispatching decisions for military and civilian EMS response systems may be determined by leveraging operations research techniques to build models that maximize system performance. Some researchers measures system performance with response time thresholds (RTTs), and others measure system performance utilizing patient survivability rates. This thesis incorporates monotonically decreasing patient survivability rates with respect to increasing response times as the optimality criterion for measuring the performance of the medical evacuation (MEDEVAC) system. We review the current literature and summarize the key contributions in military and civilian EMS response system research. Lastly, we discuss how the contributions in the current literature relate to this research and how our research extends these contributions.

2.1.1 Military MEDEVAC

The medical planners for military MEDEVAC system development are typically concerned with locating MEDEVAC staging areas and medical treatment facilities

(MTFs) as well as the allocation of aeromedical helicopters (Jenkins *et al.*, 2021a, 2020a, 2021c). The MEDEVAC dispatching problem is specifically concerned with the decision of which MEDEVAC unit to dispatch in response to a service request. In military contingency operations, a 9-line MEDEVAC request refers to a service request, which contains nine specific lines of information the dispatching authority needs to decide how to service the request. Currently, the military employs a myopic policy, sending the closest available unit to service an incoming request. However, this policy does not consider important system characteristics such as the priority of the request, threat levels, and request arrival rates. Nicholl *et al.* (1999), Graves *et al.* (2021), and Jenkins (2019) have shown that the myopic policy is not always optimal. Previous military EMS response system research focuses on variations of the MEDEVAC dispatching problem, exploring a myriad of problem features and solution approaches.

Keneally *et al.* (2016) present a Markov decision process (MDP) model that generates optimal policies for the MEDEVAC dispatching problem using a scenario in the Afghanistan theater. The authors assume the location of the staging areas and MTFs are pre-determined and do not change for the duration of the combat operations. The author also assumes arrivals occur sequentially according to a Poisson process. The objective of the MDP model is to maximize the system's long-run average utility gained over an undiscounted infinite horizon. The problem formulation in Keneally *et al.* (2016) seeks to determine which unit to dispatch to an incoming 9-line MEDEVAC request based on the priority level of the casualties (i.e, urgent, priority, routine) and also considers the possibility of an armed escort requirement due to high threat level. The optimality criterion for the reward function in the MDP model uses an RTT. Results from the authors' formulation indicate that a myopic policy is not always the optimal choice for dispatching MEDEVAC units.

Rettke *et al.* (2016) contribute to the literature by determining high-quality policies for dispatching MEDEVAC units, utilizing an approximate dynamic programming (ADP) solution approach. The authors apply an approximate policy iteration (API) algorithm framework that uses least-square temporal differences (LSTD) for policy evaluation. The authors develop a representation of a military operations scenario in Syria to demonstrate the model's applicability. The results indicate the ADP-generated policies outperform the myopic policy by approximately 30 percent with regard to a life saving performance metric.

Jenkins *et al.* (2018) expand upon Keneally *et al.* (2016) research by incorporating a queue and admission control into the system. The authors seek to determine optimal dispatching policies that maximize system performance in terms of patient survivability. The system incorporates a queue and allows the dispatching authority to accept or reject incoming requests based on priority level and location of the request. Uniformization is applied to convert the continuous-time MDP to an equivalent discrete-time MDP formulation. The authors compare a linear programming and policy iteration solution approach while also measuring performance against a myopic policy. The results reveal that a myopic policy is not always optimal compared to a system that considers the current MEDEVAC unit status, priority level, queue status, and status of incoming requests.

Robbins *et al.* (2018) add to the MEDEVAC dispatching literature by generating an MDP model utilizing a zone tessellation scheme of a large-scale combat scenario in Afghanistan. An API framework with a hierarchical aggregation value function approximation scheme is utilized to obtain high-quality solutions within one percent of optimality. Robbins *et al.* (2018) compare the results to the benchmark, myopic policy (i.e, closest available dispatching policy) used in practice. The results in the 6-zone, 12-zone, and 34-zone problem instances generate a 9.6, 9.2, and 12.4 percent

improvement over the myopic policy, respectively.

Jenkins *et al.* (2021a) add to the literature in MEDEVAC dispatching policies by incorporating previous aspects of admission control and queueing as well as expanding upon the work with ADP solution approaches, for large problem instances where exact solution methodologies are not feasible. API algorithm solution techniques are applied. The authors develop a planning scenario of combat operations in southern Azerbaijan to determine the efficacy of the MDP and ADP solution approaches. Due to the dimensionality and uncountable state space, computing the optimal policy with the MDP policy evaluation solution approach is intractable. Thus, the authors use two ADP solution approaches, LSTD and neural network (NN) learning, to solve the problem instances. The results of the designed experiments indicate that the ADP policies show significant improvement in response time compared to the benchmark closest available policies. The NN-API and LSTD-API algorithms showed improvement in 27 and 24 of the 30 problem instances, respectively. The authors also note the policies generated from the best NN-API parameter settings performed significantly better than the policies generated from the best LSTD-API parameter settings.

Jenkins *et al.* (2021b) further contribute to the EMS literature by developing high-quality policies for the dispatching, preemption-rerouting, and redeployment problem. The formulation is a discounted, infinite-horizon MDP that maximizes the system's expected total discounted reward. The authors incorporate an ADP algorithm that utilizes a support vector regression value function approximation scheme within an API framework. Computational results indicate the rate at which requests enter the system impacts how the ADP-generated policies perform against the closest-available benchmark policies.

Dennie (2021) investigates MEDEVAC dispatching policies utilizing an MDP and ADP model measuring patient survivability. His research contributes to the literature

by incorporating Air Force MEDEVAC helicopters in addition to the Army assets typically modeled. The Air Force asset studied is the Pave Hawk, which can enter high threat level zones unaccompanied. Using an API framework, the author specifies an ADP algorithm that utilizes kernel regression to approximate the post-decision state value function. The model seeks to maximize the expected total discounted reward for an infinite-horizon continuous-time Markov decision process to determine dispatching policies for the MEDEVAC system. Excursions demonstrate how asset type, arrival rate, and threat level impact system performance. The author examines a notional scenario based on combat operations in southern Afghanistan with 6-zone, 12-zone, and 34-zone problem instances. Results indicate the optimal and ADP policies obtain approximately 5 and 4 percent improvement over the myopic policy, respectively, in the 6-zone and 12-zone instances. The ADP-generated policies in the 34-zone problem instance demonstrated a 1 percent improvement over the myopic policy.

2.1.2 Civilian EMS response systems

Although military EMS response systems have unique problem features such as force protection and logistic constraints, the civilian EMS ambulance dispatching problem has significant overlap in problem features. More specifically, there is overlap in leveraging approximation techniques to determine high-quality policies for large problem instances. Furthermore, civilian EMS research has examined patient severity classification errors, where the patient's status upon receipt of the service request varies from the actual severity of the request. Existing ambulance dispatching problem research examines queueing requests as well as relocation and redeployment decisions. We briefly review the research on the ambulance dispatching problem that is relevant to this thesis.

McLay & Mayorga (2013b) contribute to the ambulance dispatching problem by developing an MDP model to help determine which servers to dispatch to customers in a service system. The author incorporates classification errors where the service call's reported priority level is different from the true priority level. Since the scenario is a small problem instance, the authors use exact dynamic programming solution approaches via the relative value iteration algorithm to determine optimal policies. Optimal dispatch policies are compared to a myopic policy to study system performance, which is measured utilizing an RTT for true high-risk calls. The authors discuss how future research may consider modeling low-risk calls to be serviced by the police department or fire department when applicable to ensure proper utilization of ambulances for high-risk calls. The results from a simulation performed in McLay & Mayorga (2013b) indicate that even with the assumption of exponentially distributed service times, the optimal policies from the MDP still provide relevant insights.

McLay & Mayorga (2013a) further contribute to the ambulance dispatching problem introduced in McLay & Mayorga (2013b) by examining balancing and equity problem features. The authors examine the impact of dispatch policies on trade-off performance in low population rural areas to more densely populated areas. The model seeks to maximize the expected total reward per stage given the minimum equity standards using an RTT. The authors analyze four different equity measures by formulating a constrained linear programming model that solves the ambulance dispatching problem. The results indicate that in some scenarios the notion of equity could improve for both the customers and servers simultaneously.

Both McLay & Mayorga (2013b) and McLay & Mayorga (2013a) do not consider a system queue or admission control. The authors also do not consider redeployment and relocation. Redeployment considers sending an ambulance to a new service request before returning to its staging location after completing a request. Relo-

cation considers changing the staging area of the ambulance to maximize coverage. The subsequent two papers examine larger problem instances that use approximation techniques as solution approaches and include some of the problems features the authors McLay and Mayorga did not.

Nasrollahzadeh *et al.* (2018) examine a modification to the ambulance dispatching problem by exploring queuing requests as well as relocation and redeployment decisions. Although an MDP model is formulated and applied to a response scenario in North Carolina, the authors apply an ADP solution approach due to the size of the state space. The model is a discounted, infinite-horizon MDP seeking to minimize the discounted, priority-adjusted expected total response time and expected fraction of late calls. The results indicate improved performance when utilizing the ADP-generated policies as compared to benchmark policies.

Park & Lee (2019) consider aspects of redeployment and patient severity classification errors. The authors develop a two-tier system that models ambulances with different capabilities. The authors discuss impacts on policies due to classification errors and risk considerations and develop computational experiments from Seoul, South Korea. The authors formulate a semi-MDP discounted model and ADP solution approach to solve the problem. In comparison to the myopic policy, the computational results indicate that, on average, the policies generated can reduce the patient's risk level index by 11.2 percent.

2.2 Thesis contribution

The research conducted in this thesis will build on the MEDEVAC dispatching problem research by formulating an MDP model that explicitly includes the armed escort asset. Previous literature accounts for the approximate wait time for the armed escort request but does not model the armed escort as an asset controlled by the dis-

patching authority. Furthermore, we examine the utilization of Air Force and Army aeromedical assets with different capabilities and their impact on system performance. We also examine a new scenario in central and western Africa while including problem features previously examined such as admission control and a system queue. The high dimensionality and relatively large state space in our MEDEVAC dispatching problem render classic dynamic programming techniques computationally intractable. Therefore, we implement an ADP solution approach to develop high-quality dispatching policies. The ADP solution approach utilizes an approximate value iteration (AVI) algorithmic strategy incorporating gradient descent Q-learning to approximate the value function, which has yet to be explored in military MEDEVAC research.

III. Methodology

In this chapter we describe the medical evacuation (MEDEVAC) dispatching problem and the Markov decision process (MDP) model formulation. Within the mathematical model formulation we outline the parameter definitions, decision epochs, state space, action space, transition probabilities, rewards, and objective function.

3.1 Problem description

The military MEDEVAC dispatching problem encompasses the decision process and dispatching policies for MEDEVAC units and armed escorts. When a service member submits a request to evacuate injured battlefield personnel, the dispatching authority must determine whether to dispatch a MEDEVAC unit and, if so, which unit to send. The incoming service request typically contains the following information: location, priority level, threat level, and the number of casualties. Once a MEDEVAC unit is assigned to service a request, the unit assigned is required to travel to the staging area, arrive at the casualty collection point (CCP), load the injured personnel, depart the CCP, travel to the nearest medical treatment facility (MTF), and unload the patients. Then, the MEDEVAC unit will head back to its dedicated staging area, complete a re-equip, and refuel. If the service request has a high threat level, an armed escort will depart to the CCP and protect the CCP until the MEDEVAC unit has departed the CCP. Once the MEDEVAC departs, the escort returns to a specified loiter point until tasked with another request. We incorporate admission control so the dispatching authority can elect to accept or reject an incoming request. If the dispatching authority rejects the request, we assume the service request is served by another evacuation service such as casualty evacuation (CASEVAC). Table 1 represents an event timeline depicting the dispatching process. Events

E8-E2 represent the MEDEVAC system response time and events E10-E2 represent the MEDEVAC system service time.

Table 1: MEDEVAC System Event Types

Event	**Description**
E1	Receive submission of 9-line MEDEVAC request.
E2	MEDEVAC unit and armed escort (when applicable) unit tasked to service a request.
E3	MEDEVAC and armed escort (when applicable) unit travels to CCP.
E4	MEDEVAC unit and armed escort (when applicable) unit arrives at CCP.
E5	MEDEVAC unit travels from CCP to nearest MTF, and, if applicable, a escort. travels back to the loiter point
E6	Armed escort unit arrives at dedicated loiter point.
E7	MEDEVAC unit arrives at nearest MTF.
E8	MEDEVAC unit completes transfer of the combat casualties to the MTF staff.
E9	MEDEVAC unit travels from the MTF to its dedicated staging area.
E10	MEDEVAC unit completes refuel and re-equip.
E11	MEDEVAC unit becomes idle at a staging facility.

3.2 MDP Formulation

3.2.1 Decision Epoch

The decision epochs in the MEDEVAC dispatching problem are the points in time wherein the dispatch authority is required to make a decision and are given by

$$\mathcal{T} = \{1, 2, \ldots\}.$$

We observe a decision epoch when one of three event types occurs. The first event type is the submission of a 9-line MEDEVAC request (i.e., event type E1). The second event type is the change in a MEDEVAC unit's status from busy to available (i.e., event type E11). The third event type is the change in an armed escort unit status from busy to available (i.e., event type E6).

3.2.2 State space

At decision epoch t $\in \mathcal{T}$, the state $S_t \in \mathcal{S}$ contains the minimum information of the MEDEVAC system required to compute the decision function, transition function, and reward function. We represent the state variable by the tuple

$$S_t = (M_t, A_t, \hat{R}_t),$$

wherein M_t represents the MEDEVAC status tuple at decision epoch t, A_t represents the armed escort status tuple at decision epoch t, and $\hat{R}_t$ represents the request status tuple at decision epoch t.

The MEDEVAC status tuple represents the status of every MEDEVAC unit in the system at decision epoch t. We represent M_t as follows

$$M_t = (M_{tm})_{m \in \mathcal{M}} \equiv (M_{t1}, M_{t2}, ..., M_{t|\mathcal{M}|}),$$

wherein the set of MEDEVAC units in the system is represented by $\mathcal{M} = (1, 2, ..., |\mathcal{M}|)$. The M_{tm} tuple contains information pertaining to each MEDEVAC unit $m \in \mathcal{M}$ at decision epoch t and is given by

$$M_{tm} = (i_{tm}, e_{tm}, r_{tm}, u_{tm}, p_{tm}, l_{tm}),$$

wherein i_{tm} represents the availability status of each MEDEVAC unit m at epoch t, e_{tm} represents the entry time of the request into the system at epoch t, r_{tm} represents the expected response time of MEDEVAC m at epoch t, u_{tm} represents the expected service time of MEDEVAC m at epoch t, p_{tm} represents the triage level of the service request for each MEDEVAC unit m at epoch t, and l_{tm} represents the threat level of the service request for each MEDEVAC m at epoch t. Note $i_{tm} = 0$ if the MEDEVAC

unit is available at epoch t and $i_{tm} = 1$ if MEDEVAC unit m is busy at epoch t. Note $p_{tm} = 0$ if no request is assigned to MEDEVAC unit m, and $p_{tm} = k \in K$ if a request is assigned, where $K = \{1, 2, 3\}$ (i.e., 1 for urgent, 2 for priority, and 3 for routine). Note $l_{tm} = 0$ when the request does not require an escort and $l_{tm} = 1$ when the request requires and armed escort. The armed escort status tuple represents the status of every escort unit in the system at decision epoch t and is represented by

$$A_t = (A_{ta})_{a \in \mathcal{A}} \equiv (A_{t1}, A_{t2}, ..., A_{t|\mathcal{A}|}),$$

wherein the set of armed escort units in the system is represented by $\mathcal{A} = (1, 2, ..., |\mathcal{A}|)$. The A_{ta} tuple contains information pertaining to each armed escort unit $a \in \mathcal{A}$ at decision epoch t and is given by

$$A_{ta} = (i_{ta}, r_{ta}, u_{ta}),$$

wherein i_{ta} represent the availability status of each escort unit a at epoch t, r_{ta} represents the expected response time of escort unit a at epoch t, u_{ta} represents the expected service time of escort unit a at epoch t. Note $i_{ta} = 0$ if the armed escort unit is available at epoch t and $i_{ta} = 1$ if the armed escort unit a is busy at epoch t. The escort response time indicates the time from when the escort unit travels from its loiter point to the CCP in response to a request. The escort service time indicates the time from when the escort leaves the loiter point to service a request until the escort unit returns to its dedicated loiter point, after the MEDEVAC unit has departed the CCP for the service request.

The request status tuple $\hat{R}_t$ is given by

$$\hat{R}_t = (\hat{o}_t^{sr}, \hat{p}_t^{sr}, \hat{l}_t^{sr}),$$

wherein the random variable $\hat{o}_t^{sr}$ is the location of the incoming service request at epoch t, $\hat{p}_t^{sr}$ is the random variable representing the triage level of the incoming service request at epoch t, and $\hat{l}_t^{sr}$ is the random variable representing the threat level of the incoming service request at epoch t. The information within our request status tuple $\hat{R}_t$ at decision epochs $1, 2, ..., t-1$ are considered random because the information is still uncertain. At decision epoch t the information is no longer uncertain. If there is not an incoming service request at decision epoch t, we let the request status tuple be $\hat{R}_t = (0,0,0)$.

3.2.3 Action space

The action space consists of an admission control and dispatch decision. A compact representation of our actions is given by

$$x_t = (x_t^{reject}, x_t^d),$$

wherein $x_t^{reject} \in \{\Delta, 0, 1\}$ is the admission control decision variable at epoch t. When $x_t^{reject} = 1$, the incoming service request is rejected from entering the system. When $x_t^{reject} = 0$, the incoming request is accepted into the system. When $x_t^{reject} = \Delta$, there is no incoming service request and the system continues with no impact from the admission control variable. Before we discuss the dispatch decision, let $\mathcal{I}(S_t) = \{m : m \in \mathcal{M}, i_{tm} \neq 1\}$ denote the set of idle MEDEVAC units and and $\mathcal{E}(S_t) = \{a : a \in \mathcal{A}, e_{ta} \neq 1\}$ denote the set of idle armed escort units at the system state S_t. The dispatch decision is given by

$$x_t^d = ((x_{tm}^{dm})_{m \in \mathcal{M}}, (x_{ta}^{da})_{a \in \mathcal{A}}),$$

wherein $x_{tm}^{dm} \in \{0,1\} \; \forall \; m \in \mathcal{I}(S_t)$ represents the MEDEVAC unit dispatch decision variable. Note $x_{tm}^{dm} = 1$ when MEDEVAC unit m at epoch t is tasked to service a request and $x_{tm}^{dm} = 0$ otherwise. The armed escort decision variable is given by $x_{ta}^{da} \in \{0,1\} \; \forall \; a \in \mathcal{E}(S_t)$. Note $x_{ta}^{da} = 1$ when armed escort unit a is tasked to service a request at epoch t and $x_{ta}^{da} = 0$ otherwise. Anytime the status of a MEDEVAC unit or escort changes or if a new request enters the system, the dispatching authority needs to make a dispatch decision.

The dispatching decision authority is bounded by two constraints at decision epoch t, which limit the dispatching authority from sending more than one MEDEVAC and escort (when applicable) on a service request.The constraints are given by

$$\sum_{m \in \mathcal{I}(S_t)} x_{tm}^{dm} = 1 - I_R \tag{1}$$

$$\sum_{a \in \mathcal{E}(S_t)} x_{ta}^{da} = (1 - I_R) I_E \tag{2}$$

wherein the indicator variable $I_R = 1$ if the service request was rejected or not present at decision epoch t (i.e., $x_t^{reject} \in \{\Delta, 1\}$) and the indicator variable $I_E = 1$ if the incoming request has a high threat level (i.e., $\hat{l}_t^{sr} = 1$).

The set of feasible actions at each decision epoch, subject to the constraints in Equations (1) and (2), is given by

$$\mathcal{X}_{S_t} = \begin{cases} (\Delta, \{0\}^{|\mathcal{I}(S_t)|}, \{0\}^{|\mathcal{E}(S_t)|}) & \text{if } \hat{R}_t = (0,0,0) \\ (\{0,1\}, (\{0,1\}^{|\mathcal{I}(S_t)|}, \{0,1\}^{|\mathcal{E}(S_t)|}) & \text{if } \hat{l}_t^{sr} = 1 \\ (\{0,1\}, (\{0,1\}^{|\mathcal{I}(S_t)|}, \{0\}^{|\mathcal{E}(S_t)|}) & \text{if } \hat{l}_t^{sr} = 0 \end{cases} . \tag{3}$$

The first case indicates the feasible actions when an event occurs that changes

the MEDEVAC unit or armed escort status from busy to available. The second case indicates the feasible actions when a request occurs with a high threat level (i.e., requiring an armed escort). The third case indicates the feasible actions when a request occurs with a low threat level (i.e., does not require an escort).

3.2.4 Transition function

The transition function determines how the MEDEVAC system evolves as new information arrives. We represent the state transition function as follows

$$S_{t+1} = S^M(S_t, x_t, W_{t+1}),$$

wherein the system model, S^M, represents the dynamics of the MEDEVAC system. At the beginning of decision epoch $t+1$, the state is determined by the current state of the system at epoch t (i.e., S_t), the action that is taken at epoch t (i.e., x_t), and the new information that has arrived at epoch $t+1$ (i.e., W_{t+1}). The exogenous information variable W_{t+1}, represents the unknown information that arrives at decision epoch $t+1$ (e.g., the arrival of a new request).

3.2.5 Rewards

When the dispatching authority tasks a MEDEVAC unit and armed escort unit (when applicable) to service an incoming 9-line MEDEVAC request, the system earns reward based on the triage level, threat level, and response time. Thus, the location of the request, escort, and MEDEVAC impacts the amount of reward obtained by the MEDEVAC system. Let $C(S_t, x_t)$ denote the contribution (i.e., reward) the MEDEVAC system obtains when MEDEVAC unit $m \in \mathcal{M}$ is tasked to service a request of

triage level k. We compute the reward by

$$C(S_t, x_t) \equiv w_k \delta(r_{tm}, e_{tm}),$$

wherein w_k is a parameter that varies based off the triage level of the request (i.e., urgent, priority, or routine), and $\delta(r_{tm}, e_{tm})$ is a utility function that is monotonically decreasing with respect to the MEDEVAC system response time (r_{tm}) and the entry time of the request (e_{tm}).

3.2.6 Objective function

The objective function of the MDP model can be represented by

$$\max_{\pi \in \Pi} \mathbb{E}^{\pi} \left[\sum_{t=1}^{\infty} \gamma^{t-1} C\big(S_t, X^{\pi}(S_t)\big) \right],$$

wherein $X^{\pi}(S_t)$ is the decision function that returns x_t (i.e., the decision) for state $S_t \in \mathcal{S}$ for a given policy, π. We seek to compute the optimal policy within the class of policies Π that maximizes the expected total discounted reward obtained by the MEDEVAC system over the specified horizon. The discount factor γ is a fixed value between 0 and 1. We compute the optimal policy, π^*, using the Bellman equation as follows

$$V(S_t) = \max_{x_t \in \mathcal{X}_{S_t}} \left(C(S_t, x_t) + \gamma \mathbb{E}[V(S_{t+1}) | S_t, x_t] \right). \qquad (4)$$

Due to the curse of dimensionality and uncountable state space, solving the MDP model using the Equation (4) is intractable. Thus, we utilize an ADP solution approach to develop high-quality policies with respect to the myopic policy. We compare the ADP-generated policies against the myopic (i.e., closest-available) dispatching policy via a synthetically generated scenario presented in Chapter IV.

3.3 ADP Formulation

Due to the size of the state space, solving our MEDEVAC dispatching problem to optimality is computationally intractable. Therefore, we present an ADP solution approach that utilizes a value function approximation scheme via a fixed set of basis functions to determine an approximate solution. We leverage a post-decision state convention for the computational advantages, which allows us to avoid explicitly computing expectations and reduce the state space's dimensionality. The post-decision state (i.e., S_t^x) refers to the state of the MEDEVAC system immediately after an action x_t is taken. We modify the Equation 4 to represent the post-decision state convention as follows

$$V^x(S_{t-1}^x) = \mathbb{E}\left[\max_{x_t \in \mathcal{X}_{S_t}} \left(C(S_t, x_t) + \gamma V^x(S_t^x)\right) | S_{t-1}^x\right]. \tag{5}$$

One of the primary challenges in our approximation scheme is identifying basis functions and problem features that are important to our variation of the MEDEVAC dispatching problem. We leverage four of the basis functions developed from Jenkins *et al.* (2021a) and develop three conceptually motivated basis functions to solve our problem and obtain high-quality dispatching policies. The four basis functions we leverage from Jenkins *et al.* (2021a) relate to MEDEVAC system response time, MEDEVAC system service time, MEDEVAC unit availability status, and the triage level of the service request. The three conceptually motivated basis functions we develop relate to the armed escort availability status, threat level of the service request, and a high order term related to the triage level of the service request. Let $\phi_f(S_t^x)$ be a basis function where $f \in \mathcal{F}$ is a feature and $\mathcal{F}$ is the set of features. Our first basis function describes the MEDEVAC unit availability status of each MEDEVAC unit m,

$$\phi_{1m}(S_t^x) = i_{tm}, \forall m \in \mathcal{M}.$$

The second basis function describes the armed escort unit availability status for each escort unit a,

$$\phi_{2a}(S_t^x) = i_{ta}, \forall a \in \mathcal{A}.$$

The next six basis functions contain information from the 9-line MEDEVAC service request entering the system. We note τ_t as the current system time. The third and fourth basis function capture the expected system response time and expected system service time for each MEDEVAC unit m, respectively as follows

$$\phi_{3m}(S_t^x) = \begin{cases} r_{tm} - \tau_t, & \text{if } i_{tm} = 1, \tau_t < r_{tm} \\ 0, & \text{otherwise} \end{cases}, \forall m \in \mathcal{M},$$

$$\phi_{4m}(S_t^x) = \begin{cases} u_{tm} - \tau_t, & \text{if } i_{tm} = 1 \\ 0, & \text{otherwise} \end{cases}, \forall m \in \mathcal{M}.$$

The fifth basis function captures information pertaining to the triage level of the service requests in the system

$$\phi_{5m}(S_t^x) = \begin{cases} p_{tm}, & \text{if } i_{tm} = 1, \tau_t < r_{tm} \\ 0, & \text{otherwise} \end{cases}, \forall m \in \mathcal{M}.$$

The sixth basis function captures information pertaining to the threat level of the

service requests in the system

$$\phi_{6m}(S_t^x) = \begin{cases} l_{tm}, & \text{if } i_{tm} = 1, i_{ta} = 1, \tau_t < r_{tm} \\ 0, & \text{otherwise} \end{cases}, \forall m \in \mathcal{M}.$$

The seventh basis function represents a second order polynomial of our fifth basis function.

$$\phi_{7m}(S_t^x) = \begin{cases} (p_{tm})^2, & \text{if } i_{tm} = 1, \tau_t < r_{tm} \\ 0, & \text{otherwise} \end{cases}, \forall m \in \mathcal{M}.$$

3.4 Semi-gradient Q-learning

The ADP solution approach utilizes an approximate value iteration (AVI) algorithmic strategy incorporating gradient descent Q-learning to approximate the value function (Sutton & Barto, 2018). AVI algorithms will iteratively update the value function approximation, which immediately updates the policy. Before presenting our AVI algorithm, we leverage the basis functions to define our post-decision state value function approximation scheme. We let

$$\bar{V}^x(S_t^x|\theta) = \sum_{f \in \mathcal{F}} \theta_f \phi_f(S_t^x) \equiv \theta^T \phi(S_t^x),$$

denote the the linear function approximation architecture, where $\theta = (\theta_f)_{f \in \mathcal{F}}$ is our column vector of basis function weights and $\phi(S_t^x)$ is a column vector of basis function evaluations. For a given vector θ, decisions are made utilizing the function

$$X^\pi(S_t|\theta) = \underset{x_t \in \mathcal{X}_{S_t}}{\operatorname{argmax}} \, \gamma \bar{V}^x(S_t^x|\theta).$$

We now present a pseudo-algorithm description of our gradient descent Q-learning algorithm.

Algorithm 1 Gradient descent Q-Learning Approximate Value Iteration (AVI) Algorithm

Initialize $\theta = \mathbf{0}$.
Define ϵ_0 and ϵ_1
$\epsilon \leftarrow \epsilon_1$
Initialize $\bar{V}^x(S_t^x|\theta) = 0, \forall S_t \in S, x_t \in \mathcal{X}(S_t)$.
for $n = 1$ to N **do**
    Set $S_{t,j=1}^x$ to initial post decision state (i.e., all assets available and idle and no requests in the system)
    for $j = 1$ to J **do**
        Simulate to a pre-decision state $S_{t+1,j}$
        Determine action x_t using an ϵ greedy policy.
        with probability ϵ choose a random action $x_{t+1} \in \mathcal{X}(S_t)$
        with probability $1 - \epsilon$ choose an action x_{t+1} using $X^\pi(S_{t+1,j}|\theta)$
        Immediately transition to post-decision state $S_{t+1,j+1}^x$
        Compute the sample value for state-action pair (S_{t+1}, x_{t+1})

$$\hat{q} = C(S_{t+1,j}, x_{t+1}) + \gamma \max_{x_t \in \mathcal{X}_{S_t}} \bar{V}^x(S_{t+1,j+1}^x|\theta)$$

        Update θ

$$\theta \leftarrow \theta + \alpha[\hat{q} - \bar{V}^x(S_{t+1,j+1}^x|\theta)]\phi(S_{t+1,j+1}^x)$$

        $t \leftarrow t + 1$
    end for
    Update ϵ

$$\epsilon \leftarrow \epsilon_0 + (\epsilon_1 - \epsilon_0)\exp(-dn)$$

end for
Return the approximate value function $\bar{V}^x(\cdot)$.

We start our algorithm by initializing the value function approximation (VFA) parameter vector θ to a 0 vector and defining ϵ_0 and ϵ_1, which are respectively the lower and upper bounds of the exploration parameter ϵ. The algorithm then loops through each episode, which starts at an empty and idle system state (i.e., all assets are available and idle with no requests in the system). Next, the algorithm simulates to a pre-decision state, $S_{t+1,j}$, where j indicates the system state and environmental

step in our simulation. We then determine our action using an ϵ greedy policy and immediately transition to a post-decision state $S^x_{t+1,j+1}$ and compute a sample value (i.e., $\hat{q}$) for the state-action pair (S_{t+1}, x_{t+1}). Next, the algorithm updates θ according to gradient descent, using the comparison of the predicted state value and actual state value to estimate the gradients. Once we complete the $\hat{q}$ estimate, the algorithm utilizes a constant α to smooth the previous θ estimate with the current θ estimate (Sutton & Barto, 2018). After each episode n, the algorithm updates the ϵ value using a decay rate parameter d. This is done by taking a convex combination of ϵ_0 and ϵ_1 with exponentially decaying weight given to ϵ_1. The algorithm continues to loop through each episode and return the approximate value function, $\bar{V}^x(\cdot)$. The tunable parameters are the number of episodes, episode length, learning rate, decay rate, maximum exploration probability, and minimum exploration probability, which are represented by N, J, α, d, ϵ_1, and ϵ_0, respectively.

IV. Testing, Results, and Analysis

In this chapter, we examine a notional scenario of the military MEDEVAC dispatching problem. We define a specific problem instance and apply our MDP model to demonstrate its applicability for military MEDEVAC planning operations. We develop a baseline policy that leverages the current myopic policy (i.e., dispatch the closest available unit) and compare the results with our ADP-generated dispatching policies. Once we establish the baseline scenario, we conduct excursions and sensitivity analysis to compare how different problem and algorithm parameters impact system performance.

4.1 Baseline Scenario

The baseline scenario is representative of a notional military MEDEVAC contingency operation in Niger, Africa. The 2021 Niger Country Security Report, the Overseas Security Advisory Council (OSAC), Bureau of Diplomatic Security, U.S. Department of State, has identified Niamey, the capital city of Niger, as "being a HIGH-threat location for terrorism directed at or affecting official U.S. government interests" (Department of State, 2021). We base our problem scenario on data related to previous historical attacks and threats in the region. The twenty-five casualty cluster centers (CCCs) indicate realistic casualty event locations based on historical attacks in the region and known high threat areas. The CCCs represent regions for possible casualty events. The actual casualty event location may occur within several miles of each CCP. Once the dispatching authority receives a 9-line request, the exact location of the request is known, and the dispatching authority can dispatch a MEDEVAC and escort unit based on the request's location. Our planning scenario has two MTFs located in Tilaberi, Niger, and the capital city of Niger, Niamey. The

MTFs are not collocated staging areas, meaning once the MEDEVAC unit completes the transfer of combat casualty care to the MTF personnel, the MEDEVAC unit travels back to its dedicated staging area and completes a refuel and resupply. Once the refuel and resupply are complete, the MEDEVAC unit is considered available to dispatch. MEDEVAC unit staging areas are chosen based on smaller cities that can potentially support staging areas closer to the CCCs. In the planning scenario, escort loiter points allow armed escort units to wait for the dispatching authority to assign them to a 9-line MEDEVAC request. Loiter points were selected to maximize coverage of the current CCCs and are depicted in Figure 1. An escort can loiter in the air, ready to respond to a high threat request. When a 9-line request is received that requires an escort, the dispatching authority will task the closest available escort and MEDEVAC unit to service the request. The escort will travel from the loiter point to the casualty event location and wait until the MEDEVAC arrives at the causality collection point location. Once the MEDEVAC unit completes the pick-up of the casualty and departs to the MTF, the escort will return to its designated loiter point. The baseline scenario considers three MEDEVAC unit staging areas, two MTFs, 25 CCCs, and four escort loiter points. In the baseline scenario, we have four MEDEVAC units placed evenly across each staging area (i.e., one unit at each staging area) and two armed escorts. The map in Figure 1 provides a visual depiction of the planning scenario locations for the armed escort loiter points, staging areas, and MTFs.

For our baseline problem scenario, we consider several key parameters to evaluate the MEDEVAC system performance. The request arrival rate, $\lambda = 1/30$, indicates that we expect the MEDEVAC system to receive an incoming service request on average every 30 minutes according to a Poisson Process. We consider three priority triage classification levels (i.e., urgent, priority, and routine), four MEDEVAC units, and two armed escorts. Our scenario considers two threat levels, which are low and

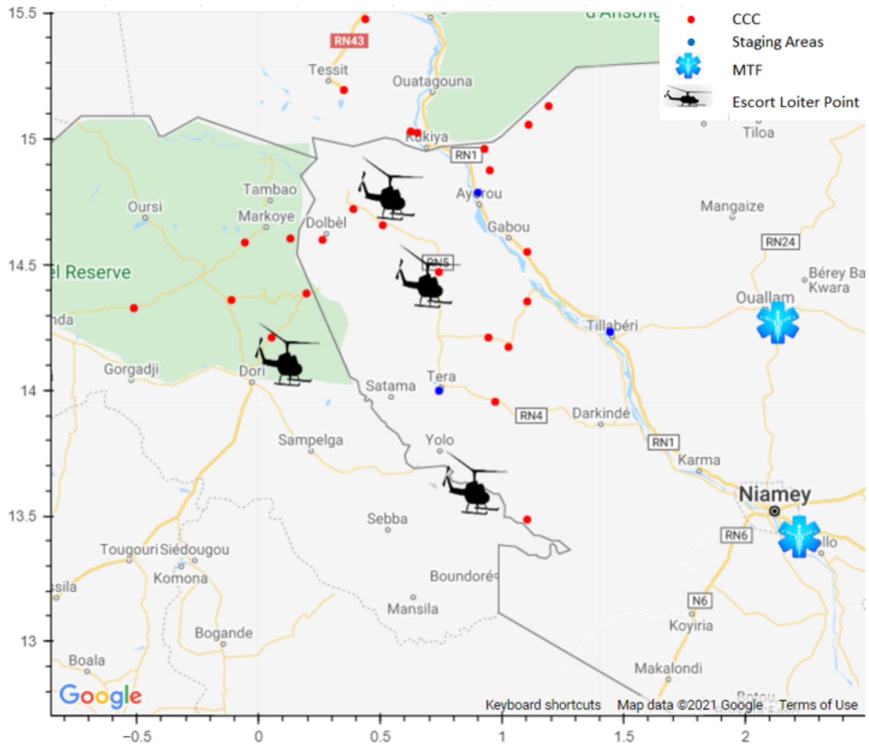

Figure 1: Niger, Africa Baseline Scenario Map

high. A low threat level indicates the request has little to no threat concern and does not require an escort. A high threat level indicates the request has significant concern and can only be serviced with an armed escort. We respectively set w_1, w_2 , and w_3 equal to 0.1, 0.01, and 0.001 within our reward function to prioritize urgent requests over priority requests and priority requests over routine requests. The baseline proportions of incoming request triage levels are 0.7, 0.2, and 0.1 for urgent, priority, and routine, respectively. The speed of each MEDEVAC unit and armed escort unit is 4.83 and 4.9 kilometers per minute which respectively corresponds to the average speed of an HH-60M Black Hawk aircraft and HH-60G Pavehawk. We assume an equal probability of a service request in any of the CCCs for the baseline scenario. We capture the parameters in the baseline problem sceanrio in Table 2.

Table 2: Baseline Parameter Settings

Parameter setting	Description	Setting
λ	9-line MEDEVAC request arrival rate	$\frac{1}{30}$
$\lvert\mathcal{M}\rvert$	Number of MEDEVAC units	4
$\lvert\mathcal{A}\rvert$	Number of armed escort units	2
$\lvert\mathcal{K}\rvert$	Number of triage categories	3
$\lvert\mathcal{L}\rvert$	Number of threat levels	2
$\mathbb{P}(urgent, priority, routine)$	distribution of request triage level	(0.7,0.2,0.1)
$\mathbb{P}(low-threat, high-threat)$	distribution of threat level	(0.3,0.7)
w_1	Weight for urgent requests	0.1
w_2	Weight for priority requests	0.01
w_3	Weight for routine requests	0.001
MEDEVAC unit speed	MEDEVAC unit average speed	4.83 kpm
Armed escort speed	Escort unit average speed	4.9 kpm
Request location distribution	Distribution of request locations	Uniform random

4.2 Algorithmic Experimental Design

We conduct all testing on an Apple MacBook pro with an M1 pro processor. The relevant performance specification are 16GB of random access memory (RAM), a 10-core CPU, 16 core Neural-Engine, and 16 core GPU. We implement our algorithm in Python and create a custom openAI gym environment (Brockman *et al.*, 2016) for our research problem. We use JMP 16.1 to conduct statistical analysis on our results. We identified the tunable parameters from our previous chapter as the number of episodes, episode length, learning rate, decay rate parameter, and our maximum and minimum epsilon values represented by N, J, α, d, ϵ_1, and ϵ_0 respectively. We conduct initial testing and screening designs to determine appropriate episode length and number of episodes to quickly obtain high-quality results before conducting our initial experimental design. We also determine values for our minimum and maximum ϵ values in our screening designs. We determine that $N = 150$ training episodes, $J = 5000$ environment steps (i.e., episode length), $\epsilon_0 = 1$, and $\epsilon_1 = 0.1$ as the

minimum and maximum ϵ values yielded the best results for these parameters. An environment step occurs anytime the system changes states (i.e., service request, arrival at MTF, unit becomes available). We also test the use of a polynomial step-size rule, but found superior results with a constant α step-size. When testing our polynomial step-size rule, $\alpha_n = \frac{1}{n^\beta}$, we examine different values of $\beta \in (0.1, 1]$. A lower value of β will slow the rate at which α_n declines. For the constant α values, we test the learning rate between $\alpha \in [0.01, 0.9]$.

From our initial screening designs we then proceed to a 3^2 full-factorial design testing three levels of our decay rate and constant α values. We also conducted a 3^2 full-factorial design testing three levels of our decay rate and constant polynomial step-size β values. The design levels tested from our experimental design are presented in Tables 3 and 4.

Table 3: Factor Levels Polynomial Step-Size

β	d
0.2	0.1
0.3	0.01
0.4	0.05

Table 4: Factor Levels Constant α

α	d
0.1	0.1
0.01	0.01
0.3	0.2

We tuned the algorithm under the same environment conditions, using the problem settings in our baseline problem instance highlighted in Table 2. The results from our experimental designs are presented in Tables 5 and 6. Our best algorithm parameter settings were a constant $\alpha = 0.1$ and $d = 0.1$ with respect to maximizing ETDR. The

highlighted row in table 6 indicates the superior algorithm settings from our testing.

Table 5: Polynomial Step-Size Experimental Design Results

j	N	ϵ_1	ϵ_0	β	d	**Mean ETDR ± Half Width**	σ	**% improvement over myopic**
5000	150	1	0.1	0.2	0.05	1.7027 ± 0.0303	0.0846	9.52
5000	150	1	0.1	0.2	0.1	1.6753 ± 0.0257	0.0717	7.77
5000	150	1	0.1	0.3	0.05	1.6256 ± 0.0256	0.0715	4.57
5000	150	1	0.1	0.3	0.1	1.5809 ± 0.0288	0.0804	1.69
5000	150	1	0.1	0.2	0.01	1.5724 ± 0.0257	0.0717	1.15
5000	150	1	0.1	0.3	0.01	1.5024 ± 0.0258	0.0721	-3.35
5000	150	1	0.1	0.1	0.05	1.4806 ± 0.0350	0.0979	-4.76
5000	150	1	0.1	0.1	0.1	1.4798 ± 0.0358	0.1000	-4.81
5000	150	1	0.1	0.1	0.01	1.4363 ± 0.0341	0.0954	-7.61

Table 6: Constant α Experimental Design Results

j	N	ϵ_1	ϵ_0	α	d	**Mean ETDR ± Half Width**	σ	**% improvement over myopic**
5000	150	1	0.1	0.1	0.1	1.7128 ± 0.0292	0.0817	10.18
5000	150	1	0.1	0.1	0.2	1.6910 ± 0.0268	0.0748	8.77
5000	150	1	0.1	0.1	0.01	1.6209 ± 0.0286	0.0798	4.27
5000	150	1	0.1	0.01	0.2	1.5735 ± 0.0271	0.0758	1.84
5000	150	1	0.1	0.01	0.1	1.5633 ± 0.0255	0.0712	0.56
5000	150	1	0.1	0.01	0.01	1.4927 ± 0.0324	0.0906	-3.98
5000	150	1	0.1	0.3	0.1	1.4798 ± 0.0358	0.1000	-4.76
5000	150	1	0.1	0.3	0.01	1.4363 ± 0.0341	0.0954	-4.81
5000	150	1	0.1	0.3	0.2	0.6216 ± 0.0066	0.0184	-7.61

We conducted all additional testing under the best constant α settings highlighted in Table 6. Our remaining testing included multiple problem parameter settings such as different triage request probabilities (i.e., Triage $\mathbb{P}$), threat level probabilities (i.e., Threat $\mathbb{P}$), number of MEDEVAC units (i.e., $|\mathcal{M}|$), number of armed escort units (i.e., $|\mathcal{A}|$), and request arrival rates (i.e., λ).

4.3 Baseline results

The baseline analysis measures the performance of our myopic policy and best ADP-generated policy by the reward obtained over a simulated infinite horizon. We

simulate a 10,000 minute trajectory to produce a reasonable approximation. Table 7 highlights the ETDR earned by our myopic and ADP-generated policy, a 95% confidence interval, the standard deviation, and the percent improvement over the myopic.

Table 7: Baseline Results

Agent	$\lvert\mathcal{M}\rvert$	$\lvert\mathcal{A}\rvert$	**Triage** $\mathbb{P}$	**Threat** $\mathbb{P}$	$1/\lambda$	**Average ETDR** $\pm$ **Half Width**	σ	**% Improvement over myopic**
myopic	4	2	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	30	1.5546 $\pm$ 0.0292	0.0984	-
Q-Learning	4	2	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	30	1.7128 $\pm$ 0.0352	0.0817	10.18

Our results in the baseline problem instance indicate a 10% improvement in system performance over the myopic benchmark policy. The myopic policy (i.e., closest available dispatching policy) does not consider several problems features such as the request triage level and request arrival rate, which is why we observe improved performance in our ADP-generated policy. When the MEDEVAC system has limited resources, and requests are entering the system faster than the MEDEVAC system service time, the dispatch authority must account for these problem characteristics to achieve improved performance. In subsequent analysis, we conduct testing on the impact on system performance by various parameters including arrival rates, triage probabilities, threat level probabilities, number of MEDEVAC units, and number of escort units.

4.4 Excursions

We conduct additional testing to determine significant problem features leading to performance gaps between the ADP policy and myopic policy. We used the same superlative algorithm settings from our baseline problem instance in all additional testing. We acknowledge that changes to any problem parameters can change the best-tuned algorithm hyper-parameters. However, we still yield significant results

under the same settings. The ADP policy still outperforms the myopic policy in most problem instances.

In Table 8 note $|M|$ as the number of MEDEVAC units, $|A|$ as the number of armed escort units, triage probability as the request triage level probabilities (urgent, priority, routine), threat level probabilities as the probabilities associated with a low and high threat request (i.e., $[0.3, 0.7]$) indicating 30 percent probability of low threat and 70 percent of high threat), λ as the rate at which request enter the system (e.g., 1/20 indicating every 20 minutes according to a Poisson Process), ETDR ADP and myopic as the average ETDR obtained in our simulation testing, and the % over myopic as the percent improvement over the myopic policy.

4.4.1 Excursion 1 - Request Arrival Rate

Our first excursion investigates the impact of the request arrival rate, λ, on our baseline problem instance. Table 8 highlights the results on the baseline problem when we vary the λ between 1/10 and 1/40.

Table 8: Excursion 1 Results Varying λ With Baseline Problem Settings

$\|\mathcal{M}\|$	$\|\mathcal{A}\|$	**Triage $\mathbb{P}$**	**Threat $\mathbb{P}$**	$1/\lambda$	**Average ETDR ADP**	**Average ETDR myopic**	**% Improvement over myopic**
4	2	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	10	0.8812	0.7008	25.74 ± 0.034
4	2	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	20	1.4044	1.1969	17.34 ± 0.027
4	2	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	30	1.7128	1.5546	10.18 ± 0.024
4	2	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	40	1.8840	1.7754	6.12 ± 0.020

As the request arrival rates decreases, the performance gap between our myopic and ADP polices shrinks. We anticipate this system behavior because as the intensity of operations decreases, the system will have more available assets, and the myopic policy shifts toward the optimal dispatching policy. Figure 2 provides a visual depiction of the performance gap between the policies generated by our ADP policy and the myopic policy as the mean request inter-arrival time changes from 10 to 40 minutes.

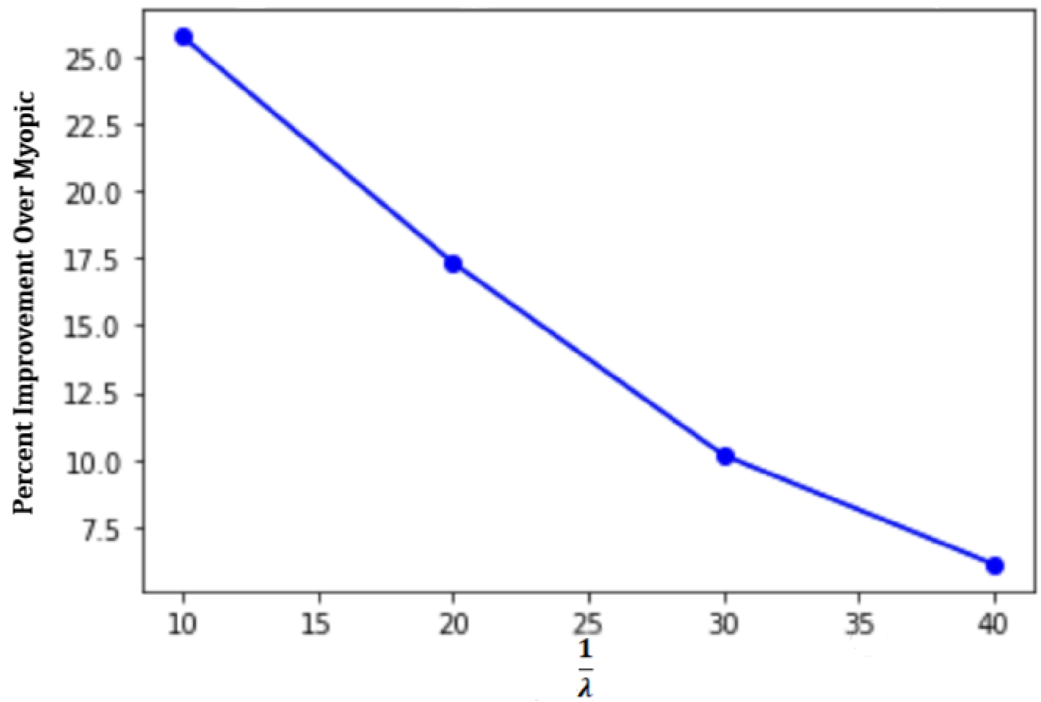

Figure 2: Excursion 1 Varying λ With Baseline Problem Settings

4.4.2 Excursion 2 - Request Arrival Rate While Varying the number of MEDEVAC and Armed Units

Our next excursion investigates the impact of the request arrival rate when we vary the number of available MEDEVAC and armed escort units. We keep the same triage level and threat level probabilities from our baseline problem (i.e., threat level $\mathbb{P}\,(0.3, 0.7)$ and triage level $\mathbb{P}\,(0.7, 0.2, 0.1)$). The results for these problem instances are displayed in Table 9 and graphical representations in Figures 3 and 4.

In every instance when the request arrival rate is 1/20 minutes or less, we observe the policies generated by our ADP policy outperform the myopic policy between $1 - 28\%$. When the request arrival rate is $\lambda \in \{1/30, 1/40\}$, the numbers of available MEDEVAC and armed escort units substantially impact system performance. Generally, the policy performance gap shrinks as more MEDEVAC and armed escort units are available. The myopic policy outperforms the ADP policy as we approach

Table 9: Excursion 2 Results Varying λ, $|\mathcal{M}|$, $|\mathcal{A}|$

$\lvert\mathcal{M}\rvert$	$\lvert\mathcal{A}\rvert$	**Triage $\mathbb{P}$**	**Threat $\mathbb{P}$**	$1/\lambda$	**ETDR ADP**	**ETDR myopic**	**% Improvement over myopic ± Half Width**
4	2	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	10	0.8812	0.7008	25.74 ± 0.034
4	2	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	20	1.4044	1.1969	17.34 ± 0.027
4	2	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	30	1.7128	1.5546	10.18 ± 0.024
4	2	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	40	1.8840	1.7754	6.12 ± 0.020
6	2	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	10	1.2355	1.0227	20.81 ± 0.019
6	2	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	20	1.7489	1.6524	5.84 ± 0.019
6	2	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	30	1.9744	1.9616	0.66 ± 0.016
6	2	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	40	2.0660	2.1258	-2.81 ± 0.007
8	2	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	10	1.4283	1.2530	13.99 ± 0.033
8	2	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	20	1.8848	1.8496	1.90 ± 0.018
8	2	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	30	1.9976	2.0773	-3.84 ± 0.007
8	2	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	40	2.1071	2.1862	-3.62 ± 0.010
4	4	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	10	0.8942	0.6995	27.82 ± 0.044
4	4	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	20	1.4075	1.2101	16.31 ± 0.034
4	4	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	30	1.7071	1.5629	9.22 ± 0.016
4	4	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	40	1.9015	1.8061	5.28 ± 0.018
6	4	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	10	1.1836	1.0484	12.89 ± 0.019
6	4	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	20	1.8534	1.7075	8.55 ± 0.013
6	4	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	30	2.0237	2.0475	-1.16 ± 0.015
6	4	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	40	2.0951	2.2024	-4.87 ± 0.008
8	4	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	10	1.5752	1.3360	17.90 ± 0.026
8	4	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	20	2.0404	2.0134	1.34 ± 0.013
8	4	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	30	2.0995	2.2354	-6.08 ± 0.007
8	4	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	40	2.1708	2.3166	-6.29 ± 0.004

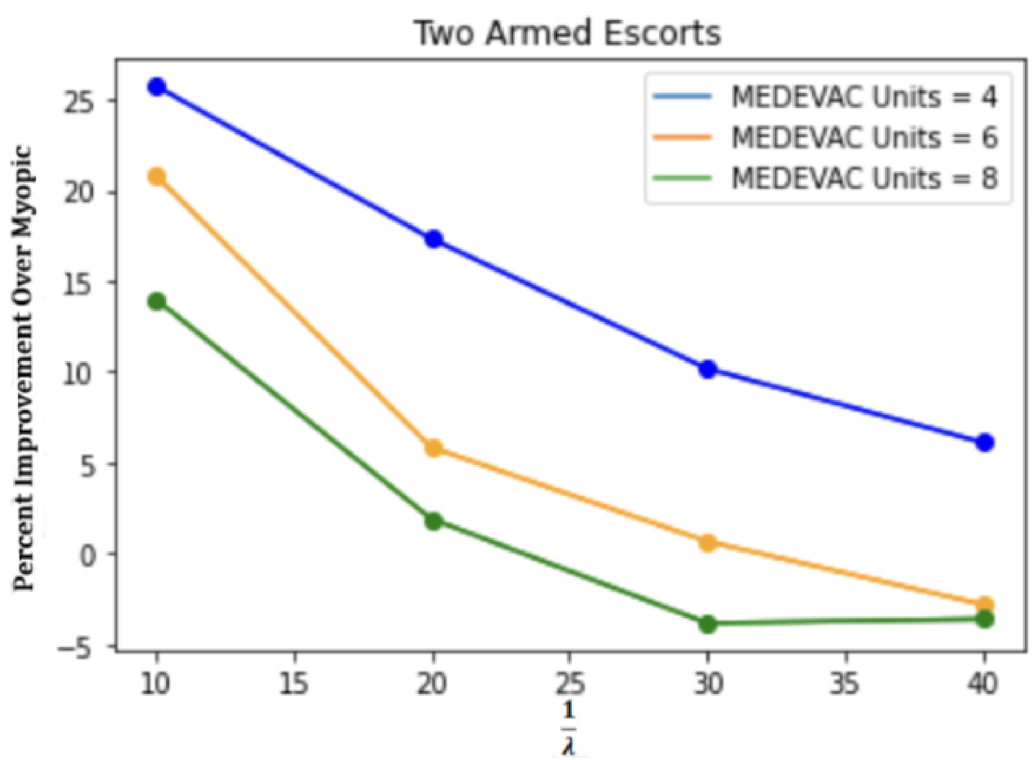

Figure 3: Excursion 2 Varying λ, $|\mathcal{M}|$, Two Armed Escorts

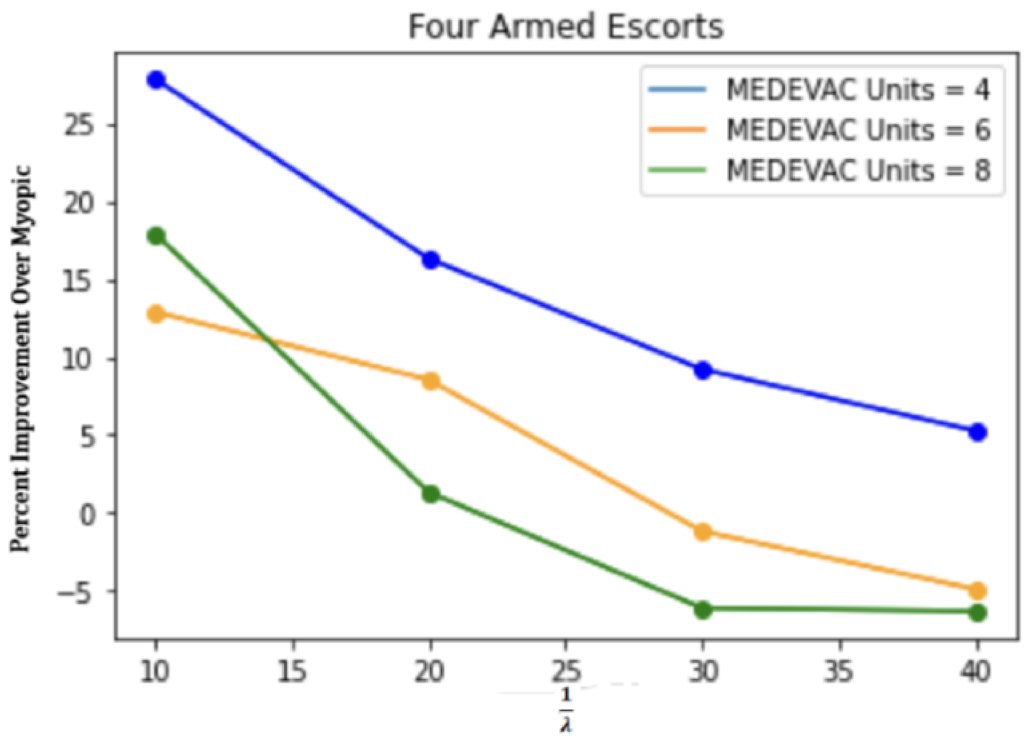

Figure 4: Excursion 2 Varying λ, $|\mathcal{M}|$, Four Armed Escorts

eight MEDEVAC units and a $\lambda = 1/40$ arrival rate. The graphs in Figures 3 and 4 also depict this trend except for the problem instance involving six MEDEVAC units and a $\lambda = 1/10$ arrival rate. We would expect the policies generated by the ADP algorithm to outperform in the problem instance with eight MEDEVAC units and a $\lambda = 10$ request arrival rate. We would expect the problem instance with six MEDEVAC units to have a larger performance gap than the instance with eight MEDEVAC units, when measured by the % improvement over the myopic policy. We believe this is likely the result of using the same algorithm hyper-parameters for each problem instance examined instead of re-tuning the algorithm for each problem instance.

4.4.3 Excursion 3 - Analyzing Interaction Affects of Problem Features

Our next excursion examines the interaction effects and impact on system performance, varying the number of MEDEVAC and armed escort units, triage level

probabilities, threat level probabilities, and request arrival rates. We test these problem features under the same algorithm settings used in our baseline analysis. We test every combination of problem features in Table 10 and we include the results of every design point tested from our excursion analysis in the Appendix.

Table 10: Excursion 3 Problem Feature Interaction Affects

$\lvert\mathcal{M}\rvert$	$\lvert\mathcal{A}\rvert$	**Triage** $\mathbb{P}$	**Threat** $\mathbb{P}$	$1/\lambda$
4	2	$(0.7, 0.2, 0.1)$	$(0.3, 0.7)$	10
6	4	$(0.5, 0.4, 0.1)$	$(0.2, 0.8)$	20
8	-	$(0.8, 0.2, 0.0)$	$(0.1, 0.9)$	30
-	-	-	$(0.5, 0.5)$	40
-	-	-	$(0.7, 0.3)$	-

Figure 5 depicts the prediction values from the interaction effects of different problem features. The y axis indicates the predicted performance for the policy generated by our ADP algorithm in terms of percent improvement over the myopic policy. The x axis indicates the level for each problem feature we are testing. The threat level has virtually no impact on the system performance when λ is set to $1/30$ or $1/40$ regardless of the number of available MEDEVAC units, armed escort units, and triage probabilities. The number of MEDEVAC units and request arrival rate λ still has the most significant impact on the percent improvement over the myopic policy.

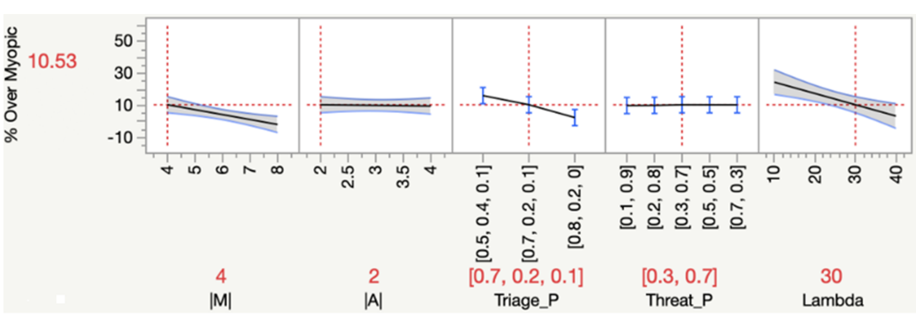

Figure 5: Excursion 3 Analyzing When Threat Level Probability Does Not Impact System Performance

We note that when $\lambda = 1/10$ or $1/20$, the system has four MEDEVAC units, two armed escort units, and the triage $\mathbb{P}$ is $(0.5, 0.4, 0.1)$, the threat level $\mathbb{P}$ does impact system performance. Figure 6 highlights these problem settings to illustrate the instances where the threat level $\mathbb{P}$ does impact system performance.

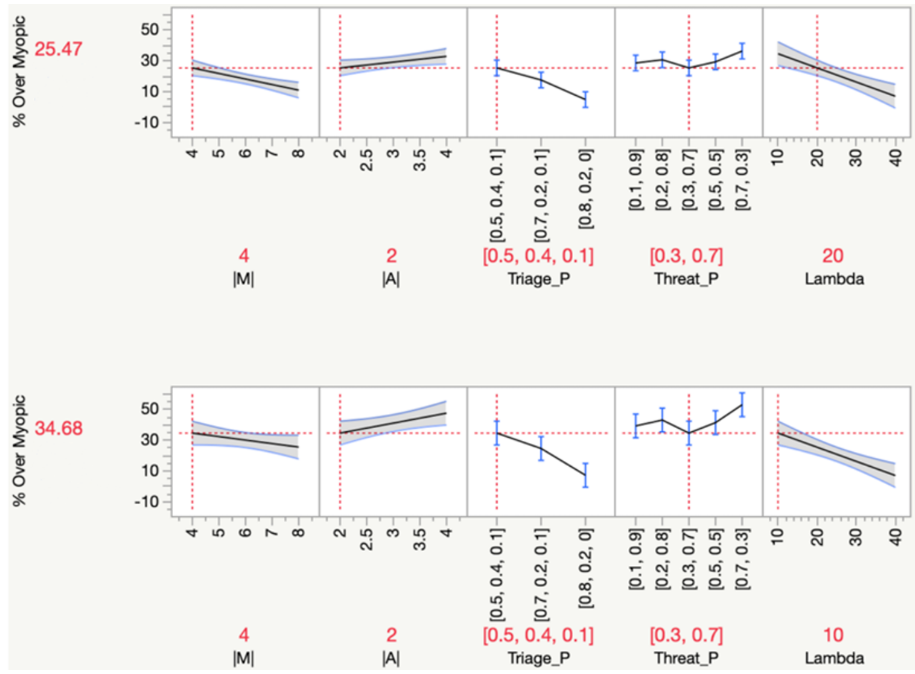

Figure 6: Excursion 3 Threat Level Probability Impact On System Performance

The impact of triage $\mathbb{P}$ on system performance increases as our λ value decreases, regardless of the number of MEDEVAC and escort units available. We observe better system performance concerning percent improvement over the myopic policy when the probability of urgent requests increases. We anticipate this trend in performance because the myopic policy does not consider these problem features, whereas the policies generated from our ADP algorithm does. This trend is highlighted in Figure 7 across various problem settings.

Next, we observe which problem settings impact the significance of the number of armed escorts available. Our results show that the fewer MEDEVAC units available, the lower the λ value, and the lower the probability of urgent request, the greater

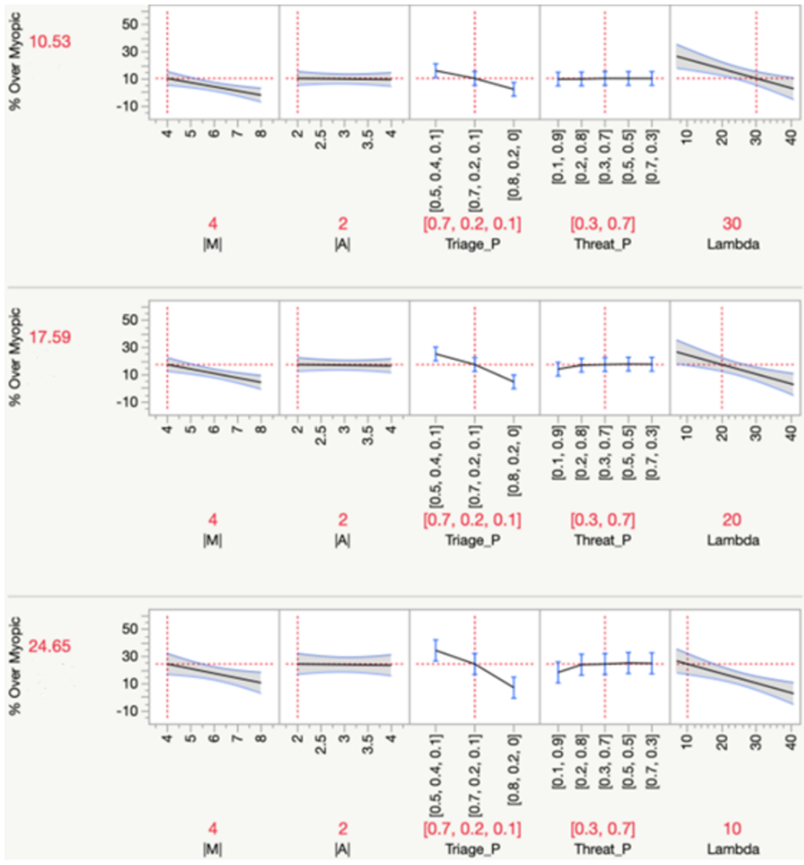

Figure 7: Excursion 3 Analyzing Triage Probability Impact On System Performance

significance the number of armed escorts has on system performance. Generally, the number of armed escorts in most problem settings does not substantially impact system performance. However, as the probability of urgent requests goes down, the more imperative the number of escorts available is to system performance. We would expect this because the myopic policy will never reject high threat requests based on the triage level. However, the policies generated by our ADP algorithm may reject a request of lower triage level that requires an armed escort in order to conserve the resource for urgent requests that also require armed escorts.

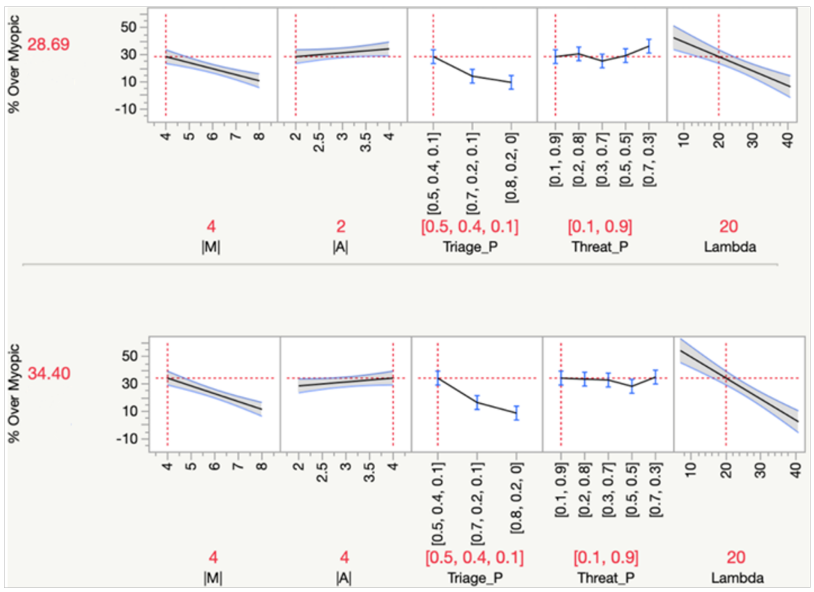

Figure 8: Excursion 3 Analyzing The Armed Escorts Impact on System Performance

We observe how various problem features impact system performance throughout our baseline and excursion analysis. The number of available MEDEVAC units and the request arrival rate significantly impacted system performance regardless of all other problem features. The triage request probabilities, threat level probabilities, and the number of available escorts significantly impacted system performance under specific problem settings outlined in our excursion analysis. The most significant interaction effects were the interactions between the triage probability and λ, the

number of MEDEVAC units and the triage probabilities, and the number of armed escort units and λ. The policies generated by our ADP algorithm outperformed the myopic policy in 241 of the 360 (i.e., 67%) different problem setting examined in our excursion analysis. When there were only four available MEDEVAC units, the myopic policy only outperformed the policies generated by our ADP algorithm once. When the myopic policy outperforms the ADP algorithm, we generally see request arrival rates of $\lambda = 1/40$ or $\lambda = 1/30$ and 8 or 6 MEDEVAC units. If we tune our ADP algorithm for each problem instance, we would likely see the ADP policies outperform or perform the same as the myopic benchmark policy in each problem instance.

V. Conclusions

This thesis examined a variation of the military medical evacuation dispatching problem by incorporating new problem features not previously examined. Our research aims to develop high-quality dispatching policies that improve the medical evacuation (MEDEVAC) system performance and ultimately reduce casualties on the battlefield. We developed a discounted, infinite-horizon continuous-time Markov decision process (MDP) to model the MEDEVAC dispatching problem and examine system performance under various problem features and combat scenarios. Due to the size of the state space, we utilize approximate dynamic programming (ADP) to design and implement our solution techniques for our problem instances in a tractable amount of time. The ADP solution approach utilizes an approximate value iteration (AVI) algorithm strategy incorporating gradient descent Q-learning to approximate the value function. We develop seven conceptually motivated basis functions based on critical problem features to the MEDEVAC dispatching problem to approximate the value function around the post-decision state. We develop a synthetically generated scenario based on historical terrorism activities around Niamey, the capital city of Niger, to demonstrate the applicability of our MDP model and ADP solution approach.

The results from our computational experiments indicate a 10% increase in performance over the closest-available benchmark policy in our baseline scenario. Excursion analysis into various problem features demonstrated that the number of available MEDEVAC units and the request arrival rate had the most significant impact on system performance. As requests come in faster, we will see an increase in the performance gap between the ADP-generated policies and the myopic policy. As the number of available MEDEVAC units increases, the policy generated by our ADP algorithm tends to perform similar or worse than the myopic policy. When testing

the interaction effects of multiple problem features, we found the triage probabilities and λ; the number of MEDEVAC units and the triage probabilities; and the number of armed escort units and λ to have a significant impact on system performance.

The research in this thesis can impact both military and civilian medical planners. By applying our MDP model and ADP solution techniques, we can compare various dispatching policies for different planning scenarios with limited resources, dedicated MEDEVAC staging areas, MTF locations, and armed escort loiter points. Implementing the proposed ADP solution technique will require improvements in communication and decision support systems to help the dispatching authority in the decision process. However, this research still demonstrates the applicability of our ADP solution techniques to improve system performance over the policies currently being employed by the military, which can reduce system response time and combat causalities.

Although our research includes several of the features of the most pertinent problems related to the MEDEVAC dispatching problem, there are still several areas future researchers can improve upon to make further contributions. While we selected fixed loiter points for the armed escort units, future researchers can optimize the location of the escort units and solve a location problem in conjunction with our MEDEVAC dispatching problem. Futures researchers may also include a system queue to allow the dispatching authority the option to add requests to a queue rather than immediately reject the request. Furthermore, researchers can include additional problem features such as triage miss-classification, bed capacity, and other aeromedical evacuation system platforms. Including these problem features will make the problem scenario more realistic and further exemplify how there are operations research techniques that may develop even higher quality dispatching policies that outperform the myopic benchmark policies.

Appendix A. Detailed Excursion Analysis Results

Table 11: Excursion Analysis Results

$\lvert\mathcal{M}\rvert$	$\lvert\mathcal{A}\rvert$	**Triage $\mathbb{P}$**	**Threat $\mathbb{P}$**	λ	**ETDR ADP**	**ETDR Myopic**	**% Improvement over myopic**
4	2	[0.7, 0.2, 0.1]	[0.7, 0.3]	10	0.8892	0.7003	26.98
4	2	[0.7, 0.2, 0.1]	[0.7, 0.3]	20	1.4059	1.2091	16.27
4	2	[0.7, 0.2, 0.1]	[0.7, 0.3]	30	1.7277	1.5659	10.33
4	2	[0.7, 0.2, 0.1]	[0.7, 0.3]	40	1.8907	1.8051	4.74
4	2	[0.7, 0.2, 0.1]	[0.5, 0.5]	10	0.8892	0.6989	27.22
4	2	[0.7, 0.2, 0.1]	[0.5, 0.5]	20	1.4235	1.2115	17.50
4	2	[0.7, 0.2, 0.1]	[0.5, 0.5]	30	1.7259	1.5662	10.20
4	2	[0.7, 0.2, 0.1]	[0.5, 0.5]	40	1.8993	1.7963	5.74
4	2	[0.8, 0.2, 0.0]	[0.7, 0.3]	10	0.9212	0.7942	16.00
4	2	[0.8, 0.2, 0.0]	[0.7, 0.3]	20	1.5054	1.3635	10.41
4	2	[0.8, 0.2, 0.0]	[0.7, 0.3]	30	1.8713	1.7700	5.72
4	2	[0.8, 0.2, 0.0]	[0.7, 0.3]	40	2.0919	2.0491	2.09
4	2	[0.8, 0.2, 0.0]	[0.5, 0.5]	10	0.9034	0.7940	13.78
4	2	[0.8, 0.2, 0.0]	[0.5, 0.5]	20	1.4461	1.3651	5.94
4	2	[0.8, 0.2, 0.0]	[0.5, 0.5]	30	1.8516	1.7699	4.62
4	2	[0.8, 0.2, 0.0]	[0.5, 0.5]	40	2.0831	2.0403	2.10
4	2	[0.5, 0.4, 0.1]	[0.7, 0.3]	10	0.8267	0.5219	58.40
4	2	[0.5, 0.4, 0.1]	[0.7, 0.3]	20	1.2177	0.9111	33.65
4	2	[0.5, 0.4, 0.1]	[0.7, 0.3]	30	1.3941	1.1703	19.13
4	2	[0.5, 0.4, 0.1]	[0.7, 0.3]	40	1.4657	1.3476	8.76
4	2	[0.5, 0.4, 0.1]	[0.5, 0.5]	10	0.7456	0.5257	41.82
4	2	[0.5, 0.4, 0.1]	[0.5, 0.5]	20	1.1576	0.9101	27.19
4	2	[0.5, 0.4, 0.1]	[0.5, 0.5]	30	1.3843	1.1698	18.33
4	2	[0.5, 0.4, 0.1]	[0.5, 0.5]	40	1.4593	1.3399	8.91
4	4	[0.7, 0.2, 0.1]	[0.7, 0.3]	10	0.8942	0.6995	27.82
4	4	[0.7, 0.2, 0.1]	[0.7, 0.3]	20	1.4112	1.2101	16.62
4	4	[0.7, 0.2, 0.1]	[0.7, 0.3]	30	1.6932	1.5629	8.33
4	4	[0.7, 0.2, 0.1]	[0.7, 0.3]	40	1.8815	1.8061	4.17
4	4	[0.7, 0.2, 0.1]	[0.5, 0.5]	10	0.8932	0.6995	27.68
4	4	[0.7, 0.2, 0.1]	[0.5, 0.5]	20	1.4302	1.2101	18.19

4	4	[0.7, 0.2, 0.1]	[0.5, 0.5]	30	1.7337	1.5629	10.92
4	4	[0.7, 0.2, 0.1]	[0.5, 0.5]	40	1.9075	1.8061	5.61
4	4	[0.8, 0.2, 0.0]	[0.7, 0.3]	10	0.9157	0.7925	15.54
4	4	[0.8, 0.2, 0.0]	[0.7, 0.3]	20	1.5113	1.3621	10.95
4	4	[0.8, 0.2, 0.0]	[0.7, 0.3]	30	1.8727	1.7682	5.91
4	4	[0.8, 0.2, 0.0]	[0.7, 0.3]	40	2.0920	2.0487	2.12
4	4	[0.8, 0.2, 0.0]	[0.5, 0.5]	10	0.9061	0.7925	14.34
4	4	[0.8, 0.2, 0.0]	[0.5, 0.5]	20	1.5014	1.3621	10.22
4	4	[0.8, 0.2, 0.0]	[0.5, 0.5]	30	1.8292	1.7682	3.45
4	4	[0.8, 0.2, 0.0]	[0.5, 0.5]	40	2.0945	2.0487	2.24
4	4	[0.5, 0.4, 0.1]	[0.7, 0.3]	10	0.8298	0.5234	58.54
4	4	[0.5, 0.4, 0.1]	[0.7, 0.3]	20	1.2161	0.9108	33.52
4	4	[0.5, 0.4, 0.1]	[0.7, 0.3]	30	1.3061	1.1691	11.71
4	4	[0.5, 0.4, 0.1]	[0.7, 0.3]	40	1.4089	1.3488	4.45
4	4	[0.5, 0.4, 0.1]	[0.5, 0.5]	10	0.6983	0.5234	33.40
4	4	[0.5, 0.4, 0.1]	[0.5, 0.5]	20	1.2168	0.9108	33.59
4	4	[0.5, 0.4, 0.1]	[0.5, 0.5]	30	1.3649	1.1691	16.75
4	4	[0.5, 0.4, 0.1]	[0.5, 0.5]	40	1.4651	1.3488	8.62
6	2	[0.7, 0.2, 0.1]	[0.7, 0.3]	10	1.2734	1.0457	21.77
6	2	[0.7, 0.2, 0.1]	[0.7, 0.3]	20	1.8506	1.7051	8.53
6	2	[0.7, 0.2, 0.1]	[0.7, 0.3]	30	2.0515	2.0478	0.18
6	2	[0.7, 0.2, 0.1]	[0.7, 0.3]	40	2.1330	2.1955	-2.85
6	2	[0.7, 0.2, 0.1]	[0.5, 0.5]	10	1.2583	1.0350	21.58
6	2	[0.7, 0.2, 0.1]	[0.5, 0.5]	20	1.7658	1.6894	4.52
6	2	[0.7, 0.2, 0.1]	[0.5, 0.5]	30	2.0333	2.0210	0.61
6	2	[0.7, 0.2, 0.1]	[0.5, 0.5]	40	2.0727	2.1739	-4.65
6	2	[0.8, 0.2, 0.0]	[0.7, 0.3]	10	1.3214	1.1770	12.27
6	2	[0.8, 0.2, 0.0]	[0.7, 0.3]	20	2.0163	1.9233	4.83
6	2	[0.8, 0.2, 0.0]	[0.7, 0.3]	30	2.2848	2.3151	-1.31
6	2	[0.8, 0.2, 0.0]	[0.7, 0.3]	40	2.3587	2.4892	-5.24
6	2	[0.8, 0.2, 0.0]	[0.5, 0.5]	10	1.3288	1.1682	13.75
6	2	[0.8, 0.2, 0.0]	[0.5, 0.5]	20	1.9725	1.9085	3.35
6	2	[0.8, 0.2, 0.0]	[0.5, 0.5]	30	2.2309	2.2810	-2.20
6	2	[0.8, 0.2, 0.0]	[0.5, 0.5]	40	2.3607	2.4652	-4.24

6	2	[0.5, 0.4, 0.1]	[0.7, 0.3]	10	1.1105	0.7846	41.54
6	2	[0.5, 0.4, 0.1]	[0.7, 0.3]	20	1.4413	1.2725	13.26
6	2	[0.5, 0.4, 0.1]	[0.7, 0.3]	30	1.5143	1.5380	-1.54
6	2	[0.5, 0.4, 0.1]	[0.7, 0.3]	40	1.5509	1.6491	-5.96
6	2	[0.5, 0.4, 0.1]	[0.5, 0.5]	10	1.1123	0.7832	42.02
6	2	[0.5, 0.4, 0.1]	[0.5, 0.5]	20	1.4601	1.2696	15.00
6	2	[0.5, 0.4, 0.1]	[0.5, 0.5]	30	1.5225	1.5171	0.36
6	2	[0.5, 0.4, 0.1]	[0.5, 0.5]	40	1.5300	1.6282	-6.03
6	4	[0.7, 0.2, 0.1]	[0.7, 0.3]	10	1.2815	1.0483	22.25
6	4	[0.7, 0.2, 0.1]	[0.7, 0.3]	20	1.8566	1.7080	8.70
6	4	[0.7, 0.2, 0.1]	[0.7, 0.3]	30	2.0731	2.0477	1.24
6	4	[0.7, 0.2, 0.1]	[0.7, 0.3]	40	2.1383	2.2040	-2.98
6	4	[0.7, 0.2, 0.1]	[0.5, 0.5]	10	1.2792	1.0483	22.03
6	4	[0.7, 0.2, 0.1]	[0.5, 0.5]	20	1.8511	1.7081	8.37
6	4	[0.7, 0.2, 0.1]	[0.5, 0.5]	30	2.0576	2.0477	0.49
6	4	[0.7, 0.2, 0.1]	[0.5, 0.5]	40	2.0847	2.2037	-5.40
6	4	[0.8, 0.2, 0.0]	[0.7, 0.3]	10	1.3188	1.1838	11.40
6	4	[0.8, 0.2, 0.0]	[0.7, 0.3]	20	2.0028	1.9278	3.89
6	4	[0.8, 0.2, 0.0]	[0.7, 0.3]	30	2.2808	2.3221	-1.78
6	4	[0.8, 0.2, 0.0]	[0.7, 0.3]	40	2.3668	2.5003	-5.34
6	4	[0.8, 0.2, 0.0]	[0.5, 0.5]	10	1.3243	1.1838	11.86
6	4	[0.8, 0.2, 0.0]	[0.5, 0.5]	20	2.0097	1.9278	4.25
6	4	[0.8, 0.2, 0.0]	[0.5, 0.5]	30	2.2661	2.3221	-2.41
6	4	[0.8, 0.2, 0.0]	[0.5, 0.5]	40	2.3948	2.5001	-4.21
6	4	[0.5, 0.4, 0.1]	[0.7, 0.3]	10	1.1425	0.7901	44.61
6	4	[0.5, 0.4, 0.1]	[0.7, 0.3]	20	1.4563	1.2750	14.23
6	4	[0.5, 0.4, 0.1]	[0.7, 0.3]	30	1.4895	1.5406	-3.32
6	4	[0.5, 0.4, 0.1]	[0.7, 0.3]	40	1.5307	1.6561	-7.57
6	4	[0.5, 0.4, 0.1]	[0.5, 0.5]	10	1.1407	0.7900	44.39
6	4	[0.5, 0.4, 0.1]	[0.5, 0.5]	20	1.4626	1.2750	14.71
6	4	[0.5, 0.4, 0.1]	[0.5, 0.5]	30	1.5285	1.5406	-0.79
6	4	[0.5, 0.4, 0.1]	[0.5, 0.5]	40	1.5686	1.6558	-5.26
8	2	[0.7, 0.2, 0.1]	[0.7, 0.3]	10	1.5929	1.3211	20.57
8	2	[0.7, 0.2, 0.1]	[0.7, 0.3]	20	1.9848	1.9946	-0.49

8	2	[0.7, 0.2, 0.1]	[0.7, 0.3]	30	2.0977	2.2211	-5.56
8	2	[0.7, 0.2, 0.1]	[0.7, 0.3]	40	2.1406	2.3035	-7.07
8	2	[0.7, 0.2, 0.1]	[0.5, 0.5]	10	1.5327	1.3065	17.31
8	2	[0.7, 0.2, 0.1]	[0.5, 0.5]	20	1.9819	1.9549	1.38
8	2	[0.7, 0.2, 0.1]	[0.5, 0.5]	30	2.0364	2.1813	-6.65
8	2	[0.7, 0.2, 0.1]	[0.5, 0.5]	40	2.1377	2.2719	-5.90
8	2	[0.8, 0.2, 0.0]	[0.7, 0.3]	10	1.6720	1.4993	11.52
8	2	[0.8, 0.2, 0.0]	[0.7, 0.3]	20	2.2562	2.2553	0.04
8	2	[0.8, 0.2, 0.0]	[0.7, 0.3]	30	2.3294	2.5165	-7.43
8	2	[0.8, 0.2, 0.0]	[0.7, 0.3]	40	2.4377	2.6110	-6.64
8	2	[0.8, 0.2, 0.0]	[0.5, 0.5]	10	1.6308	1.4790	10.26
8	2	[0.8, 0.2, 0.0]	[0.5, 0.5]	20	2.1916	2.2079	-0.74
8	2	[0.8, 0.2, 0.0]	[0.5, 0.5]	30	2.3296	2.4666	-5.55
8	2	[0.8, 0.2, 0.0]	[0.5, 0.5]	40	2.3803	2.5752	-7.57
8	2	[0.5, 0.4, 0.1]	[0.7, 0.3]	10	1.3207	0.9848	34.11
8	2	[0.5, 0.4, 0.1]	[0.7, 0.3]	20	1.4982	1.4890	0.62
8	2	[0.5, 0.4, 0.1]	[0.7, 0.3]	30	1.5397	1.6684	-7.71
8	2	[0.5, 0.4, 0.1]	[0.7, 0.3]	40	1.6220	1.7286	-6.17
8	2	[0.5, 0.4, 0.1]	[0.5, 0.5]	10	1.3007	0.9770	33.14
8	2	[0.5, 0.4, 0.1]	[0.5, 0.5]	20	1.5045	1.4623	2.88
8	2	[0.5, 0.4, 0.1]	[0.5, 0.5]	30	1.5465	1.6359	-5.47
8	2	[0.5, 0.4, 0.1]	[0.5, 0.5]	40	1.5663	1.7026	-8.00
8	4	[0.7, 0.2, 0.1]	[0.7, 0.3]	10	1.5816	1.3402	18.01
8	4	[0.7, 0.2, 0.1]	[0.7, 0.3]	20	1.9937	2.0122	-0.92
8	4	[0.7, 0.2, 0.1]	[0.7, 0.3]	30	2.1199	2.2369	-5.23
8	4	[0.7, 0.2, 0.1]	[0.7, 0.3]	40	2.1374	2.3179	-7.79
8	4	[0.7, 0.2, 0.1]	[0.5, 0.5]	10	1.5894	1.3413	18.50
8	4	[0.7, 0.2, 0.1]	[0.5, 0.5]	20	1.9442	2.0112	-3.33
8	4	[0.7, 0.2, 0.1]	[0.5, 0.5]	30	2.1363	2.2360	-4.46
8	4	[0.7, 0.2, 0.1]	[0.5, 0.5]	40	2.1567	2.3173	-6.93
8	4	[0.8, 0.2, 0.0]	[0.7, 0.3]	10	1.6642	1.5190	9.55
8	4	[0.8, 0.2, 0.0]	[0.7, 0.3]	20	2.2806	2.2763	0.19
8	4	[0.8, 0.2, 0.0]	[0.7, 0.3]	30	2.3708	2.5348	-6.47
8	4	[0.8, 0.2, 0.0]	[0.7, 0.3]	40	2.4063	2.6268	-8.39

8	4	[0.8, 0.2, 0.0]	[0.5, 0.5]	10	1.4797	1.5205	-2.68
8	4	[0.8, 0.2, 0.0]	[0.5, 0.5]	20	2.2449	2.2755	-1.34
8	4	[0.8, 0.2, 0.0]	[0.5, 0.5]	30	2.4376	2.5342	-3.81
8	4	[0.8, 0.2, 0.0]	[0.5, 0.5]	40	2.4251	2.6262	-7.66
8	4	[0.5, 0.4, 0.1]	[0.7, 0.3]	10	1.3381	0.9985	34.01
8	4	[0.5, 0.4, 0.1]	[0.7, 0.3]	20	1.5212	1.5023	1.25
8	4	[0.5, 0.4, 0.1]	[0.7, 0.3]	30	1.5623	1.6788	-6.94
8	4	[0.5, 0.4, 0.1]	[0.7, 0.3]	40	1.6106	1.7354	-7.19
8	4	[0.5, 0.4, 0.1]	[0.5, 0.5]	10	1.3337	1.0006	33.30
8	4	[0.5, 0.4, 0.1]	[0.5, 0.5]	20	1.5300	1.5019	1.87
8	4	[0.5, 0.4, 0.1]	[0.5, 0.5]	30	1.5336	1.6790	-8.66
8	4	[0.5, 0.4, 0.1]	[0.5, 0.5]	40	1.5305	1.7357	-11.82
4	2	[0.7, 0.2, 0.1]	[0.1, 0.9]	10	0.7696	0.6891	11.68
4	2	[0.7, 0.2, 0.1]	[0.1, 0.9]	20	1.3904	1.1798	17.85
4	2	[0.7, 0.2, 0.1]	[0.1, 0.9]	30	1.6710	1.5257	9.52
4	2	[0.7, 0.2, 0.1]	[0.1, 0.9]	40	1.8660	1.7523	6.49
4	2	[0.7, 0.2, 0.1]	[0.2, 0.8]	10	0.8674	0.7023	23.51
4	2	[0.7, 0.2, 0.1]	[0.2, 0.8]	20	1.4013	1.1869	18.06
4	2	[0.7, 0.2, 0.1]	[0.2, 0.8]	30	1.6976	1.5517	9.40
4	2	[0.7, 0.2, 0.1]	[0.2, 0.8]	40	1.8674	1.7656	5.77
4	2	[0.7, 0.2, 0.1]	[0.3, 0.7]	10	0.8812	0.7008	25.74
4	2	[0.7, 0.2, 0.1]	[0.3, 0.7]	20	1.4044	1.1969	17.34
4	2	[0.7, 0.2, 0.1]	[0.3, 0.7]	30	1.7128	1.5546	10.18
4	2	[0.7, 0.2, 0.1]	[0.3, 0.7]	40	1.8840	1.7754	6.12
4	2	[0.5, 0.4, 0.1]	[0.1, 0.9]	10	0.7038	0.5191	35.58
4	2	[0.5, 0.4, 0.1]	[0.1, 0.9]	20	1.1838	0.8840	33.91
4	2	[0.5, 0.4, 0.1]	[0.1, 0.9]	30	1.3476	1.1409	18.12
4	2	[0.5, 0.4, 0.1]	[0.1, 0.9]	40	1.4228	1.3134	8.32
4	2	[0.5, 0.4, 0.1]	[0.2, 0.8]	10	0.7465	0.5289	41.13
4	2	[0.5, 0.4, 0.1]	[0.2, 0.8]	20	1.1782	0.8875	32.75
4	2	[0.5, 0.4, 0.1]	[0.2, 0.8]	30	1.3631	1.1594	17.57
4	2	[0.5, 0.4, 0.1]	[0.2, 0.8]	40	1.4533	1.3188	10.20
4	2	[0.5, 0.4, 0.1]	[0.3, 0.7]	10	0.6947	0.5316	30.67
4	2	[0.5, 0.4, 0.1]	[0.3, 0.7]	20	1.1513	0.8915	29.14

4	2	[0.5, 0.4, 0.1]	[0.3, 0.7]	30	1.3651	1.1584	17.85
4	2	[0.5, 0.4, 0.1]	[0.3, 0.7]	40	1.4384	1.3261	8.47
4	2	[0.8, 0.2, 0.0]	[0.1, 0.9]	10	0.9017	0.7837	15.06
4	2	[0.8, 0.2, 0.0]	[0.1, 0.9]	20	1.4635	1.3389	9.31
4	2	[0.8, 0.2, 0.0]	[0.1, 0.9]	30	1.8272	1.7231	6.04
4	2	[0.8, 0.2, 0.0]	[0.1, 0.9]	40	2.0032	1.9884	0.75
4	2	[0.8, 0.2, 0.0]	[0.2, 0.8]	10	0.9020	0.7934	13.69
4	2	[0.8, 0.2, 0.0]	[0.2, 0.8]	20	1.4547	1.3411	8.47
4	2	[0.8, 0.2, 0.0]	[0.2, 0.8]	30	1.8335	1.7458	5.02
4	2	[0.8, 0.2, 0.0]	[0.2, 0.8]	40	2.0588	2.0022	2.83
4	2	[0.8, 0.2, 0.0]	[0.3, 0.7]	10	0.8714	0.7937	9.79
4	2	[0.8, 0.2, 0.0]	[0.3, 0.7]	20	1.3020	1.3480	-3.41
4	2	[0.8, 0.2, 0.0]	[0.3, 0.7]	30	1.8466	1.7579	5.05
4	2	[0.8, 0.2, 0.0]	[0.3, 0.7]	40	2.0504	2.0181	1.60
4	4	[0.7, 0.2, 0.1]	[0.1, 0.9]	10	0.8538	0.6995	22.05
4	4	[0.7, 0.2, 0.1]	[0.1, 0.9]	20	1.4310	1.2101	18.25
4	4	[0.7, 0.2, 0.1]	[0.1, 0.9]	30	1.7135	1.5629	9.63
4	4	[0.7, 0.2, 0.1]	[0.1, 0.9]	40	1.8720	1.8061	3.65
4	4	[0.7, 0.2, 0.1]	[0.2, 0.8]	10	0.8888	0.6995	27.05
4	4	[0.7, 0.2, 0.1]	[0.2, 0.8]	20	1.4289	1.2101	18.08
4	4	[0.7, 0.2, 0.1]	[0.2, 0.8]	30	1.6185	1.5629	3.56
4	4	[0.7, 0.2, 0.1]	[0.2, 0.8]	40	1.8982	1.8061	5.10
4	4	[0.7, 0.2, 0.1]	[0.3, 0.7]	10	0.8942	0.6995	27.82
4	4	[0.7, 0.2, 0.1]	[0.3, 0.7]	20	1.4075	1.2101	16.31
4	4	[0.7, 0.2, 0.1]	[0.3, 0.7]	30	1.7071	1.5629	9.22
4	4	[0.7, 0.2, 0.1]	[0.3, 0.7]	40	1.9015	1.8061	5.28
4	4	[0.5, 0.4, 0.1]	[0.1, 0.9]	10	0.7953	0.5234	51.95
4	4	[0.5, 0.4, 0.1]	[0.1, 0.9]	20	1.2164	0.9108	33.54
4	4	[0.5, 0.4, 0.1]	[0.1, 0.9]	30	1.3813	1.1691	18.15
4	4	[0.5, 0.4, 0.1]	[0.1, 0.9]	40	1.4527	1.3488	7.70
4	4	[0.5, 0.4, 0.1]	[0.2, 0.8]	10	0.7952	0.5234	51.92
4	4	[0.5, 0.4, 0.1]	[0.2, 0.8]	20	1.1948	0.9108	31.17
4	4	[0.5, 0.4, 0.1]	[0.2, 0.8]	30	1.3863	1.1691	18.57
4	4	[0.5, 0.4, 0.1]	[0.2, 0.8]	40	1.4581	1.3488	8.10

4	4	[0.5, 0.4, 0.1]	[0.3, 0.7]	10	0.7686	0.5234	46.84
4	4	[0.5, 0.4, 0.1]	[0.3, 0.7]	20	1.2226	0.9108	34.22
4	4	[0.5, 0.4, 0.1]	[0.3, 0.7]	30	1.3813	1.1691	18.15
4	4	[0.5, 0.4, 0.1]	[0.3, 0.7]	40	1.4231	1.3488	5.51
4	4	[0.8, 0.2, 0.0]	[0.1, 0.9]	10	0.9199	0.7925	16.07
4	4	[0.8, 0.2, 0.0]	[0.1, 0.9]	20	1.5119	1.3621	10.99
4	4	[0.8, 0.2, 0.0]	[0.1, 0.9]	30	1.8580	1.7682	5.08
4	4	[0.8, 0.2, 0.0]	[0.1, 0.9]	40	2.0628	2.0487	0.69
4	4	[0.8, 0.2, 0.0]	[0.2, 0.8]	10	0.9062	0.7925	14.35
4	4	[0.8, 0.2, 0.0]	[0.2, 0.8]	20	1.4604	1.3621	7.22
4	4	[0.8, 0.2, 0.0]	[0.2, 0.8]	30	1.8643	1.7682	5.44
4	4	[0.8, 0.2, 0.0]	[0.2, 0.8]	40	2.1066	2.0487	2.83
4	4	[0.8, 0.2, 0.0]	[0.3, 0.7]	10	0.8843	0.7925	11.58
4	4	[0.8, 0.2, 0.0]	[0.3, 0.7]	20	1.4776	1.3621	8.48
4	4	[0.8, 0.2, 0.0]	[0.3, 0.7]	30	1.8729	1.7682	5.92
4	4	[0.8, 0.2, 0.0]	[0.3, 0.7]	40	2.0974	2.0487	2.38
6	2	[0.7, 0.2, 0.1]	[0.1, 0.9]	10	1.1656	0.9608	21.31
6	2	[0.7, 0.2, 0.1]	[0.1, 0.9]	20	1.6507	1.5739	4.88
6	2	[0.7, 0.2, 0.1]	[0.1, 0.9]	30	1.9028	1.8695	1.78
6	2	[0.7, 0.2, 0.1]	[0.1, 0.9]	40	1.9987	2.0431	-2.17
6	2	[0.7, 0.2, 0.1]	[0.2, 0.8]	10	1.2184	0.9961	22.32
6	2	[0.7, 0.2, 0.1]	[0.2, 0.8]	20	1.7140	1.6111	6.39
6	2	[0.7, 0.2, 0.1]	[0.2, 0.8]	30	1.9263	1.9219	0.23
6	2	[0.7, 0.2, 0.1]	[0.2, 0.8]	40	1.9930	2.0944	-4.84
6	2	[0.7, 0.2, 0.1]	[0.3, 0.7]	10	1.2355	1.0227	20.81
6	2	[0.7, 0.2, 0.1]	[0.3, 0.7]	20	1.7489	1.6524	5.84
6	2	[0.7, 0.2, 0.1]	[0.3, 0.7]	30	1.9744	1.9616	0.66
6	2	[0.7, 0.2, 0.1]	[0.3, 0.7]	40	2.0660	2.1258	-2.81
6	2	[0.5, 0.4, 0.1]	[0.1, 0.9]	10	1.0242	0.7250	41.27
6	2	[0.5, 0.4, 0.1]	[0.1, 0.9]	20	1.2719	1.1781	7.96
6	2	[0.5, 0.4, 0.1]	[0.1, 0.9]	30	1.4482	1.4017	3.32
6	2	[0.5, 0.4, 0.1]	[0.1, 0.9]	40	1.5061	1.5270	-1.37
6	2	[0.5, 0.4, 0.1]	[0.2, 0.8]	10	1.0637	0.7446	42.85
6	2	[0.5, 0.4, 0.1]	[0.2, 0.8]	20	1.3451	1.2020	11.91

6	2	[0.5, 0.4, 0.1]	[0.2, 0.8]	30	1.4686	1.4372	2.19
6	2	[0.5, 0.4, 0.1]	[0.2, 0.8]	40	1.4846	1.5633	-5.03
6	2	[0.5, 0.4, 0.1]	[0.3, 0.7]	10	1.0516	0.7677	36.98
6	2	[0.5, 0.4, 0.1]	[0.3, 0.7]	20	1.4001	1.2341	13.45
6	2	[0.5, 0.4, 0.1]	[0.3, 0.7]	30	1.4906	1.4688	1.49
6	2	[0.5, 0.4, 0.1]	[0.3, 0.7]	40	1.4586	1.5879	-8.14
6	2	[0.8, 0.2, 0.0]	[0.1, 0.9]	10	1.2277	1.0941	12.21
6	2	[0.8, 0.2, 0.0]	[0.1, 0.9]	20	1.8117	1.7781	1.89
6	2	[0.8, 0.2, 0.0]	[0.1, 0.9]	30	2.0220	2.1169	-4.49
6	2	[0.8, 0.2, 0.0]	[0.1, 0.9]	40	2.0756	2.3140	-10.30
6	2	[0.8, 0.2, 0.0]	[0.2, 0.8]	10	1.2705	1.1269	12.75
6	2	[0.8, 0.2, 0.0]	[0.2, 0.8]	20	1.8947	1.8205	4.07
6	2	[0.8, 0.2, 0.0]	[0.2, 0.8]	30	2.1458	2.1766	-1.42
6	2	[0.8, 0.2, 0.0]	[0.2, 0.8]	40	2.2719	2.3682	-4.07
6	2	[0.8, 0.2, 0.0]	[0.3, 0.7]	10	1.2905	1.1561	11.62
6	2	[0.8, 0.2, 0.0]	[0.3, 0.7]	20	1.9073	1.8706	1.96
6	2	[0.8, 0.2, 0.0]	[0.3, 0.7]	30	2.2154	2.2236	-0.37
6	2	[0.8, 0.2, 0.0]	[0.3, 0.7]	40	2.2916	2.4078	-4.82
6	4	[0.7, 0.2, 0.1]	[0.1, 0.9]	10	1.2718	1.0475	21.41
6	4	[0.7, 0.2, 0.1]	[0.1, 0.9]	20	1.8473	1.7073	8.20
6	4	[0.7, 0.2, 0.1]	[0.1, 0.9]	30	2.0668	2.0452	1.06
6	4	[0.7, 0.2, 0.1]	[0.1, 0.9]	40	2.1370	2.2017	-2.94
6	4	[0.7, 0.2, 0.1]	[0.2, 0.8]	10	1.2391	1.0481	18.22
6	4	[0.7, 0.2, 0.1]	[0.2, 0.8]	20	1.8615	1.7082	8.97
6	4	[0.7, 0.2, 0.1]	[0.2, 0.8]	30	2.0422	2.0469	-0.23
6	4	[0.7, 0.2, 0.1]	[0.2, 0.8]	40	2.1407	2.2021	-2.79
6	4	[0.7, 0.2, 0.1]	[0.3, 0.7]	10	1.1836	1.0484	12.89
6	4	[0.7, 0.2, 0.1]	[0.3, 0.7]	20	1.8534	1.7075	8.55
6	4	[0.7, 0.2, 0.1]	[0.3, 0.7]	30	2.0237	2.0475	-1.16
6	4	[0.7, 0.2, 0.1]	[0.3, 0.7]	40	2.0951	2.2024	-4.87
6	4	[0.5, 0.4, 0.1]	[0.1, 0.9]	10	1.1295	0.7908	42.83
6	4	[0.5, 0.4, 0.1]	[0.1, 0.9]	20	1.4644	1.2729	15.04
6	4	[0.5, 0.4, 0.1]	[0.1, 0.9]	30	1.5560	1.5399	1.05
6	4	[0.5, 0.4, 0.1]	[0.1, 0.9]	40	1.5599	1.6547	-5.73

6	4	[0.5, 0.4, 0.1]	[0.2, 0.8]	10	1.1190	0.7923	41.23
6	4	[0.5, 0.4, 0.1]	[0.2, 0.8]	20	1.4300	1.2727	12.36
6	4	[0.5, 0.4, 0.1]	[0.2, 0.8]	30	1.5388	1.5402	-0.09
6	4	[0.5, 0.4, 0.1]	[0.2, 0.8]	40	1.5630	1.6544	-5.52
6	4	[0.5, 0.4, 0.1]	[0.3, 0.7]	10	1.1445	0.7914	44.62
6	4	[0.5, 0.4, 0.1]	[0.3, 0.7]	20	1.4658	1.2741	15.05
6	4	[0.5, 0.4, 0.1]	[0.3, 0.7]	30	1.5303	1.5408	-0.68
6	4	[0.5, 0.4, 0.1]	[0.3, 0.7]	40	1.5735	1.6549	-4.92
6	4	[0.8, 0.2, 0.0]	[0.1, 0.9]	10	1.1764	1.1841	-0.65
6	4	[0.8, 0.2, 0.0]	[0.1, 0.9]	20	1.9938	1.9289	3.36
6	4	[0.8, 0.2, 0.0]	[0.1, 0.9]	30	2.2934	2.3179	-1.06
6	4	[0.8, 0.2, 0.0]	[0.1, 0.9]	40	2.3949	2.4968	-4.08
6	4	[0.8, 0.2, 0.0]	[0.2, 0.8]	10	1.3496	1.1842	13.97
6	4	[0.8, 0.2, 0.0]	[0.2, 0.8]	20	2.0172	1.9276	4.64
6	4	[0.8, 0.2, 0.0]	[0.2, 0.8]	30	2.2650	2.3203	-2.38
6	4	[0.8, 0.2, 0.0]	[0.2, 0.8]	40	2.3819	2.4979	-4.64
6	4	[0.8, 0.2, 0.0]	[0.3, 0.7]	10	1.3367	1.1843	12.87
6	4	[0.8, 0.2, 0.0]	[0.3, 0.7]	20	2.0216	1.9285	4.83
6	4	[0.8, 0.2, 0.0]	[0.3, 0.7]	30	2.2681	2.3217	-2.31
6	4	[0.8, 0.2, 0.0]	[0.3, 0.7]	40	2.4088	2.4984	-3.59
8	2	[0.7, 0.2, 0.1]	[0.1, 0.9]	10	1.1167	1.1290	-1.09
8	2	[0.7, 0.2, 0.1]	[0.1, 0.9]	20	1.6266	1.6602	-2.02
8	2	[0.7, 0.2, 0.1]	[0.1, 0.9]	30	1.8667	1.9434	-3.95
8	2	[0.7, 0.2, 0.1]	[0.1, 0.9]	40	1.9817	2.0851	-4.96
8	2	[0.7, 0.2, 0.1]	[0.2, 0.8]	10	1.3743	1.2104	13.54
8	2	[0.7, 0.2, 0.1]	[0.2, 0.8]	20	1.7825	1.7636	1.07
8	2	[0.7, 0.2, 0.1]	[0.2, 0.8]	30	1.9345	2.0060	-3.57
8	2	[0.7, 0.2, 0.1]	[0.2, 0.8]	40	2.0064	2.1385	-6.17
8	2	[0.7, 0.2, 0.1]	[0.3, 0.7]	10	1.4283	1.2530	13.99
8	2	[0.7, 0.2, 0.1]	[0.3, 0.7]	20	1.8848	1.8496	1.90
8	2	[0.7, 0.2, 0.1]	[0.3, 0.7]	30	1.9976	2.0773	-3.84
8	2	[0.7, 0.2, 0.1]	[0.3, 0.7]	40	2.1071	2.1862	-3.62
8	2	[0.5, 0.4, 0.1]	[0.1, 0.9]	10	1.0684	0.8502	25.67
8	2	[0.5, 0.4, 0.1]	[0.1, 0.9]	20	1.3354	1.2444	7.31

8	2	[0.5, 0.4, 0.1]	[0.1, 0.9]	30	1.4140	1.4553	-2.83
8	2	[0.5, 0.4, 0.1]	[0.1, 0.9]	40	1.4211	1.5586	-8.82
8	2	[0.5, 0.4, 0.1]	[0.2, 0.8]	10	1.1359	0.8931	27.19
8	2	[0.5, 0.4, 0.1]	[0.2, 0.8]	20	1.3401	1.3135	2.02
8	2	[0.5, 0.4, 0.1]	[0.2, 0.8]	30	1.4972	1.4984	-0.08
8	2	[0.5, 0.4, 0.1]	[0.2, 0.8]	40	1.5081	1.5969	-5.56
8	2	[0.5, 0.4, 0.1]	[0.3, 0.7]	10	1.2119	0.9321	30.02
8	2	[0.5, 0.4, 0.1]	[0.3, 0.7]	20	1.4380	1.3857	3.78
8	2	[0.5, 0.4, 0.1]	[0.3, 0.7]	30	1.4621	1.5487	-5.59
8	2	[0.5, 0.4, 0.1]	[0.3, 0.7]	40	1.4599	1.6344	-10.67
8	2	[0.8, 0.2, 0.0]	[0.1, 0.9]	10	1.3107	1.2788	2.49
8	2	[0.8, 0.2, 0.0]	[0.1, 0.9]	20	1.8864	1.8835	0.15
8	2	[0.8, 0.2, 0.0]	[0.1, 0.9]	30	2.1047	2.1999	-4.33
8	2	[0.8, 0.2, 0.0]	[0.1, 0.9]	40	2.2063	2.3580	-6.43
8	2	[0.8, 0.2, 0.0]	[0.2, 0.8]	10	1.4529	1.3678	6.22
8	2	[0.8, 0.2, 0.0]	[0.2, 0.8]	20	1.9796	1.9965	-0.85
8	2	[0.8, 0.2, 0.0]	[0.2, 0.8]	30	2.1887	2.2697	-3.57
8	2	[0.8, 0.2, 0.0]	[0.2, 0.8]	40	2.2119	2.4253	-8.80
8	2	[0.8, 0.2, 0.0]	[0.3, 0.7]	10	1.5427	1.4154	8.99
8	2	[0.8, 0.2, 0.0]	[0.3, 0.7]	20	1.9967	2.0907	-4.50
8	2	[0.8, 0.2, 0.0]	[0.3, 0.7]	30	2.2047	2.3521	-6.27
8	2	[0.8, 0.2, 0.0]	[0.3, 0.7]	40	2.3724	2.4821	-4.42
8	4	[0.7, 0.2, 0.1]	[0.1, 0.9]	10	1.5557	1.3278	17.16
8	4	[0.7, 0.2, 0.1]	[0.1, 0.9]	20	2.0224	2.0010	1.07
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8	4	[0.7, 0.2, 0.1]	[0.1, 0.9]	40	2.1840	2.3157	-5.69
8	4	[0.7, 0.2, 0.1]	[0.2, 0.8]	10	1.5845	1.3355	18.64
8	4	[0.7, 0.2, 0.1]	[0.2, 0.8]	20	2.0523	2.0087	2.17
8	4	[0.7, 0.2, 0.1]	[0.2, 0.8]	30	2.1566	2.2359	-3.55
8	4	[0.7, 0.2, 0.1]	[0.2, 0.8]	40	2.1605	2.3165	-6.73
8	4	[0.7, 0.2, 0.1]	[0.3, 0.7]	10	1.5752	1.3360	17.90
8	4	[0.7, 0.2, 0.1]	[0.3, 0.7]	20	2.0404	2.0134	1.34
8	4	[0.7, 0.2, 0.1]	[0.3, 0.7]	30	2.0995	2.2354	-6.08
8	4	[0.7, 0.2, 0.1]	[0.3, 0.7]	40	2.1708	2.3166	-6.29

8	4	[0.5, 0.4, 0.1]	[0.1, 0.9]	10	1.3317	0.9932	34.08
8	4	[0.5, 0.4, 0.1]	[0.1, 0.9]	20	1.5406	1.4954	3.03
8	4	[0.5, 0.4, 0.1]	[0.1, 0.9]	30	1.5771	1.6767	-5.94
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8	4	[0.5, 0.4, 0.1]	[0.2, 0.8]	20	1.4912	1.4978	-0.44
8	4	[0.5, 0.4, 0.1]	[0.2, 0.8]	30	1.4998	1.6806	-10.76
8	4	[0.5, 0.4, 0.1]	[0.2, 0.8]	40	1.5619	1.7354	-10.00
8	4	[0.5, 0.4, 0.1]	[0.3, 0.7]	10	1.3422	1.0003	34.17
8	4	[0.5, 0.4, 0.1]	[0.3, 0.7]	20	1.5302	1.5032	1.80
8	4	[0.5, 0.4, 0.1]	[0.3, 0.7]	30	1.5488	1.6788	-7.74
8	4	[0.5, 0.4, 0.1]	[0.3, 0.7]	40	1.5122	1.7361	-12.90
8	4	[0.8, 0.2, 0.0]	[0.1, 0.9]	10	1.6496	1.5033	9.73
8	4	[0.8, 0.2, 0.0]	[0.1, 0.9]	20	2.2751	2.2656	0.42
8	4	[0.8, 0.2, 0.0]	[0.1, 0.9]	30	2.3603	2.5283	-6.65
8	4	[0.8, 0.2, 0.0]	[0.1, 0.9]	40	2.3615	2.6224	-9.95
8	4	[0.8, 0.2, 0.0]	[0.2, 0.8]	10	1.6635	1.5089	10.24
8	4	[0.8, 0.2, 0.0]	[0.2, 0.8]	20	2.2421	2.2698	-1.22
8	4	[0.8, 0.2, 0.0]	[0.2, 0.8]	30	2.3890	2.5321	-5.65
8	4	[0.8, 0.2, 0.0]	[0.2, 0.8]	40	2.4116	2.6242	-8.10
8	4	[0.8, 0.2, 0.0]	[0.3, 0.7]	10	1.6694	1.5099	10.57
8	4	[0.8, 0.2, 0.0]	[0.3, 0.7]	20	2.2515	2.2746	-1.01
8	4	[0.8, 0.2, 0.0]	[0.3, 0.7]	30	2.4057	2.5331	-5.03
8	4	[0.8, 0.2, 0.0]	[0.3, 0.7]	40	2.4197	2.6251	-7.83

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14. ABSTRACT

The military medical evacuation (MEDEVAC) dispatching problem seeks to determine high-quality dispatching policies to maximize the survivability of casualties within contingency operations. This research leverages applied operations research and machine learning techniques to solve the MEDEVAC dispatching problem and evaluate system performance. More specifically, we develop an infinite-horizon, continuous-time Markov decision process (MDP) model and approximate dynamic programming (ADP) solution approach to generate high-quality policies. The ADP solution approach utilizes an approximate value iteration algorithm strategy incorporating gradient descent Q-learning to approximate the value function. A notional, synthetically-generated scenario in Africa based around the capital city of Niger, Niamey is developed and utilized to compare the ADP-generated policies with the closest-available dispatching (i.e., myopic policy) currently employed by military medical planners. This research also develops a custom OpenAI gym environment in Python to evaluate system performance and the efficacy of the ADP solution approach. Initial results from our computational experiments indicate a 10.2% increase in performance over the myopic policy. Further testing indicates which problem features have the most significant impact on the system performance gap between the myopic policy and the ADP-generated policies. The model, methodologies, and results from this research may be utilized to advise current and future military medical planning procedures, operations, and tactics.

15. SUBJECT TERMS

Markov Decision Process, Artificial Intelligence, Reinforcement Learning, Machine Learning, Approximate Dynamic Programming, Q Learning, Approximate Value Iteration, Military Medical Evacuation

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