

PROTECT: An Application of Computational Game Theory for the Security of the Ports of the United States

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Abstract

Building upon previous security applications of computational game theory, this paper presents PROTECT, a game-theoretic system deployed by the United States Coast Guard (USCG) in the port of Boston for scheduling their patrols. USCG has termed the deployment of PROTECT in Boston a success, and efforts are underway to test it in the port of New York, with the potential for nationwide deployment.

PROTECT is premised on an attacker-defender Stackelberg game model and offers five key innovations. First, this system is a departure from the assumption of perfect adversary rationality noted in previous work, relying instead on a quantal response (QR) model of the adversary's behavior — to the best of our knowledge, this is the first real-world deployment of the QR model. Second, to improve PROTECT's efficiency, we generate a compact representation of the defender's strategy space, exploiting equivalence and dominance. Third, we show how to practically model a real maritime patrolling problem as a Stackelberg game. Fourth, our experimental results illustrate that PROTECT's QR model more robustly handles real-world uncertainties than a perfect rationality model. Finally, in evaluating PROTECT, this paper provides real-world data: (i) comparison of human-generated vs PROTECT security schedules, and (ii) results from an Adversarial Perspective Team's (human mock attackers) analysis.¹

Introduction

The global need for security of key infrastructure with limited resources has led to significant interest in research conducted in multiagent systems towards game-theory for real-world security. In fact, three applications based on Stackelberg games have been transitioned to real-world deployment. This includes ARMOR, used by the Los Angeles International Airport to randomize checkpoints of roadways and canine patrols; IRIS which helps the US Federal Air Marshal Service in scheduling air marshals on international flights; and GUARDS which is under evaluation by the US

Transportation Security Administration to allocate the resources available for airport protection (Tambe 2011). Yet we as a community of agents and AI researchers remain in the early stages of these deployments, and must continue to develop our understanding of core principles of innovative applications of game theory for security.

To this end, this paper presents a new game-theoretic security application to aid the United States Coast Guard (USCG), called *Port Resilience Operational/Tactical Enforcement to Combat Terrorism* (PROTECT). The USCG's mission includes maritime security of the US coasts, ports, and inland waterways; a security domain that faces increased risks in the context of threats such as terrorism and drug trafficking. Given a particular port and the variety of critical infrastructure that an adversary may attack within the port, USCG conducts patrols to protect this infrastructure; however, while the adversary has the opportunity to observe patrol patterns, limited security resources imply that USCG patrols cannot be at every location 24/7. To assist the USCG in allocating its patrolling resources, similar to previous applications (Tambe 2011), PROTECT uses an attacker-defender Stackelberg game framework, with USCG as the defender against terrorist adversaries that conduct surveillance before potentially launching an attack. PROTECT's solution is to typically provide a mixed strategy, i.e., randomized patrol patterns taking into account the importance of different targets, and the adversary's surveillance and anticipated reaction to USCG patrols.

While PROTECT builds on previous work, this paper highlights five key innovations. The first is PROTECT's departure from the assumption of perfect rationality on the part of the human adversaries. While appropriate in the initial applications as a first step, this assumption of perfect rationality is well-recognized as a limitation of classical game theory, and bounded rationality has received significant attention in behavioral game-theoretic approaches (Camerer 2003). Within this behavioral framework, quantal response equilibrium has emerged as a promising approach to model human bounded rationality (Camerer 2003; McKelvey and Palfrey 1995; Wright and Leyton-Brown 2010) including recent results illustrating the benefits of the quantal response (QR) model in security games contexts (Yang et al. 2011). Therefore, PROTECT uses a novel algorithm called PASAQ (Yang, Tambe, and Ordóñez 2012) based on the QR

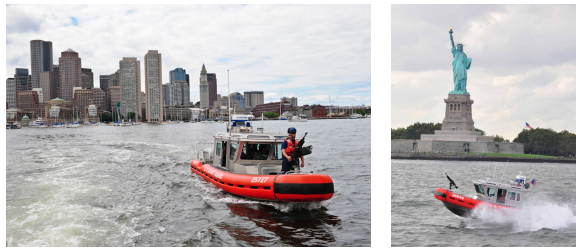
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¹This paper modifies the original paper (Shieh et al. 2012) with the inclusion of the Background section and a more condensed description of the Game Modeling, Compact Representation, and Robustness Analysis sections to provide greater accessibility for a broader audience.

model of a human adversary. To the best of our knowledge, this is the *first time that the QR model has been used in a real-world security application*.

Second, PROTECT improves PASAQ’s efficiency via a compact representation of defender strategies with experimental results showing the significant benefits of this compact representation. Third, PROTECT addresses practical concerns of modeling real-world maritime patrolling application in a Stackelberg framework. Fourth, this paper presents a detailed simulation analysis of PROTECT’s robustness to uncertainty that may arise in the real-world. For various cases of added uncertainty, the paper shows that PROTECT’s quantal-response-based approach leads to significantly improved robustness when compared to an approach that assumes full attacker rationality.

PROTECT has been in use at the port of Boston since April 2011 and been evaluated by the USCG. This evaluation brings forth our final key contribution: for the first time, this paper provides real-world data comparing human-generated and game-theoretic schedules. We also provide results from an Adversarial Perspective Team’s (APT) analysis and comparison of patrols before and after the use of the PROTECT system from a viewpoint of an attacker. Given the success of PROTECT in Boston, we are now extending it to the port of New York, and based on the outcome there, it may potentially be extended to other ports in the US.



(a) PROTECT is being used in Boston (b) Extending PROTECT to NY

Figure 1: USCG boats patrolling the ports of Boston and NY

Background

Stackelberg Game: A generic Stackelberg game has two players, a *leader*, and a *follower* (Fudenberg and Tirole 1991). A leader commits to a strategy first, and then a follower optimizes its reward, considering the action chosen by the leader (von Stengel and Zamir 2004). Each player has a set of possible *pure strategies*, or the actions that they can execute. A *mixed strategy* allows a player to play a probability distribution over pure strategies. Payoffs for each player are defined over all possible pure-strategy outcomes for both the players. The payoff functions are extended to mixed strategies by taking the expectation over pure-strategy outcomes. The follower can observe the leader’s strategy, and then act in a way to optimize its own payoffs.

Stackelberg games are used to model the attacker-defender strategic interaction in security domains. The defender commits to a mixed (randomized) strategy, whereas the attacker conducts surveillance of these mixed strategies

and responds with a pure strategy of an attack on a target. The objective of this framework is to find the optimal mixed strategy for the defender. Examples of Stackelberg games can be found in (Tambe 2011).

Quantal Response: Previous applications of Stackelberg security games assumed that the attacker is perfectly rational, i.e., chooses a strategy that maximizes his expected utility (Tambe 2011). However, in many real world domains, agents face human adversaries whose behavior may not be optimal assuming perfect rationality.

Quantal Response Equilibrium is an important model in behavior game theory that has received widespread support in the literature in terms of its superior ability to model human behavior in simultaneous-move games (McKelvey and Palfrey 1995; Wright and Leyton-Brown 2010). It suggests that instead of strictly maximizing utility, individuals respond stochastically in games: the chance of selecting a non-optimal strategy increases as the cost of such an error decreases. We assume that the attacker acts with bounded rationality; the defender is assisted by software and thus we compute the defender’s optimal rational strategy (Yang et al. 2011). Given the strategy of the defender, the Quantal Best Response of the attacker is defined as

$$q_i = \frac{e^{\lambda G_i^a(x_i)}}{\sum_{j=1}^T e^{\lambda G_j^a(x_i)}} \quad (1)$$

The parameter $\lambda \in [0, \infty]$ represents the amount of noise in the attacker’s strategy. λ with a value of 0 represents a uniform random probability over attacker strategies while a value of ∞ represents a perfectly rational attacker. q_i corresponds to the probability that the attacker chooses a target i ; $G_i^a(x_i)$ corresponds to the attacker’s expected utility of attacking target i given x_i , the probability that the defender covers target i ; and T is the total number of targets.

USCG and PROTECT’s Goals

The USCG continues to face challenges with evolving asymmetric threats within the maritime environment not only within the Maritime Global Commons, but also within the ports and waterways that make up the United States Maritime Transportation System. The former Director of National Intelligence, Dennis Blair noted in 2010 a persistent threat “from al-Qa’ida and potentially others who share its anti-Western ideology. A major terrorist attack may emanate from either outside or inside the United States” (Blair 2010). This threat was reinforced in May of 2011 following the raid on Osama Bin Laden’s home, where a large trove of material was uncovered, including plans to attack an oil tanker. “There is an indication of intent, with operatives seeking the size and construction of tankers, and concluding it’s best to blow them up from the inside because of the strength of their hulls” (Dozier 2011). These oil tankers transit the U.S. Maritime Transportation System. The USCG plays a key role in the security of this system and the protection of seaports to support the economy, environment, and way of life in the US (Young and Orchard 2011).

Coupled with challenging economic times, USCG must operate as effectively as possible, achieving maximum ben-

efit from every hour spent on patrol. Thus, USCG is compelled to re-examine the role that optimization of resource usage plays in its mission planning — and how innovation provided by game theory can be effectively employed.

The goal of PROTECT is to use game theory to assist the USCG in maximizing its effectiveness in the Ports, Waterways, and Coastal Security (PWCS) Mission. PWCS patrols are focused on protecting critical infrastructure; without the resources to provide one hundred percent on scene presence at any, let alone all of the critical infrastructure, optimization of security resource is critical. Towards that end, unpredictability creates situations of uncertainty for an enemy and can be enough to deem a target less appealing.

The PROTECT system addresses how the USCG should optimally patrol critical infrastructure in a port to maximize protection, knowing that the adversary may conduct surveillance and then launch an attack. While randomizing patrol patterns is key, PROTECT also addresses the fact that the targets are of unequal value, understanding that the adversary will adapt to whatever patrol patterns USCG conducts. The output of PROTECT is a schedule of patrols which includes when the patrols are to begin, what critical infrastructure to visit for each patrol, and what activities to perform at each critical infrastructure. While initially pilot tested in the port of Boston, PROTECT was intended to be generalizable and applicable to other ports.

Key Innovations in PROTECT

The PWCS patrol problem was modeled as a leader-follower (or attacker-defender) Stackelberg game (Fudenberg and Tirole 1991) with USCG as the leader (defender) and the terrorist adversaries in the role of the follower. We begin by discussing how to practically cast this real-world maritime patrolling problem of PWCS patrols as a Stackelberg game. We also show how to reduce the number of defender strategies before addressing the most important of the innovations in PROTECT: its use of the quantal response model.

Game Modeling

To model the USCG patrolling domain as a Stackelberg game, we need to define (i) the set of attacker strategies, (ii) the set of defender strategies, and (iii) the payoff function. These strategies and payoffs center on the targets in a port — ports, such as the port of Boston, have a significant number of potential targets (critical infrastructure). In our Stackelberg game formulation, the attacker conducts surveillance on the mixed strategies that the defender has committed to, and can then launch an attack. Thus, the attacks an attacker can launch on different possible targets are considered as his/her pure strategies.

Instead of basing the defender strategies on individual targets, which would require significant USCG input while also micromanaging their activities, it was decided to group nearby targets into patrol areas. The presence of patrol areas led the USCG to redefine the set of defensive activities to be performed on patrol areas to provide a more accurate and expressive model of the patrols. Activities that take a longer time provide the defender a higher payoff compared to activities that take a shorter time to complete.

Patrol Schedule	Target 1	Target 2	Target 3	Target 4
$(1:k_1), (2:k_1), (1:k_1)$	50,-50	30,-30	15,-15	-20,20
$(1:k_2), (2:k_1), (1:k_1)$	100,-100	60,-60	15,-15	-20,20
$(1:k_1), (2:k_1), (1:k_2)$	100,-100	60,-60	15,-15	-20,20
$(1:k_1), (3:k_1), (2:k_1), (1:k_1)$	50,-50	30,-30	15,-15	10,-10
$(1:k_1), (2:k_1), (3:k_1), (1:k_1)$	50,-50	30,-30	15,-15	10,-10

Table 1: Portion of a simplified example of a game matrix

To generate all possible patrol schedules, a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ is created with the patrol areas as vertices \mathcal{V} and adjacent patrol areas as edges \mathcal{E} , with each patrol schedule being represented by a closed walk of \mathcal{G} that starts and ends at the patrol area $b \in \mathcal{V}$, the base patrol area for the USCG. The patrol schedules are a sequence of patrol areas and associated defensive activities, and are constrained by a maximum patrol time τ . The graph \mathcal{G} along with the constraints b and τ are used to generate the defender strategies.

Table 1 gives an example, where the rows correspond to the defender’s strategies and the columns correspond to the attacker’s strategies. There are two possible defensive activities, activity k_1 and k_2 , where k_2 provides a higher payoff for the defender than k_1 . Suppose that the time bound disallows more than two k_2 activities (given the time required for k_2) within a patrol. Patrol area 1 has two targets (target 1 and 2) while patrol areas 2 and 3 each have one target (target 3 and 4 respectively). In the table, a patrol schedule is composed of a sequence of patrol areas and a defensive activity in each area. The patrol schedules are ordered so that the first patrol area in the schedule denotes which patrol area the defender needs to visit first. In this example, patrol area 1 is the base patrol area, and all of the patrol schedules begin and end at patrol area 1. For example, the patrol schedule in row 2 first visits patrol area 1 with activity k_2 , then travels to patrol area 2 with activity k_1 , and returns back to patrol area 1 with activity k_1 . For the payoffs, if a target i is the attacker’s choice and is also part of a patrol schedule, then the defender would gain a reward R_i^d while the attacker would receive a penalty P_i^a , else the defender would receive a penalty P_i^d and the attacker would gain a reward R_i^a . Furthermore, let G_{ij}^d be the payoff for the defender if the defender chooses patrol j and the attacker chooses to attack target i . G_{ij}^d can be represented as a linear combination of the defender reward/penalty on target i and A_{ij} , the effectiveness probability of the defensive activity performed on target i for patrol j , as described by Equation 2. The value of A_{ij} is 0 if target i is not in patrol j .

$$G_{ij}^d = A_{ij}R_i^d + (1 - A_{ij})P_i^d \quad (2)$$

If a target is visited multiple times with different activities, we just consider the activity with the highest quality. While Table 1 shows a zero-sum game, the algorithm used by PROTECT is *not limited to a zero-sum game*.

Compact Representation

In our game, the number of defender strategies, i.e., patrol schedules, grows combinatorially, generating a scale-up challenge. To achieve scale-up, PROTECT uses a compact representation of the patrol schedules using two ideas: (i)

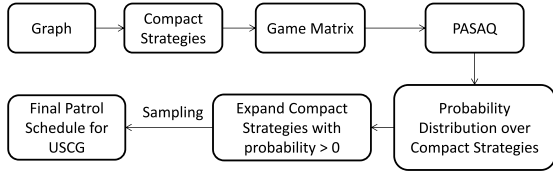


Figure 2: Flow chart of the PROTECT system

combining equivalent patrol schedules and; (ii) removal of dominated patrol schedules.

With respect to equivalence, different permutations of patrol schedules provide identical payoff results. Furthermore, if an area is visited multiple times with different activities in a schedule, only the activity that provides the defender the highest payoff requires attention. Therefore, many patrol schedules are equivalent if the set of patrol areas visited and defensive activities in the schedules are the same even if their order differs. Such equivalent patrol schedules are combined into a single compact defender strategy, represented as a set of patrol areas and defensive activities (and minus any ordering information). Table 2 presents a compact version of Table 1, which shows how the game matrix is simplified by using equivalence to form compact defender strategies, e.g., the patrol schedules in the rows 2-3 from Table 1 are represented as a compact strategy $\Gamma_2 = \{(1, k_2), (2, k_1)\}$ in Table 2.

Compact Strategy	Target 1	Target 2	Target 3	Target 4
$\Gamma_1 = \{(1:k_1), (2:k_1)\}$	50,-50	30,-30	15,-15	-20,20
$\Gamma_2 = \{(1:k_2), (2:k_1)\}$	100,-100	60,-60	15,-15	-20,20
$\Gamma_3 = \{(1:k_1), (2:k_1), (3:k_1)\}$	50,-50	30,-30	15,-15	10,-10

Table 2: Example compact strategies and game matrix

Next, the idea of dominance is illustrated using Table 2 and noting the difference between Γ_1 and Γ_2 is the defensive activity on patrol area 1. Since activity k_2 gives the defender a higher payoff than k_1 , Γ_1 can be removed from the set of defender strategies because Γ_2 covers the same patrol areas while giving a higher payoff for patrol area 1.

Figure 2 shows a high level view of the steps of the algorithm using the compact representation. In this expansion from a compact strategy to a full set of patrol schedules, we need to determine the probability of choosing each patrol schedule, since a compact strategy may correspond to multiple patrol schedules. The focus here is to increase the difficulty for the attacker to conduct surveillance by increasing unpredictability, which we achieve by randomizing uniformly over all expansions of the compact defender strategies. The uniform distribution provides the maximum entropy (greatest unpredictability).

Human Adversary Modeling

While previous game-theoretic security applications have assumed a perfectly rational attacker, PROTECT takes a step forward by addressing this limitation of classical game theory. Instead, PROTECT uses a model of a boundedly rational adversary by using a quantal response (QR) model of an adversary, which has shown to be a promising model

t_i	Target i
R_i^d	Defender reward on covering t_i if it's attacked
P_i^d	Defender penalty on not covering t_i if it's attack
R_i^a	Attacker reward on attacking t_i if it's not covered
P_i^a	Attacker penalty on attacking t_i if it's covered
A_{ij}	Effectiveness probability of compact strategy Γ_j on t_i
a_j	Probability of choosing compact strategy Γ_j
J	Total number of compact strategies
x_i	Marginal coverage on t_i

Table 3: PASAQ notation as applied to PROTECT

of human decision making (McKelvey and Palfrey 1995; Rogers, Palfrey, and Camerer 2009; Yang et al. 2011). A recent study demonstrated the use of QR as an effective prediction model of humans (Wright and Leyton-Brown 2010). An even more relevant study of the QR model was conducted by Yang et al. (Yang et al. 2011) in the context of security games where this model was shown to outperform competitors in modeling human subjects. Based on this evidence, PROTECT uses a QR model of a human adversary. (Aided by a software assistant, the defender still computes the optimal mixed strategy.)

To apply the QR model in a Stackelberg framework, PROTECT employs an algorithm known as PASAQ (Yang, Tambe, and Ordonez 2012). PASAQ computes the optimal defender strategy (within a guaranteed error bound) given a QR model of the adversary by solving the following non-linear and non-convex optimization problem P , with Table 3 listing the notation:

$$P : \begin{cases} \max_{x,a} \frac{\sum_{i=1}^T e^{\lambda R_i^a} e^{-\lambda(R_i^a - P_i^a)x_i} ((R_i^d - P_i^d)x_i + P_i^d)}{\sum_{i=1}^T e^{\lambda R_i^a} e^{-\lambda(R_i^a - P_i^a)x_i}} \\ x_i = \sum_{j=1}^J a_j A_{ij}, \quad \forall i \\ \sum_{j=1}^J a_j = 1, \quad 0 \leq a_j \leq 1, \quad \forall j \end{cases}$$

The first line of P corresponds to the computation of the defender's expected utility resulting from a combination of Equations 1 and 2. Unlike previous applications (Tambe 2011; Kiekintveld, Marecki, and Tambe 2011), x_i in this case not just summarizes presence or absence on a target, but also the effectiveness probability A_{ij} on the target.

As with all QR models, a value for λ is needed to represent the noise in the attacker's strategy. Based on discussions with USCG experts about the attacker's behavior, a λ value of 0 and ∞ were ruled out. Given the payoff data for Boston, an attacker's strategy with $\lambda = 4$ starts approaching a fully rational attacker — the probability of attack focuses on a single target. It was determined from the knowledge gathered from USCG that the attacker's strategy is best modeled with a λ value that is in the range [0.5, 4]. A discrete sampling approach was used to determine a λ value that gives the highest average expected utility across attacker strategies within this range to get $\lambda = 1.5$. Selecting an appropriate value for λ remains a complex issue however, and it is a key agenda item for future work.

Evaluation

This section presents evaluations based on (i) experiments completed via simulations and (ii) real-world patrol data along with USCG analysis. All scenarios and experiments, including the payoff values and graph (composed of 9 patrol areas), were based off the port of Boston. The defender’s payoff values have a range of $[-10,5]$ while the attacker’s payoff values have a range of $[-5,10]$. The game was modeled as a zero-sum game² in which the attacker’s loss or gain is balanced precisely by the defender’s gain or loss. For PASAQ, the defender’s strategy uses $\lambda = 1.5$ as mentioned before. All experiments are run on a machine with an Intel Dual Core 1.4 GHz processor and 2 GB of RAM.

Memory Analysis

This section presents the results based on simulation to show the efficiency in memory of the compact representation versus the full representation. In Figure 3, the x-axis is the maximum patrol time allowed and the y-axis is the memory needed to run PROTECT. The maximum patrol time allowed determines the number of combinations of patrol areas that can be visited — so the x-axis indicates a scale-up in the number of defender strategies. When the maximum patrol time is set to 90 minutes, the full representation uses 540 MB of memory while the compact representation requires 20 MB of memory. Due to the exponential increase in the memory that is needed for the full representation, it cannot be scaled up beyond 90 minutes. The graph of the runtime comparison is similar to the memory comparison graph.

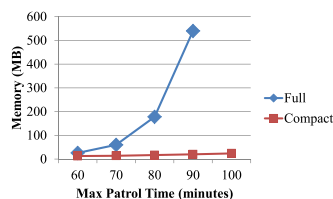


Figure 3: Memory comparison

Utility Analysis

Given that we are working with real data, it is useful to understand whether PROTECT using PASAQ with $\lambda = 1.5$ provides an advantage when compared to: (i) a uniform random defender’s strategy; (ii) a mixed strategy with the assumption of the attacker attacking any target uniformly at random ($\lambda = 0$) or; (iii) a mixed strategy assuming a fully rational attacker ($\lambda = \infty$). The previously existing DOBSS algorithm was used for $\lambda = \infty$ (Tambe 2011). Additionally, comparison with the $\lambda = \infty$ approach is important because of the extensive use of this assumption in previous applications. Typically, we may not have an estimate of the exact value of the attacker’s λ value, only a possible range. Therefore, ideally we would wish to show that PROTECT (with $\lambda = 1.5$) provides an advantage over a range of λ values assumed for the attacker (not just over a point estimate), justifying our use of the PASAQ algorithm.

²In general these types of security games are non-zero-sum (Tambe 2011), however for Boston as a first step it was decided to cast the game as zero-sum.

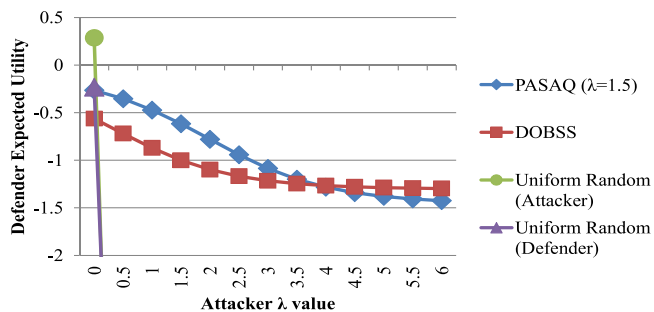


Figure 4: Defender’s Expected Utility when varying λ for attacker’s strategy

To achieve this, we compute the average defender utility of the four approaches above as the λ value of the attacker’s strategy changes from $[0, 6]$, which subsumes the range $[0.5, 4]$ of reasonable attacker strategies. In Figure 4, the y-axis represents the defender’s expected utility and the x-axis is the λ value that is used for the attacker’s strategy. Both uniform random strategies perform well when the attacker’s strategy is based on $\lambda = 0$. However, as λ increases, both strategies quickly drop to a very low defender expected utility. In contrast, the PASAQ strategy with $\lambda = 1.5$ provides a higher expected utility than that assuming a fully rational attacker over a range of attacker λ values (and indeed over the range of interest), not just at $\lambda = 1.5$.

Robustness Analysis

In the real world, observation, execution, and payoffs, are not always perfect due to the following: noise in the attacker’s surveillance of the defender’s patrols, the many tasks and responsibilities of the USCG where the crew may be pulled off a patrol, and limited knowledge of the attacker’s payoff values. Our hypothesis is that PASAQ with $\lambda = 1.5$ is more robust to such noise than a defender strategy which assumes full rationality of the attacker such as DOBSS (Tambe 2011), i.e., PASAQ’s expected defender utility will not degrade as much as DOBSS over the range of attacker λ of interest. This is illustrated by comparing both PASAQ and DOBSS against observation, execution, and payoff noise (Kiekintveld, Marecki, and Tambe 2011; Korzhyk, Conitzer, and Parr 2011; Yin et al. 2011).

Figure 5 shows the performance of different strategies while considering execution noise. The y-axis represents the defender’s expected utility and the x-axis is the attacker’s λ value. If the defender covered a target with probability p , this probability now changes to be in $[p - x, p + x]$ where x is the noise. The low execution error corresponds to $x = 0.1$ whereas high error corresponds to $x = 0.2$. The key takeaway here is that execution error leads to PASAQ dominating DOBSS over all tested values of λ . For both algorithms, the defender’s expected utility decreases as more execution error is added because the defender’s strategy is impacted by the additional error. When execution error is added, PASAQ dominates DOBSS because the latter seeks to maximize the minimum defender’s expected utility so multiple targets will have the same minimum defender utility. For DOBSS, when execution error is added, there is a greater probability that

one of these targets will have less coverage, resulting in a lower defender's expected utility. For PASAQ, typically only one target has the minimum defender expected utility. As a result changes in coverage do not impact it as much as DOBSS. As execution error increases, the advantage in the defender's expected utility of PASAQ over DOBSS increases even more. This section only shows the execution noise results; the details of the observation and payoff noise results can be found in (Shieh et al. 2012).

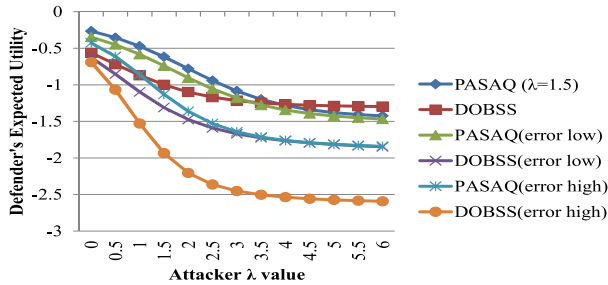


Figure 5: Defender's expected utility: Execution noise

USCG Real-World Evaluation

Real-world scheduling data: Unlike prior publications of real-world applications of game theory for security, a key novelty of this paper is the inclusion of actual data from USCG patrols before and after the deployment of PROTECT at the port of Boston. Figure 6(a) and Figure 6(b) show the frequency of visits by USCG to different patrol areas over a number of weeks. The x-axis is the day of the week, and the y-axis is the number of times a patrol area is visited for a given day of the week. The y-axis is intentionally blurred for security reasons as this is real data from Boston. There are more lines in Figure 6(a) than in Figure 6(b) because during the implementation of PROTECT, new patrol areas were formed which contained more targets and thus fewer patrol areas in the post-PROTECT figure. Figure 6(a) depicts a definite pattern in the patrols. While there is a spike in patrols executed on Day 5, there is a dearth of patrols on Day 2. Besides this pattern, the lines in Figure 6(a) intersect, indicating that some days, a higher value target was visited more often while on other days it was visited less often. This means that there was not a consistently high frequency of coverage of higher value targets before PROTECT. In Figure 6(b), we notice that the pattern of low patrols on Day 2 (from Figure 6(a)) disappears. Furthermore, lines do not frequently intersect, i.e., higher valued targets are visited consistently across the week. The top line in Figure 6(b) is the base patrol area and is visited at a higher rate than all other patrol areas.

Adversary Perspective Teams(APT): To obtain a better understanding of how the adversary views the potential targets in the port, the USCG created the Adversarial Perspective Team (APT), a mock attacker team. The APT provides assessments from the terrorist perspective and as a secondary function, assesses the effectiveness of the patrol activities before and after deployment of PROTECT. In their evaluation, the APT incorporates the adversary's known in-

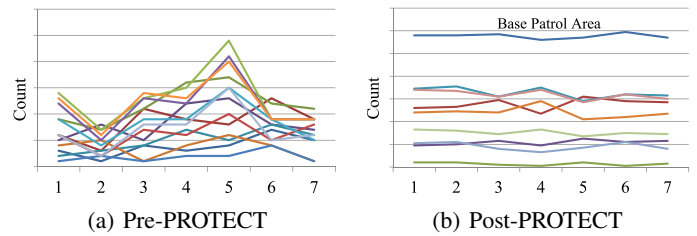


Figure 6: Patrol visits per day by area

tent, capabilities, skills, commitment, resources, and cultural influences. In addition, it screens attack possibilities and assists in identifying the level of deterrence projected at and perceived by the adversary. For the purposes of this research, the adversary is defined as an individual(s) with ties to al-Qa'ida or its affiliates.

The APT conducted a pre- and post-PROTECT assessment of the system's impact on an adversary's deterrence at the port of Boston. This analysis uncovered a positive trend where the effectiveness of deterrence increased from the pre- to post- PROTECT observations.

Additional Real-world Indicators: The use of PROTECT and APT's improved guidance given to boat crews on how to conduct the patrol jointly provided a noticeable increase in the quality and effectiveness of the patrols. Prior to implementing PROTECT, there were no documented reports of illicit activity. After implementation, USCG crews, reported more illicit activities within the port and provided a noticeable "on the water" presence with industry port partners commenting, "the Coast Guard seems to be everywhere, all the time." With no actual increase in the number of resources applied, and therefore no increase in capital or operating costs, these outcomes support the practical application of game theory in the maritime security environment.

Outcomes after Boston Implementation: The USCG viewed this system as a success and as a result, PROTECT is now getting deployed in the port of New York. We were presented an award for the work on the PROTECT system for the Boston Harbor which reflects USCG's recognition of the impact and value of PROTECT.

Lessons Learned: Putting Theory into Practice

Developing the PROTECT model was a collaborative effort involving university researchers and USCG personnel representing decision makers, planners and operators. Building on the lessons reported in (Tambe 2011) for working with security organizations, we informed the USCG of (i) the assumptions underlying the game-theoretic approaches, e.g., full adversary rationality, and strengths and limitations of different algorithms — rather than pre-selecting a simple heuristic approach; (ii) the need to define and collect correct inputs for model development and; (iii) a fundamental understanding of how the inputs affect the results. We gained three new insights involving real-world applied research; (i) unforeseen positive benefits because security agencies were compelled to reexamine their assumptions; (ii) requirement to work with multiple teams in a security organization at

multiple levels of their hierarchy and; (iii) need to prepare answers to end-user practical questions not always directly related to the "meaty" research problems.

The first insight came about when USCG was compelled to reassess their operational assumptions as a result of working through the research problem. A positive result of this reexamination prompted USCG to develop new PWCS mission tactics, techniques and procedures. Through the iterative development process, USCG reassessed the reasons why boat crews performed certain activities and whether they were sufficient. For example, instead of "covered" vs "not covered" as the only two possibilities at a patrol point, there are now multiple sets of activities at each patrol point.

The second insight is that applied research requires the research team to collaborate with planners and operators of a security organization to ensure the model accounts for all aspects of a complex real world environment. Initially when we started working on PROTECT, the focus was on patrolling each individual target. This appeared to micro-manage the activities of boat crews, and it was through their input that individual targets were grouped into patrol areas associated with a PWCS patrol. On the other hand, input from USCG headquarters and the APT mentioned earlier, led to other changes in PROTECT, e.g., departing from a fully rational model of an adversary to a QR model.

The third insight is the need to develop answers to end-user questions which are not always related to the "meaty" research question but are related to the larger knowledge domain on which the research depends. One example of the need to explain results involved the user citing that one patrol area was being repeated and hence, randomization did not seem to occur. After assessing this concern, we determined that the cause for the repeated visits to a patrol area was its high reward — order of magnitude greater than the rarely visited patrol areas. PROTECT correctly assigned patrol schedules that covered the more "important" patrol areas more frequently. These practitioner-based issues demonstrate the need for researchers to not only be conversant in the algorithms and math behind the research, but also be able to explain from a user's perspective how solutions are accurate. An inability to address these issues would result in a lack of real-world user confidence in the model.

Summary

This paper reports on PROTECT, a game-theoretic system deployed by the USCG in the port of Boston since April 2011. USCG has deemed the deployment of PROTECT in Boston a success and efforts are underway to deploy PROTECT in the port of New York, and to other ports in the United States. PROTECT has advanced the state of the art beyond previous applications of game theory for security such as ARMOR, IRIS or GUARDS (Tambe 2011). The use of a QR model also sets PROTECT apart from other Stackelberg models such as (Basilico, Gatti, and Amigoni 2009; Vanek et al. 2011). Building on this initial success, we hope to deploy it at more and much larger-sized ports.

Acknowledgments

We thank the USCG offices, and particularly sector Boston, for their exceptional collaboration. The views expressed herein are those of the author(s) and are not to be construed as official or reflecting the views of the Commandant or of the USCG. This research was supported by the US Department of Homeland Security through the National Center for Risk and Economic Analysis of Terrorism Events (CREATE) under award number 2010-ST-061-RE0001.

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