Computing Optimal Mixed Strategies for Security Games with Dynamic Payoffs

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Abstract

Security agencies in the real world often need to protect targets with time-dependent values, e.g., tourist sites where the number of travelers changes over time. Since the values of different targets often change asynchronously, the defender can relocate security resources among targets dynamically to make the best use of limited resources. We propose a game-theoretical scheme to develop dynamic, randomized security strategies in consideration of adversary’s surveillance capability. This differs from previous studies on security games by considering varying target values and continuous strategy spaces of the security agency and the adversary. The main challenge lies in the computational intensiveness due to the continuous, hence infinite strategy spaces. We propose an optimal algorithm and an arbitrarily near-optimal algorithm to compute security strategies under different conditions. Experimental results show that both algorithms significantly outperform existing approaches.

1 Introduction

Security is a grand challenge faced by the world. Recently, facing rising threats from ISIS, many major cities have boosted security measures to protect potential attack targets, e.g., subway stations, tourist sites, shopping centers [Park, 2014]. Since strategic attackers can take advantage of patterns of security strategies, it is important to develop randomized security strategies considering both different weights of targets and attacker’s surveillance capability.

One challenge lies in designing efficient security resource allocation strategies is that the relative importance of different targets can change over time. Thus the limited security resources need to be dynamically allocated for the best use of them. For example, the entrances of museums are usually crowded in the morning, leading to their high weights in security at that time; while the bar streets and entertainment centers usually require more security measures in the evening. Intuitively, to make the best use of limited security resources, the security agency should assign more resources to the museums in the morning, then transfer some resources to the bar streets in the evening. In this work, we aim at computing randomized dynamic defender strategies to protect targets with time-dependent payoffs.

There has been lots of research on game theory based security resource allocation [Tambe, 2011; Yang et al., 2011; An et al., 2013]. Many systems based on defender-attacker security game models have been successfully deployed [Tambe et al., 2014]. However, most work assumes that the payoffs of targets are static over time [Shieh et al., 2012; An et al., 2011; Gan et al., 2015; Vorobeychik et al., 2014]. Some work considers changing target values, but they only allow the security agency or the adversary to move at pre-defined, discretized time points [Varakantham et al., 2013; Fang et al., 2013; Xu et al., 2014] without analyzing how much loss the discretization can lead to when continuous strategy spaces are considered. While Yin et al. [2014] considered varying target values and that the defender can move resources at any time, their algorithms can only compute optimal pure defender strategies, which is unsuitable in domains where the attacker can easily conduct surveillance and recognize patterns of the defender’s pure strategy.

We make five key contributions in this work. First, we propose a new Stackelberg game model, in which the targets’ weights are time-dependent and both the defender and the attacker can act at any time, i.e., the defender can transfer resources at any time while the attacker can attack at any time. Thus both agents have continuous strategy spaces. Second, we propose COCO (Computing Optimal Coverage withOut transfer time) to compute the optimal mixed strategy for the defender when she can move security resources among targets without time delay. COCO represents mixed strategies in a compact way and avoids traversing the whole strategy space by exploiting the properties of the optimal defender strategies. Our third contribution is an approach to sample pure strategies based on the compact mixed strategy computed by COCO. The defender can only make a finite number of transfers of resources in a time period in the real world, despite that she can transfer resources at any time point in this period. We sample such ‘implementable’ pure strategies to realize the compact optimal mixed strategy.

We also consider a more general case in which it takes non-negligible time to move resources among targets. Our forth contribution is an efficient approximation scheme to compute the near optimal defender mixed strategy. We propose
an algorithm ADEN (computing Approximately optimal De-
fender strategies in games with Nonzero transfer time) which
leads to a defender utility at most $\epsilon$ less than the optimal
defender utility. Our fifth contribution is detailed experimental
analysis on the solution quality and computational efficiency
of the proposed algorithms. Experimental results show that
both COCO and ADEN make the defender better off than
algorithms based on the assumptions of static payoffs or dis-
cretized strategy spaces.

2 Model
Assume that there are $n$ targets $T = \{1, \ldots, n\}$ and the
defender has $m$ identical security resources $(n \geq m)$. The
defender protects the targets during a time period $[0, t_e]$ (e.g.
the operation hours of a day) everyday. The importance of
targets changes over time. We use a continuous function
$v_i(t) (i \in T, t \in [0, t_e], v_i(t) > 0)$ to represent the value of
a target $i$ at time $t$ and assume $v_i(t)$ to be piecewise linear\(^1\).

As in previous work, we model the problem as a Stackelberg
game, where the defender commits to a randomized strategy
first, and the attacker responds to this strategy.

**Strategies.** A pure defender strategy $S$ includes the initial
assignment of resources at time $0$ and the subsequent trans-
fers during $[0, t_e)$, i.e., $S = \langle (i, j, t) : i, j \in T, t \in [0, t_e]\rangle$,
where $i, j \in T$ represents a resource is transferred from
target $i$ to target $j$ at time $t$. (If a target $i$ is protected at time
$0$, then $(i, i, 0) \in S$). We denote $D = \langle d_{ij} : i, j \in T\rangle$
$d_{ij}$ represents the time needed to transfer resources from tar-
get $i$ to target $j$. We denote $q_i(S, t)$, a 0-1 indicator, to rep-
resent whether target $i$ is protected at time $t$ if the defender
plays pure strategy $S$. $q_i(S, t)$ is a piecewise constant func-
tion over time $t \in [0, t_e]$ with values in $\{0, 1\}$. Let $S$ be the
defender strategy space. Since the defender can trans-
fer resources at any time during $[0, t_e]$, $S$ is continuous. A
mixed defender strategy can be represented by a distribution
$x = (x_S : S \in S)$ with $x_S$ representing the probability den-
sity that pure strategy $S$ is played by the defender. As in pre-
vious work, we restrict attacker strategies to pure strategies,
denoted as $A = \langle i, t_a \rangle$, representing that the attacker attacks
target $i$ at time $t_a$.\(^2\)

**Utilities and Equilibrium.** We assume the game to be
zero-sum. If the attacker plays $A = \langle i, t_a \rangle$ while the
defender plays a strategy $S$ with $q_i(S, t_a) = 0$, i.e., the at-
tack succeeds, the attacker will gain the value of target $i$ at
time $t_a$, $v_i(t_a)$, and the defender gains $-v_i(t_a)$. Otherwise,
if $q_i(S, t_a) = 1$, the attack fails and both players get utility
0. Given a defender’s mixed strategy $x$ and an attacker’s pure
strategy $A = \langle i, t_a \rangle$, the expected attacker utility is
\begin{equation}
U_a(x, A) = v_i(t_a) \cdot (1 - \int_S x_S \cdot q_i(S, t_a)).
\end{equation}
The expected defender utility is $U_d(x, A) = -U_a(x, A)$ due
to the zero-sum assumption.
The Stackelberg equilibrium is the same as the maximin
equilibrium given the zero-sum assumption: the defender
maximizes her minimum utility, or equivalently, minimizes
the maximum attacker utility, which indicates that the at-
tacker responds the best.

**Compact Representation.** It is complicated to directly
compute $x$ given its infinite dimensions. We map a mixed
defender strategy into a compact form for the ease of compu-
tation. Given a mixed strategy $x$, for each target $i \in T$, we
define a coverage function $c_i(t)$ which describes the proba-
bulk of target $i$ being covered by a resource at time $t$.

\begin{equation}
c_i(t) = \int_S x_S q_i(S, t).
\end{equation}
$c_i(t)$ is a function ranging in $[0, 1]$ over time $t \in [0, t_e]$. A
mixed strategy $x$ corresponds to a coverage vector, $c(t) =
\langle c_i(t) : i \in T, t \in [0, t_e] \rangle$. Given $x$ and $A = \langle i, t_a \rangle$,
the expected attacker utility can also be represented as
\begin{equation}
U_a(c(t), A) = v_i(t_a) \cdot (1 - c_i(t_a)).
\end{equation}

3 Negligible Transfer Time
We begin with a simple case in which the transfer time of
resources is negligible, i.e., $d_{ij} = 0$. Zero transfer time is
a realistic assumption in domains in which targets are close
to each other or resources can be transferred quickly (e.g.,
using helicopters), thus transfer time is negligible compared
with the operation time of a pure strategy, i.e., $[0, t_e]$. We will
relax this assumption in the next section. In this section, we
first propose an approach to compute the optimal coverage
vector, then propose an approach to sample pure strategies
with finite transfers to produce the optimal coverage vector.

3.1 Computing Optimal Coverage Vector
If the transfer time is negligible, we can treat each time point
in $[0, t_e]$ as an independent time point, and just need to com-
pute the optimal coverage vector by computing the ‘locally’
optimal coverage at each time point. Formally, at a specific
time point $t_0$, $c(t_0)$ is locally optimal at $t_0$ if it satisfies that
\begin{equation}
\max_{i \in T} v_i(t_0) (1 - c_i(t_0)) \leq \max_{i \in T} v_i(t_0) (1 - c_i'(t_0)), \forall c'(t_0).
\end{equation}
This indicates that the locally optimal coverage minimizes
the maximum attacker utility if he attacks at $t_0$. We then ex-
\[\text{ploration of how to achieve the locally optimal coverage. Let } I \text{ rep-}
\begin{equation}
v_i(t_0) (1 - c_i(t_0)) = v_j(t_0) (1 - c_j(t_0)), \forall i, j \in I.
\end{equation}
\begin{equation}
v_i(t_0) (1 - c_i(t_0)) > v_j(t_0) (1 - c_j(t_0)), \forall i, j \in T \setminus I.
\end{equation}
We have the following Lemma on the properties of a locally
optimal coverage.

**Lemma 1.** A coverage vector $c(t)$ is locally optimal at $t_0$
if and only if it satisfies $\sum_{i \in I} c_i(t) = m$, hence $c_i(t_0) = 0, \forall j \in T \setminus I$. $m$ is the number of resources.

The detailed proofs for lemmas, propositions, and theo-
rems in this paper are available in the online appendix\(^2\). We

\[\text{http://www.ntu.edu.sg/home/boan/papers/IJCAI15_Dynamic_Appendix.pdf}\]
now consider computing a coverage vector which is locally optimal at any $t \in [0, t_e]$. We first assume that all targets are in the attack set all the time. Such an assumption may enlarge the attack set, and result in infeasible coverage on some targets during some time intervals, i.e., some targets need to be protected with negative probability. We then find these time intervals, revise the attack set and the coverage. We use an example to illustrate the process.

**Example 1.** Assume that $t_e = 2$. There are 3 targets, $I$ resource. The value functions of targets are: $v_1(t) = t, v_2(t) = -t + 10, v_3(t) = -0.5t^2 + 5$. First, assume that all targets are in the attack set all the time. Based on Lemma 1 and the definition of attack set, the coverage functions satisfy that

$$
\begin{align*}
\sum_{i \in \{1, 2, 3\}} c_i(t) &= 1 \\
v_1(t) \cdot (1 - c_1(t)) &= v_2(t) \cdot (1 - c_2(t)) = v_3(t) \cdot (1 - c_3(t)).
\end{align*}
$$

Thus we can get coverage functions based on value functions $v_i(t)$. It is easy to compute that when $t \in [0, 2], c_1(t) < 0, c_2(t) > 0, c_3(t) > 0$. It indicates that target 1 should not be in the attack set during $[0, 2]$. Thus we can set $c_1(t) = 0$ for $t \in [0, 2]$, and remove target 1 from the attack set. Similar to the previous step, we now compute the coverage functions for targets 2 and 3 which stay in the attack set:

$$
\begin{align*}
\sum_{i \in \{2, 3\}} c_i(t) &= 1 \\
v_2(t) \cdot (1 - c_2(t)) &= v_3(t) \cdot (1 - c_3(t)).
\end{align*}
$$

The new functions $c_2(t) \geq 0, c_3(t) \geq 0, \forall t \in [0, 2]$. Thus the coverage vector $c = \langle c_i(t) \rangle$ is now locally optimal $\forall t \in [0, 2]$ since it satisfies the condition in Lemma 1 everywhere.

We propose COCO (Computing Optimal Coverage without transfer time) in Algorithm 1, which computes the optimal coverage vector for targets in set $I$ during time period $[b, e]$ recursively. We call COCO($I = \mathcal{T}, b = 0, e = t_e$) to compute the optimal coverage vector. In COCO, we first assume that the target set $I$ is the attack set during time period $[b, e]$, then compute the corresponding coverage value functions of the targets in $I$ (Line 2). $E$ is a vector of all roots of the coverage functions with elements in increasing order, i.e., $t_k$ represents the $k^{th}$ smallest root in time period $(b, e)$ (Line 3). If $E$ is empty, Line 5 checks the sign of coverage functions during $(b, e)$. If there does not exist any function with negative value in this time period, the coverage vector is feasible in $(b, e)$ and the algorithm terminates (Line 6). Otherwise assume the attack set includes all targets with positive coverage during $(b, e)$ and repeat the process (Lines 7-9). If $E$ is not empty, during $(t_k, t_{k+1})$, no coverage function has values with opposite signs since $(t_k, t_{k+1})$ is a time period between the adjacent roots of any function. Line 15 uses a set $I'$ to record targets with positive coverage during $(t_k, t_{k+1})$. Targets in $I'$ are considered as in the attack set in time period $[t_k, t_{k+1})$ while other targets are not (Line 16). The process is repeated for each time period $[t_k, t_{k+1})$ (Line 17) to compute the coverage of targets in $I'$ until the coverage vector at any time is feasible.

**Theorem.** COCO computes the optimal coverage vector.

### Algorithm 1: COCO($I, b, e$)

1. while true do
   2. \[ c_i(t) \leftarrow 1 - \frac{(m-n) v_i(t)}{\sum_{j \in I} v_j(t)}, \forall i \in I, t \in [b, e); \]
   3. \[ E \leftarrow \{t_k; c_i(t_k) = 0, t_k \in (b, e), \forall i \in I\}; \]
   4. if $E = \emptyset$ then
      5. \[ I' \leftarrow \{i : i \in I, c_i(t) \geq 0, \forall t \in (b, e)\}; \]
      6. if $I' = I$ then break
      7. else \[ c_i(t) = 0, \forall i \in I \setminus I', \forall t \in [b, e); \]
      8. COCO($I', b, e$);
   9. else \[ E \leftarrow E \cup \{t_0 = b, t_{|E|+1} = e\}; \]
   10. for $k \in \{0, \ldots, |E|\}$ do
      11. \[ I' \leftarrow \emptyset; \]
      12. if $c_i(t) \geq 0, \forall i \in I, \forall t \in (t_k, t_{k+1})$ then
      13. \[ I' \leftarrow I' \cup \{k\}; \]
      14. else \[ c_i(t) = 0, \forall t \in [t_k, t_{k+1}); \]
      15. COCO($I', t_k, t_{k+1}$);
   16. return $c = \{c_i(t) : i \in I, t \in [b, e)\}$;

### 3.2 Sampling Pure Strategies

Coverage functions computed by COCO can be continuously changing over time. It is computationally infeasible to treat any $t \in [0, t_e)$ as an independent time point and sample an allocation of resources based on the coverage at $t$. We now propose an approach to sample pure strategies. Given a coverage vector $c(t)$, we first discretize time period $[0, t_e)$ as a sequence of time points $\theta = \{\theta_i\}$ ($k$ is an index) such that $\forall t \in (\theta_k, \theta_{k+1}), \forall i \in \mathcal{T}, c_i(t)$ is differentiable and monotone. Given the piecewise linear assumption of value functions, Line 2 in COCO ensures $c_i(t)$ to be piecewise differentiable functions. Hence the discretization is feasible. The procedure of sampling a pure strategy is as follows.

**Step 1:** Sample an allocation of resources at $\theta_k$.

**Step 2:** Given the allocation at $\theta_k$, sample the departure targets and destination targets of transfers during $(\theta_k, \theta_{k+1})$.

**Step 3:** Given the transfers sampled in the previous step, sample the time of each transfer.

**Step 4:** Go to time point $\theta_{k+1}$ and repeat steps 1 - 3.

Next, we describe the implementation of the first three steps. For Step 4, although resources need to be reallocated at $\theta_{k+1}$, the number of transfers at this time point is finite given the finite number of resources.

**Step 1:** Let $L = \{L_i : i \in \mathcal{T}, L_i \in \{0, 1\}, \sum_i L_i = m\}$ represent an allocation of resources with $L_i$ indicating whether target $i$ is protected by a resource. Let $y_{L}$ represent the probability of playing allocation $L$ at time $\theta_k$. Step 1 can be implemented once we get the value of $y_{L}$. Given $c(\theta_k)$, $y_L$ can be computed by approaches used in previous work on security games [Kiekintveld et al., 2009; Letchford and Conitzer, 2013].
Step 2: We first show that a coverage vector can be realized by a specific set of transfers, which is formally shown in Proposition 3. Let $\Lambda = \{ u : u \in \mathcal{T}, \frac{dc_u(t)}{dt} < 0, \forall t \in (\theta_k, \theta_{k+1}) \}$ be a set of targets whose coverage decreases during $(\theta_k, \theta_{k+1})$; let $V = \{ v : v \in \mathcal{T}, \frac{dc_v(t)}{dt} > 0, \forall v \in (\theta_k, \theta_{k+1}) \}$ be a set of targets whose coverage increases during $(\theta_k, \theta_{k+1})$.

**Proposition 3.** For $t \in (\theta_k, \theta_{k+1})$, (c(t)) can be implemented by sampling from pure strategies in which resources are only transferred from targets $u \in \Lambda$ to targets $v \in V$, and each resource is transferred for at most once.

**Proof Sketch:** Assume that the defender uses a pure strategy $S_1$ with nonzero probability in which a resource is transferred from a target $v \in V$ to another target $i \in \mathcal{T}$ at $t_0 \in (\theta_k, \theta_{k+1})$. Since $c_u(t)$ increases continuously in $(\theta_k, \theta_{k+1})$, the defender must also use some other pure strategy $S_2$ with nonzero probability in which a resource is transferred from some target $j \in \mathcal{T}$ to target $v$ at $t_0$. Thus the defender can cancel the transfer made from $v \in S_1$ and directly transfer a resource from $j$ to $i$ in strategy $S_2$. If the defender uses a pure strategy $S_3$ in which a resource is transferred from some target $i \in \mathcal{T}$ to a target $u \in \Lambda$ at $t_0 \in (\theta_k, \theta_{k+1})$, she can get rid of this transfer in a similar way. Given that resources are only transferred from targets $u \in \Lambda$ to targets $v \in V$, a resource will not be transferred from $V$ to target $v$ to other targets during $[\theta_k, \theta_{k+1}]$. Thus each resource is transferred for at most once.

We now consider implementing Step 2. Let $\Gamma_L = \{(u,v) : u \in \Lambda, v \in V, L_u = 1, L_v = 0\}$ represent a ‘transfer set’ of target pairs, i.e., $\forall (u,v) \in \Gamma_L$, a resource is transferred from target $u$ to target $v$ during $(\theta_k, \theta_{k+1})$. Step 2 can be done once we get the probability of choosing each $\Gamma_L$, i.e., $p(\Gamma_L)$. To compute $p(\Gamma_L)$, we first denote $p((u,v)|L)$ as the probability that a resource is transferred from target $u$ to target $v$ during $(\theta_k, \theta_{k+1})$ after $L$ is set as the allocation at $\theta_k$. Once we get the value of $p((u,v)|L), p(\Gamma_L)$ can be computed based on the following class of equations.

$$\sum_{\Gamma_L \ni (u,v)} p(\Gamma_L) = p((u,v)|L), \forall L$$

To compute $p((u,v)|L)$, we let $Z((u,v), t)$ represent the probability that a resource is transferred from target $u$ to target $v$ before time $t$. For $t \in [\theta_k, \theta_{k+1}]$, $Z((u,v), t)$ is a function with respect to $t$. If we can get the expression of $Z((u,v), t)$, $p((u,v)|L)$ can be computed based on the following equations.

$$\sum_{L} y_{L} \cdot (1 - L_v) \cdot p((u,v)|L) = Z((u,v), \theta_{k+1}), \forall u, v$$

$$p((u,v)|L) = 0, \forall u \in \Lambda \text{ with } L_u = 0, \forall v \in V \text{ with } L_v = 1$$

Eq. 6 is based on the law of total probability. Eq. 7 indicates that a resource can only be transferred from a target which is protected at $\theta_k$ to a target which is not protected at $\theta_k$. Our problem now lies in computing the expression of $Z((u,v), t)$.

**Computing $Z((u,v), t)$:** First, a feasible expression of $Z((u,v), t)$ satisfies the following $\forall t \in [\theta_k, \theta_{k+1}]$.

$$\sum_{v \in V} Z((u,v), t) = c_u(\theta_k) - c_u(t), \forall u \in \Lambda$$

(8)

$$\sum_{u \in \Lambda} Z((u,v), t) = c_v(t) - c_v(\theta_k), \forall v \in V$$

(9)

$$Z((u,v), t) \geq 0, \forall u \in \Lambda, \forall v \in V$$

(10)

$$\lim_{\Delta t \to 0} \frac{Z((u,v), t + \Delta t) - Z((u,v), t)}{\Delta t} \geq 0, \forall u \in \Lambda, \forall v \in V$$

(11)

Eqs. 8 - 9 are based on Proposition 3. Eqs. 10 - 11 are based on the definition of $Z((u,v), t)$. At a time point $t \in [\theta_k, \theta_{k+1}]$, the value of $Z((u,v), t)$ can be computed based on Eqs. 8 - 11. But it is impossible to compute the expression of $Z((u,v), t)$ in this way due to the continuity of time. Note that given Eqs. 8 and 9, the function $Z((u,v), t)$ can be represented as linear combinations of coverage functions $(\forall t \in [\theta_k, \theta_{k+1}])$, i.e.,

$$Z((u,v), t) = \sum_{i \in \Lambda} z_{iuv}^\theta(t)(c_u(\theta_k) - c_u(t)) + \sum_{j \in V} z_{juv}^\theta(t)(c_v(t) - c_v(\theta_k)).$$

(12)

Here $z_{iuv}^\theta(t)$ are parameters depending on $t$, or ‘parameter functions’. We can get $Z((u,v), t)$ by computing these ‘parameter functions’. At a specific time point $t \in [\theta_k, \theta_{k+1}]$, we can get the value of the parameter functions based on Eqs. 8 - 11. In addition, we have the following proposition which discusses the properties of the parameter functions.

**Proposition 4.** There exist parameter functions which lead to a feasible expression of $Z((u,v), t)$ satisfying that each $z_{iuv}^\theta(t)$ is piecewise constant during $[\theta_k, \theta_{k+1}]$.

The proof of Proposition 4 is based on Lemma 5.

**Lemma 5.** If $|\Lambda| > 2$ and $|V| > 2$, there exists feasible $Z((u,v), t)$ satisfying $\lim_{\Delta t \to 0} \frac{Z((u,v), t + \Delta t) - Z((u,v), t)}{\Delta t} > 0, \forall u, \forall v, \forall t \in [\theta_k, \theta_{k+1}]$.

Based on Proposition 4 and Lemma 5, we propose Algorithm 2 to compute the parameter functions, hence $Z((u,v), t)$. We first compute the value of the parameter functions at a time point $t_0$, hence we can get an expression of $Z((u,v), t)$ whose parameter functions are constant in $[t_0, \theta_{k+1}]$. Let $R$ be the set of the roots of functions $\frac{dZ((u,v), t)}{dt}$ (Line 4). The expression of $Z((u,v), t)$ is feasible from time $t_0$ to the minimum time point in $R$ (Line 8) since for $t > t_m$, Eq. 11 is violated. The process is repeated for $t_m$ until we get the feasible expression of $Z((u,v), t)$ for $t \in [\theta_k, \theta_{k+1}]$.

**Theorem 6.** Algorithm 2 computes a feasible expression of $Z((u,v), t)$, $\forall t \in [\theta_k, \theta_{k+1}]$ after finite loops.

**Step 3:** Let $Z(t|L, (u,v))$ be the cumulative distribution function of $t$, representing the probability that a resource is transferred from target $u$ to target $v$ before time $t$ ($t \in [\theta_k, \theta_{k+1}]$) after $L$ is set as the allocation at $\theta_k$ and step 2
Algorithm 2: Computing $Z((u, v), t)$

1. $t_0 = \theta_k, k_{uv} = 0$;
2. while $t_m < \theta_{k+1}$ do
   3. solve $z_{ij}^t(t_0)$ based on Eqs. 8 - 11 (change the ‘0’ in Eq. 10 to $k_{uv}$, change the ‘$\geq$’ in Eq. 11 to ‘$>$’);
   4. $R = (t, \frac{dZ((u, v), t)}{dt} = 0$ and $t \in (t_0, \theta_{k+1})$);
   5. if $R = 0$ then
      6. break;
   7. else
      8. $t_m = \min_t R; k_{uv} = Z((u, v), t_0)$;
      9. $z_{ij}^t(t) = z_{ij}^t(t_0), \forall t \in [t_m, t_0); t_0 = t_m$;

Algorithm 2 computes $Z((u, v), t)$ based on Eqs. 8 - 11. It initializes $t_0 = \theta_k, k_{uv} = 0$ and then iteratively solves for $z_{ij}^t(t_0)$ until $t_m = \theta_{k+1}$. The algorithm then updates $z_{ij}^t(t)$ for all $t \in [t_m, t_0)$ and $t_0 = t_m$.

4 Nonzero Transfer Time

In this section, we address general cases with non-negligible transfer time, i.e., $d_{ij} \geq 0$ and propose an efficient approximation scheme to compute the optimal defender’s mixed strategy. We first obtain a discretized version of the game by properly partitioning the time space, and more importantly, show that the defender’s optimal utility is at most $\epsilon$ less than the optimal utility in the original continuous version. We then approach the discrete game with a flow formulation. For constructing the discretized game, we first define an $(\epsilon, \delta)$-Mesh.

Definition 7. $(\epsilon, \delta)$-Mesh. An $(\epsilon, \delta)$-Mesh is a uniform discretization of the time space $[0, t_\xi]$ denoted as $\zeta = (t_0, t_1, ..., t_{\xi})$ with $t_0 = 0, t_{\xi} = t_\xi$, such that $\delta = t_\xi - t_{k-1}$ and $\text{var}(t_{k-1}, t_k) \leq \epsilon$ for all $k = 1, ..., \xi$, where $\text{var}(t_{k-1}, t_k) = \max_{t \in [t_{k-1}, t_k]} v_i(t) - \min_{t \in [t_{k-1}, t_k]} v_i(t)$ is the oscillation of $v_i(t)$ in interval $[t_{k-1}, t_k]$.

Continuity of value functions guarantees the existence of such an $(\epsilon, \delta)$-Mesh, which can be easily found. We now convert a general game $G$ into a discretized game $G_d$. First, we restrict the defender’s resource move can only happen at time points $t_k \in \zeta$ and so is the attacker’s attack. Thus the strategy space of $G_d$ is a subset of the strategy space of $G$.

The value functions of $G_d$ are denoted using the $(\epsilon, \delta)$-Mesh: $v_i(t) \text{ at } t \in [t_{k-1}, t_k] \text{ and } v_i(t) = \max_{t' \in [t_{k-1}, t_k]} v_i(t'), \forall t \in [t_{k-1}, t_k]$ be the value functions of $G_d$. Note that $v_i(t)$ is a constant in $[t_{k-1}, t_k]$ and satisfies $|v_i(t) - v_i(t')| \leq \epsilon, \forall t \in [t_{k-1}, t_k]$. We also assume that $d_{ij}$ are multipliers of $\delta$, i.e., $d_{ij} = a_{ij}\delta$ with $a_{ij}$ being some integer. This assumption holds if each $d_{ij}$ is given as a rational number and $\delta$ is small enough. To show the gap between the optimal defender utility in $G_d$ and the initial game $G$, we introduce a bridge game $G_{b}$, in which the value functions are $v_i(t)$ as in $G_d$ while the defender and the attacker can act at any time as in $G$. The following lemma shows the relationship between defender utilities in $G_d$ and $G_b$.

Lemma 8. Let $x$ be a defender’s mixed strategy of $G_d$, then $U_d^{G_d}(x) = U_d^{G_b}(x)$, where $U_d^{G_d}(x)$ and $U_d^{G_b}(x)$ are the defender’s utility in $G_d$ and $G_b$, respectively if the defender plays $x$ and the attacker responds the best.

This is because the value functions of $G_d$ and $G_b$ are the same. Furthermore, a deeper conclusion holds.

Lemma 9. Assume that transfer time between any target pair $d_{ij}$ is multiplier of $\delta$. If $x$ is an equilibrium strategy of $G_d$, it is an equilibrium strategy of $G_b$.

Note that this does not apply directly from Lemma 8, since the strategy space of $G_d$ is a subset of the strategy space of $G_b$. Now we are ready to bound the defender’s utility gap between $G_d$ and $G$, as summarized in the following theorem.

Theorem 10. Let $x'$ be an equilibrium strategy of $G_d$ and $x$ be an equilibrium strategy of $G$, we have

$$U_d^{G_d}(x') - U_d^{G_d}(x) \geq -\epsilon,$$

where $U_d^{G_d}(x')$ is the defender utility in $G$ if the defender plays $x'$ and the attacker responds the best, while $U_d^{G_d}(x)$ is the optimal defender utility in $G$.

In addition, we have $U_d^{G_d}(x') = U_d^{G_d}(x)$ based on Eq. 14. Our task now reduces to computing the equilibrium of $G_d$. $G_d$ is a discretized spatio-temporal game as is shown in Figure 1(a), in which $x$-axis is the $(\epsilon, \delta)$-Mesh and $y$-axis indicates the targets, i.e., node $(k, i)$ is target $i$ at time $t_k$. An attacker’s pure strategy is a node in the graph. If we add a departure node and a destination node to the graph as is shown in Figure 1(b) and require that any edge of the graph has capacity 1, the defender’s pure strategy is a $m$-unit 0 - 1 integer $s - t$ flow on the graph, i.e., if the defender transfers a resource from target $i$ to target $j$ at time $t_k$, add an edge between node $(k, j)$ and $(k + a_{ij}, j)$; if the defender does not transfer the resource on target $i$ at time $t_k$, add an edge between node $(k, i)$ and node $(k + 1, i)$. We have the following theorem about the defender’s mixed strategies in $G_d$. 

Figure 1: Construction of the discrete game
Theorem 11. A mixed strategy of $G_d$ is an $m$-unit fractional flow, and vise versa.

Let $f(i, j, t_k)$ represent the probability that a resource is transferred from target $i$ to target $j$ at $t_k$. The optimal defender utility can be computed by the following LP which we call ADEN (computing Approximately optimal DEfender strategies in games with Nonzero transfer time).

$$\text{ADEN: } \min U$$

subject to

$$U \geq v_i'(t_k) (1 - f(i, i, t_k)) \forall i \in \mathcal{T}, t_k \in \zeta \tag{16}$$

$$\sum_{i \in \mathcal{T}} f(i, i, t_0) = m, \tag{17}$$

$$f(s, i, t_0) - \sum_{j \in \mathcal{T}} f(i, j, t_0) = 0, \forall i \in \mathcal{T} \tag{18}$$

$$\sum_{j \in \mathcal{T}} f(j, i, t_k - a_j) - \sum_{j \in \mathcal{T}} f(i, j, t_k) = 0, \forall i \in \mathcal{T}, t_k - a_j, t_k \in \zeta \tag{19}$$

Note that the probability that a target $i$ is covered by a resource at time $t_k$ is equal to the probability that a resource stays at target $i$ during the time period after $t_k$, i.e., $c_i(t_k) = f(i, i, t_k)$. Thus we have the objective and Eq. 16 together to guarantee the optimal defender utility. Eqs. 17 - 19 are for the properties of $m$-units $s - t$ flow. The coverage vector $c = \{f(i, i, t_k) : i \in \mathcal{T}, t_k \in \zeta\}$ computed by ADEN can be directly mapped back to a mixed strategy with a finite support, i.e., pure strategies which transfer resources at $t_k(\forall t_k \in \zeta)$. Technically, for a resource at any target $i$ and time $t_k$, we can sample its next destination $j$ with probability proportional to $f(i, j, t_k)$ ($j = i$ means staying at $i$). If there is a move, this resource will be in transition from $t_k$ to $t_k + a_j$. The initial assignment of resources can be sampled based on $f(s, j, t_0)$. This LP has size $poly(M^2 n^2)$. When the value functions are all Lipschitz continuous functions satisfying $|v_i(t) - v_i(t')| \leq K|t - t'|$ for all $i$, we take $\epsilon = K\delta$ and generate an LP with size $poly(KL^2 n^2)$, which gives an $\epsilon$-approximation to the original problem.

5 Experimental Evaluation

We evaluate the performance of the proposed algorithms in terms of attacker utility. A lower attacker utility indicates a higher defender utility given the zero-sum assumption. We assume $t_e = 100$. To illustrate the solution quality of the proposed algorithms, we consider two baseline strategies. The first one is the ORIGAMI algorithm [Kiekintveld et al., 2009] assuming static payoffs. The second one, which we call PDT, is based on the assumption that both the defender and the attacker act at pre-defined, discretized time points $\Phi = \{\frac{n \epsilon}{2} : n = 0, 1, \cdots, 7\}$ as in Xu et al. [Xu et al., 2014]. We also evaluate the scalability of the proposed algorithms.

In each game, we sample piecewise linear value functions with at most two sections, i.e., the number of sections is randomly sampled in $\{1, 2\}$. If a value function is determined to have two linear sections, the discontinuity point will be randomly chosen in $(0, t_e)$, then the values of the function at time $0, t_e$ and the discontinuity point will be randomly chosen in $(0, 100]$, thus the value of a value function ranges in $(0, 100]$. We perform 4 experiment sets to show the performance of the algorithms. In the first experiment set, we restrict transfer time to be zero, and test the solution quality of the algorithms against increasing (1) number of targets; (2) number of resources. We then test the effect of changing $\epsilon$ and changing transfer time on the solution quality of ADEN. The third experiment set tests the scalability of the proposed algorithms. We also test the runtime of the sample procedure.

We first evaluate the solution quality of the algorithms. In Figure 2, the y-axis of all subfigures indicate the optimal attacker utility. Figures 2(a) and 2(b) consider zero transfer time. In Figures 2(a), the x-axis indicates the number of targets. In Figure 2(b), the x-axis indicates the number of resources. These two figures show that despite the number of targets or resources, ADEN and COCO significantly perform better than the baseline strategies. COCO achieves lower attacker utilities than ADEN since it can compute the optimal defender strategies. Figures 2(c) and 2(d) further evaluate the solution quality of ADEN. Figure 2(c) evaluates the effect of increasing $\epsilon$ on ADEN. As the value of $\epsilon$ increases, the optimal attacker utility computed by ADEN increases gently. Since $\epsilon$ is an upper bound of the defender’s loss, the defender’s loss can be far less than $\epsilon$ in reality. Solution quality of PDT is not affected by the value of $\epsilon$, but ADEN outperforms PDT even when $\epsilon = 30$. Figure 2(d) evaluates the effect of increasing transfer time on ADEN and PDT ($\epsilon$ is fixed at 10). The x-axis indicates different levels of transfer time, i.e., for $x = 10$, transfer time of resources is randomly generated in $[10, 20]$. Figure 2(d) shows that as transfer time increases, both ADEN and PDT performs worse. While the effect of increasing transfer time is more obvious on ADEN than it is on PDT. ADEN outperforms PDT even when the maximum transfer time reaches 30. If the transfer time is very large, i.e., larger than the operation time of pure strategies, then the defender’s optimal strategy is static and ADEN and PDT will perform the same as ORIGAMI.

We then evaluate the scalability of the proposed algorithms. In Figure 3, the y-axis indicates runtime in seconds. In Figure 3(a), the x-axis indicates the number of targets. Runtime of COCO shows obvious increasing trend while that of ADEN does not change much as the number of targets
ranges from 6 to 14. In Figure 3(b), the x-axis indicates the number of resources, which does not affect the runtime of COCO or ADEN much as is shown. Figure 3(c) extends the number of targets to 100 and shows the scalability of ADEN against different values of $\epsilon$. Smaller $\epsilon$ leads to longer runtime and more obvious increasing trend in runtime. When $\epsilon = 30$, ADEN can solve games with 100 targets in 20 minutes. We did not show the runtime of COCO in Figure 3(c) since it runs out of memory and fails to return a solution when the number of targets $n > 15$. Figure 3(d) shows the runtime of the sample procedure for sampling pure defender strategies based on the compact optimal mixed strategy computed by COCO.

## 6 Conclusion

This paper makes four key contributions in computing optimal mixed strategies to protect targets with dynamic payoffs: (1) A Stackelberg game model in which both agents have continuous strategy spaces and the payoffs are dynamic. (2) COCO for computing the optimal mixed defender strategy in a compact form when the defender can move resources from one target to another immediately. (3) A sample procedure for sampling implementable pure strategies based on the compact optimal mixed strategy computed by COCO. (4) ADEN for computing an approximately optimal mixed strategy when transfer time of resources is non-negligible. We also provide extensive experimental analysis that shows the solution quality and scalability of the proposed algorithms.

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## References


