A Receding-Horizon MDP Approach for Performance Evaluation of Moving Target Defense in Networks

Zhentian Qian, Jie Fu, and Quanyan Zhu

Abstract—In this paper, we study the problem of assessing the effectiveness of a proactive defense-by-detection policy with a network-based moving target defense. We model the network system using a probabilistic attack graph—a graphical security model. Given a network system with a proactive defense strategy, an intelligent attacker needs to repeatedly perform reconnaissance to learn about the locations of intrusion detection systems and re-plan optimally to reach the target while avoiding detection. To compute the attacker’s strategy for security evaluation, we develop a receding-horizon planning algorithm in a risk-sensitive Markov decision process with a time-varying reward function. Finally, we implement both defense and attack strategies in a synthetic network and analyze how the frequency of network randomization and the number of detection systems can influence the success rate of the attacker. This study provides insights for designing proactive defense strategies against online and multi-stage attacks carried out by a resourceful attacker.

I. INTRODUCTION

Cyber networks in industrial control systems are often targeted by malicious and resourceful attackers. An attacker can identify system vulnerabilities through reconnaissance and compromise the security of a network through calculated, multi-stage attacks. To counter the attacks, a network system may employ a mix of cybersecurity mechanisms, from traditional firewalls, intrusion detection, to moving target defense [1] and cyberdeception [2] with honeyey [3]. However, it is difficult to measure the effectiveness of dynamic defense techniques. The lack of understanding the security gains hinders the practical deployment of advanced dynamic defenses.

Formal security models, such as attack graphs [4] and attack-defense trees [5], have been developed [6] for evaluating security properties in a system. An attack graph captures multiple paths that an attacker can carry out by exploiting vulnerabilities to reach the attack goal. Recent work [7], [8] investigated the security property with Moving Target Defense (MTD) using probabilistic attack graphs, where probabilistic transitions are uncertainties created by network-based randomization. However, there has not been an analytical model for evaluating the effectiveness of MTD for detection.

To detect the presence of an attacker, network administrators often place Intrusion Detection System (IDSs) at several points within the network to monitor traffic to and from all devices on the network and detect suspicious activities. It is an essential component to proactive defense, where the defender is not aware of the existence of the attacker but deploys some pre-defined security protocols. The question we investigate is that, given a proactive defense strategy and an attacker who needs to perform a sequence of actions in order to reach the target, as in lateral movement attacks [9], how effective is a proactive defense strategy to detect the attacker before the attacker succeeds?

For IDSs with fixed locations, an attacker can learn the locations during reconnaissance and avoid these IDSs while carrying out an attack. An effective detection, called “roaming IDSs”, is to randomize the location of IDSs in the network. For example, flow-based IDS [10] allows network flow to pass through and examined by IDS on a per-flow basis using software-defined networking. Roaming decoy [11] has also been used for mitigating Denial-of-Service attacks by shuffling the decoy locations in a network. Detection capabilities of decoys would be leveraged as “roaming IDSs”. This randomization creates uncertainty for the attacker and also increases its cost, as the attacker has to perform reconnaissance to determine the new IDS locations frequently in order to avoid detection.

To understand how effective the defense strategy is, it is necessary to understand how the attacker behaves given the uncertainty. To do this, we model the network with dynamic defense as a time-varying probabilistic attack graph, which is an Markov Decision Process (MDP) with time-varying probabilistic transition function and reward function. Then, we solve the attack strategy using risk-sensitive finite-horizon planning and iterative re-plan the attack strategy using a receding horizon framework. Given the proposed attack strategy, we can evaluate the effectiveness of the detection and defense strategy by characterizing the relation between the probability of successful and stealthy attack, the number of IDSs, and how frequently the IDSs shuffle.

Finally, the paper is structured as follows: In Section III we introduce some preliminaries about attack graphs, and roaming IDS defense strategy, and formulate the problem. In Section IV we design the receding horizon attack planning in the time-varying network. In Section V we evaluate the performance of defense against the proposed online attacker planner. Section VI concludes.

II. RELATED WORK

In the context of moving target defense, attack graph models [12], [13] and dynamic game models [14], [15] have been proposed to capture the strategic interactions between
an attacker and a defender. In [14], a multi-stage game has been proposed to model the kill chain of the adversary. In recent work [16]–[18], attack-defense trees are developed to incorporate defender’s countermeasure [19] and capture the dependencies between actions and subgoals for both attacker and defender. These models are used to verify quantitative security properties expressed via temporal logic, based on solutions of omega-regular games [20]–[22]. These approaches are applicable for synthesizing reactive defense: The defender is aware of the presence of the attacker and reacts to the attack actions in real time. In this work, we study proactive defense when the defender uses a fixed randomization strategy without knowing whether there is an attacker in the network.

For both reactive and proactive defense, one of the critical challenges in applying game theory to security is the performance evaluation of the attack behaviors. This work leverages a receding-horizon technique together with probabilistic attack graphs to assess the effectiveness of a class of cyber defense that explicitly account for the attacker’s uncertainties. The adversary model captures the key properties of the cyber kill chain [23], [24], in which an attacker explores the network and its vulnerability, moves laterally in the network, and take actions to achieve the attack goals, such as data exfiltration, data destruction, or encryption for ransom. Performance evaluation is an essential first step toward the design of effective moving target defense. This work provides informative metrics that would be useful for addressing issues related to defense design, resource planning, and investment.

III. PRELIMINARIES AND PROBLEM FORMULATION

In this section, we introduce the necessary background on formal graphical security models and then formulate the problem to evaluate the effectiveness of the proactive defense strategy.

Definition III.1 (Probabilistic attack graph). A Probabilistic Attack Graph (PAG) is a probabilistic transition system $G = (S, A, P, s_0)$ where $S$ is a set of network nodes, $A$ is a set of attack actions, and $P : S \times A \rightarrow \text{Dist}(S)$ is a probabilistic transition function—that is, $P(s'|s, a)$ is the probability of the attacker reaching node $s'$ from a (compromised) node $s$ with an attack action $a$ (targeted at $s'$ only). The probability of failing to exploit a vulnerability results in self-loop $P(s|s, a) = 1 - P(s'|s, a)$. The state $s_0$ is the initial entry node for the attacker.

The reader may think of the PAG as an MDP, in which the set of actions are the attacker’s exploitation actions. The probability of an attacker successfully exploiting a vulnerability can be estimated based on the Common Vulnerability Scoring System (CVSS) [25], as used in [26], [27].

Using network-based MTD techniques, it is possible to randomize the software/hardware or the topology of the network. We consider a case of IDS randomization techniques where the locations of IDSs can be sampled from the set of nodes of the network. For example, if $s \in S$ is sampled, then all flows to node $s$ will be examined by an IDS. We say that the node $s$ is equipped with an IDS.

For simplicity, we assume that when the attacker sends a package to exploit the vulnerability of a target node and if the node is equipped with an IDS, the attacker will be detected and blocked from the network.

We aim to evaluate the security level of the system for a proactive defense strategy, defined as follows:

Definition III.2. A periodic defender strategy $\delta(t + T_r) = \delta(t)$ that randomly selects $k$ out of a subset $N \subseteq S$ of nodes in the network as the IDS locations every $T_r$ steps.

Assumption III.1. The following assumptions are made for the attacker:

- The attacker knows the PAG but does not know the defender strategy $\delta$ and $T_r$.
- The attacker can exercise the network scan every step, before taking any attack action, to learn about the locations of IDSs at that moment.
- The defender’s action of sampling IDSs is taken concurrently with the attackers’ actions.

It is noted that if the defender uses a Poisson distribution over the period $T_r$, even the attacker learns the mean and variance, it cannot know exactly when the IDSs have been shuffled. Thus, the assumption that the attacker does not know $T_r$ is not necessary.

Definition III.3 (Reach-avoid attack objective). Given the PAG and let $s_f \in S$ be the target for the attacker, the objective of the attacker is to avoid detection while reaching $s_f$.

Definition III.4 (Detection events). An attacker can be detected if it attempts any action $a \in A$ at node $s$ to reach target $s'$ and $s'$ is equipped with an IDS.

In other words, the attacker can be detected by exploiting a node equipped with an IDS, no matter if the attack action is successful or not.

Example III.1. We introduce an example to illustrate the concept. Figure 1 depicts a small network with three hosts, equipped with SDN-enabled roaming IDS. At each time step, the IDS can be randomly assigned to a target host and monitor the flow. Figure 2a shows a transition in the PAG where the attacker has gained trust on host 1 which is an FTP server. The FTP server consists of a vulnerability which allows the attacker to obtain reverse shell (rsh) on the system. By carrying out rsh attack on host 1, the attacker succeeds with probability $p$ to gain user access on host 1, and with probability $1−p$ that the action fails. When the IDS is equipped with host 1, then the attacker’s action rsh will be detected, leading to the sink state—detected—in Fig. 2b.

Problem 1. Given a defense strategy $\delta$ and an initial state $s_0 \in S$ of PAG, with what probability the attacker can achieve its attack objective? What is the best response of the attacker given the lack of knowledge in the defender’s strategy?
IV. ATTACKER’S BEHAVIOR MODELING

To understand how the attacker plans given the nonstationary environment, we introduce an attack behavior model using online planning in MDPs. In this section, we first introduce a preliminary on risk-sensitive, finite horizon planning, and then present a receding horizon framework that iteratively solves finite-horizon problems in a time-varying MDP.

A. Preliminaries: Risk-sensitive planning in MDPs

Given an MDP $G = (S, A, P, \nu)$ where $(S, A, P)$ are state, action spaces and transition function, $\nu$ is the initial state distribution, we introduce an immediate reward function as:

$$r_t : S \times A \rightarrow \mathbb{R}^+, \forall t \in [t_0, t_0 + T - 1]$$

(1)

where $T \geq 0$ is a constant for finite horizon length. The terminal reward $r_{t_0+T} : S \rightarrow \mathbb{R}^+$ depends only upon the state $s \in S$. The finite horizon risk-sensitive optimal planning problem is described as follows: Given the MDP, the immediate reward function $r_t, t \in [t_0, t_0 + T - 1]$ and the terminal reward function $r_{t_0+T}$, compute a policy $\Pi^\nu = (\pi_{t_0}, \pi_{t_0+1}, \ldots, \pi_{t_0+T-1})$ where $\pi_t : S \rightarrow \text{Dist}(A)$ such that the following objective is maximized:

$$J_{t_0}(\nu, \Pi^\nu) = 
\mathbb{E}^{\nu, \Pi^\nu}\left[ \exp\left( \lambda \sum_{n=t_0}^{t_0+T-1} r_n(S_n, A_n) + r_{t_0+T}(S_{t_0+T}) \right) \right]$$

(2)

where $\lambda$ is a discounting factor, $\nu$ is the distribution over states at $t = t_0$, the expectation $\mathbb{E}^{\nu, \Pi^\nu}$ is computed from the Markov chain induced by policy $\Pi^\nu$; i.e., the state and action processes $\{S_t\}_{t_0 \leq t \leq t_0+T}, \{A_t\}_{t_0 \leq t \leq t_0+T-1}$.

As shown in [28], the risk-sensitive objective can be minimized using linear programming, with the primal and dual linear programs formulated as:

**Primal Linear Program:**

\[
\min \left\{ u_t(s) \mid s \in S, t_0 \leq t \leq t_0 + T - 1 \right\} \sum_{s \in S} \nu(s) u_t(s),
\]

subject to:

\[
  u_{t_0+T-1}(s) \geq b_{s,a}, \quad \forall s \in S, \forall a \in A,
\]

\[
  u_t(s) - \mathbb{E}^{\nu}(s,a) \sum_{s' \in S} P(s'|s,a) u_{t+1}(s') \geq 0,
\]

\[
  \forall s \in S, \forall a \in A \text{ and } \forall t : t_0 \leq t \leq t_0 + T - 2,
\]

(3)

where:

$$b_{s,a} := \mathbb{E}^{\nu}(s,a) \sum_{s' \in S} P(s'|s,a) e^{r_{t_0+T-1}(s,a)}.$$  

(4)

The solution of the primal LP provides $\{u_t(s) \mid s \in S, t_0 \leq t \leq t_0 + T - 1\}$ where $u_t(s) = \max_{\Pi^t} J_t(s, \Pi^t)$ (see [2]) with $\Pi^t = [\pi_t, \ldots, \pi_{t_0+T-1}]$.

**Dual Linear Program:** With decision variables: $y = \{y(t,s,a) \mid t_0 \leq t \leq t_0 + T - 1\}$.

\[
\max_y \sum_{a \in A} \sum_{s \in S} b_{s,a} y(t_0 + T - 1, t, s, a)
\]

subject to:

\[
\sum_{a \in A} y(t_0, s', a) = \nu(s'), \quad \forall s' \in S,
\]

\[
\sum_{a \in A} y(t, s', a) = \mathbb{E}^{\nu}(s,a) \sum_{s'' \in S} P(s'|s,a) y(t-1, t, s, a),
\]

\[
\forall t : t_0 + 1 \leq t \leq t_0 + T - 1, \forall s' \in S.
\]

(5)

The solution to the dual LP would define the optimal policy of the risk sensitive MDP: For each $t$ such that $t_0 \leq t \leq t_0 + T - 1$, the nonstationary policy is

$$\pi_t(s,a) := \frac{y(t,s,a)}{\sum_{a'} y(t,s,a')}, \forall s \in S \text{ and } \forall a \in A.$$  

(6)

B. Receding-horizon attack planning

As the PAG is varying over time, we view the attacker as a receding horizon planner. The receding-horizon models captures the lateral movement of the reconnaissance-exploitation-actions kill chain of an attacker. At each horizon, the attacker intends to map out the locations of IDSs in the network using reconnaissance techniques. Then the attacker exploits the vulnerability to act and move to the next node. This process iterates until the attacker reaches his target.

At each step $t$, the attacker has an MDP with set $S_{IDS,t} \subseteq S$ of nodes equipped with IDSs. We treat these nodes as obstacles which the attacker is to avoid. Given the MDP
\((S, A, P, s_0)\) with IDS placing at \(S_{IDS,t} \subseteq S\) and the current state \(s_t\), the reward function is defined as follows.

\[ r_{t+k}(s, a) = 0, \ \forall s \in S, \forall a \in A; \forall k \in \{t, t+T-1\}; \] (7)

\[ r_{t+T}(s) = \begin{cases} 1 & \text{if } s = s_f; \\ 0 & \text{otherwise} \end{cases} \] (8)

In addition, let sink be an absorbing states with zero reward. The transition function is revised as follows: For each \(s \in S\), for each \(a \in A\), if \(P(s'|s, a) > 0\) and \(s' \in S_{IDS,t}\), then \(P(\text{sink}|s, a) = 1\). In words, when the attacker exploits a vulnerability that has a positive probability to reach a node with IDS, then it will reach a sink state with probability one—that is, it is detected.

**Remark 1.** It is noted that the detection occurs due to the concurrency of actions by the defender and an attacker. If the attacker always knows where the IDSs are in the next moment, then it can avoid these IDSs by either doing nothing or exploits vulnerabilities only on hosts that are not equipped with IDSs. However, randomization and concurrency together create the unknown effects when the attacker exploits.

This receding-horizon attack planner is described in Alg. 1. It starts with time step \(t = 0\), the attacker carries out network scanning and determines the location \(S_{IDS,t}\) of IDSs. Then, the attacker generates the reward function \(r_t\) and \(r_{t+T}\) and solve the finite-horizon risk-averse MDP and obtain the policy \(\Pi_t\). The attacker then takes an action \(a_t\) from the policy. This process iterates until either the attacker reaches the goal, or is detected, or uses all the time.

Given that the attacker uses an online planner, the performance can be evaluated based on regret. To evaluate this regret, we need to solve the optimal policy of the attacker assuming the attacker knows exactly the sequence of locations for IDSs sampled over its planning horizon. This optimal policy can be obtained from the following MDP as a stochastic shortest path problem, described below.

**Definition IV.1.** Given an MDP \(G = (S, A, P, s_0)\) and the attacker’s goal state \(s_f\), let \([S_{IDS,0}, S_{IDS,1}, \ldots, S_{IDS,T_{max}}]\) be a sequence of sampled subsets of nodes equipped with IDSs over the time horizon \([0, T_{max}]\). A time-augmented MDP \(\tilde{G} = (S \times [0, \ldots, T_{max}] \cup \{\text{sink}\}, A, P, (s_0, 0), \tilde{r})\) is defined as follows: \(S \times [0, \ldots, T_{max}] \cup \{\text{sink}\}\) are the set of states, \(A\) is the set of actions, \((s_0, 0)\) is the initial state. The transition function is defined as: For each \(t \in [0, T_{max}-1]\), each \(a \in A\), and each \(s \in S\), there are four cases:

1. If \(s \neq s_f\), \(P(s'|s, a) > 0\), \(s' \neq S_{IDS,t+1}\) and \(s' \neq s\), then \(P(s'|s, a) = P(s|s, a)\) and \(P((s,t+1)|(s,t), a) = P(s|s, a)\).
2. If \(s = s_f\), let \(P(\text{sink}|s,t), a) = 1\), where sink is an absorbing state for any action \(a \in A\).
3. If \(P(s'|s, a) > 0\), \(s' \in S_{IDS,t+1}\), and \(s \neq s'\), then let \(P(\text{sink}|s,t), a) = 1\).
4. If \(t = T_{max}\), \(P(\text{sink}|(s,T_{max}), a) = 1\).
ute how effective the defense strategy is. All experiments in this section are performed on a computer equipped with an Intel R Core™ i7-5700HQ and 8GB of RAM running a python 3.6 script on a 64-bit Ubuntu R 18.04 LTS.

The graph of PAG from the synthetic network is shown in Fig. 3. The graph has twenty nodes. Note that the self-loops are omitted in the graph for clarity. The IDSs in the network are sampled using a simple random sampling process at a uniform distribution from a subset \( N = \{0, 12, 2, 8, 1, 13, 15, 10, 9, 5\} \) of all network nodes every \( k \) steps, in other words, sampled at \( \frac{1}{k} \) frequency. When \( k \) approaches infinity (i.e., 0 frequency), the locations of IDSs do not change. The attacker has no access to \( k \) and recomputes his policy every step. We assume that once the IDSs are selected, the attacker knows where the new locations of IDSs are. With such an resourceful attacker, this approach yields the worst-case scenario. Thus, the analysis against this type of attacker provides us a lower bound on the security level of the system, measured by the probability that the attacker can reach the target while avoiding IDSs.

Fig. 3: The graph of the probabilistic attack graph from a synthetic network.

We conduct a experiment to investigate how the effectiveness of the roaming IDSs policy can be influenced by (1) the frequency in re-sampling; (2) the number of IDSs; In the experiment, the number of IDSs in the network ranges from one to five. The frequency \( k \) of the sampling of the IDSs range from zero (the location of the IDSs never change) to one (the location of the IDSs change every time instant).

Table I shows the parameters used in the attacker’s receding horizon planner:

| Parameters | Values |
|------------|--------|
| Finite horizon length \( T \) | 19 |
| Maximum time length \( T_{max} \) | 100 |
| Probability of successfully exploit a vulnerability \( p \) | 0.9 |
| Attacker initial state \( s_0 \) | 17 |
| Attacker target state \( s_f \) | 7 |
| Risk factor \( \lambda \) in (2) | 1.0 |

B. The frequency of the re-sampling of the IDSs

Fig. 4: The effect of the frequency of the re-sampling of the IDSs on the success rate of the attacker.

The experiment results are shown in Fig. 4 and Fig. 5. From Fig. 4 it is observed that the success rate of the attacker reaching the target decreases as the re-sampling frequency increases. Such results are intuitive as the more frequently IDSs are being re-sampled, the more likely they are to appear where the attacker is and detect the attacker. However, more frequent shuffle of network flow may incur overhead cost including traffic delay and disruption. It is also interesting to observe that the success rate of attack when re-sampling at \( \frac{1}{5} \)Hz is higher than that of a frequency of zero. This is because re-sampling would sometime free the attacker from a deadlock. For example, when the attacker is at state 0 and the IDS is at state 17, the best strategy for the attacker is to remain put. When the IDSs are being re-sampled every \( k \) steps, the deadlock is lifted. However, the same observation may not be obtained if the static IDSs are located in different nodes initially or the attacker starts with different initial nodes in the network. The choice of sampling locations of IDSs requires game-theoretic reasoning such as resource-allocation games [29] and can be analyzed in the future work.

C. Number of IDSs

In Fig. 5 we show the experiment results that reflect how the number of the IDSs in the network influences the effectiveness of the roaming IDS policy.

From Fig. 5 it can be seen that the success rate of the attacker reaching the target decreases as the number of the IDSs in the graph increases. It suggests that the more IDSs are in the graph, the more effective the roaming IDS policy would be.

D. The distance to the target

In this experiment we further evaluate the effect of the distance of the attacker initial state to the target on the MTD policy. Optimal and online policies are computed for ten sequences of random IDS configurations. In each IDS configuration, three IDSs are randomly sampled from the IDS set \( N \) at a frequency \( k = \frac{1}{3} Hz \). Evaluation is performed on attacker initial node \( s_0 \in \{7, 13, 9, 11, 10, 0, 19\} \) with

Fig. 5: The effect of the number of the IDSs on the success rate of the attacker.
Fig. 5: The effects of the number of the IDSs on the success rate of the attacker.

Fig. 6: Dynamic regret analysis

Fig. 7: Success rate analysis

VI. CONCLUSIONS AND DISCUSSION

In this paper, we introduced a new method to evaluate the effectiveness of a MTD policy for detection. Given time-varying locations of detection systems in a network, we formulate the planning problem for a stealthy attacker using the receding horizon framework. The attacker repeatedly performs reconnaissance to know where IDSs are placed and solves a risk-sensitive finite-horizon planning problem in the probabilistic attack graph. We assess the effectiveness of the proactive defense strategy using the detection rate in the presence of such an intelligent attacker. This work provides foundations to several future extensions: (1) We will investigate adaptive attacker, who learns the dynamics of the network from past iterations. Several no-regret learning algorithms and online planning in MDPs with regret bounds [30] can be considered for attacker behavior modeling; (2) Given the evaluation result, we can construct the game between the defender, who selects subsets of nodes for randomization, against the intelligent, potentially adaptive attacker. Through game-theoretic reasoning, we can compute optimal detection strategy that trades off multiple objectives: Maximizing the detection rate and minimizing the operational cost.

REFERENCES

[1] S. Sengupta, A. Chowdhary, A. Sabur, D. Huang, A. Alshamrani, and S. Kambhampati, “A Survey of Moving Target Defenses for Network Security,” arXiv:1905.00964 [cs], May 2019.
[2] S. Jajodia, V. S. Subrahmanian, V. Swarup, and C. Wang, Eds., Cyber Deception: Building the Scientific Foundation. Springer International Publishing, 2016.
[3] N. Provos and T. Holz, Virtual honeypots: from botnet tracking to intrusion detection. Pearson Education, 2007.
[4] S. Jha, O. Sheyner, and J. Wing, “Two formal analyses of attack graphs,” in Proceedings 15th IEEE Computer Security Foundations Workshop, CSFW-15, Jun. 2002, pp. 49–63.
[5] B. Kordy, S. Mauw, S. Radomirović, and P. Schweitzer, “Foundations of Attack–Defense Trees,” in Formal Aspects of Security and Trust, ser. Lecture Notes in Computer Science, P. Degano, S. Etalle, and J. Guttman, Eds. Berlin, Heidelberg: Springer, 2011, pp. 80–95.
[6] B. Schneier, “Attack Trees,” http://www.schneier.com/paper-attacktrees-ddj-ft.html, Aug. 2007.
[7] J. B. Hong and D. S. Kim, “Assessing the Effectiveness of Moving Target Defenses Using Security Models,” IEEE Transactions on Dependable and Secure Computing, vol. 13, no. 2, pp. 163–177, Mar. 2016.
[8] J. Hong and D.-S. Kim, “HARMs: Hierarchical Attack Representation Models for Network Security Analysis,” in *Australian Information Security Management Conference*. SRI Security Research Institute, Edith Cowan University, Perth, Western Australia, December 2012.

[9] “Network lateral movement from an attacker’s perspective,” https://searchsecurity.techtarget.com/news/450427135/Network-lateral-movement-from-an-attackers-perspective.

[10] G. A. Ajaeiya, N. Adalian, I. H. Elhajj, A. Kayssi, and A. Chehab, “Flow-based intrusion detection system for sdn,” in *2017 IEEE Symposium on Computers and Communications (ISCC)*, July 2017, pp. 787–793.

[11] S. Khattab, C. Sangpachatanaruk, D. Mosse, R. Melhem, and T. Znati, “Roaming honeypots for mitigating service-level denial-of-service attacks,” in *24th International Conference on Distributed Computing Systems, 2004. Proceedings.*, Mar. 2004, pp. 328–337.

[12] M. M. Islam, Q. Duan, and E. Al-Shaer, “Specification-driven moving target defense synthesis,” in *Proceedings of the 6th ACM Workshop on Moving Target Defense*, ser. MTD’19. New York, NY, USA: Association for Computing Machinery, 2019, p. 13–24. [Online]. Available: https://doi.org/10.1145/3338468.3356830

[13] J. B. Hong and D. S. Kim, “Assessing the effectiveness of moving target defenses using security models,” *IEEE Transactions on Dependable and Secure Computing*, vol. 13, no. 2, pp. 163–177, March 2016.

[14] Q. Zhu and T. Başar, “Game-theoretic approach to feedback-driven multi-stage moving target defense,” in *Decision and Game Theory for Security*. Springer, 2013, pp. 246–263.

[15] Y. Huang, J. Chen, L. Huang, and Q. Zhu, “Dynamic Games for Secure and Resilient Control System Design,” *National Science Review*, 01 2020, nwz218. [Online]. Available: https://doi.org/10.1093/nsr/nwz218

[16] B. Kordy and W. Widel, “On Quantitative Analysis of Attack–Defense Trees with Repeated Labels,” in *Principles of Security and Trust*, ser. Lecture Notes in Computer Science, L. Bauer and R. Küsters, Eds. Cham: Springer International Publishing, 2018, pp. 325–346.

[17] Z. Aslanian, F. Nielsen, and D. Parker, “Quantitative Verification and Synthesis of Attack-Defence Scenarios,” in *International Workshop on Graphical Models for Security*. Springer, 2017, pp. 75–90.

[18] B. Kordy and W. Widel, “On Quantitative Analysis of Attack–Defense Trees with Repeated Labels,” in *Principles of Security and Trust*, ser. Lecture Notes in Computer Science, L. Bauer and R. Küsters, Eds. Cham: Springer International Publishing, 2018, pp. 325–346.

[19] B. Kordy, S. Mauw, S. Radomirović, and P. Schweitzer, “Foundations of attack–defense trees,” in *International Workshop on Formal Aspects in Security and Trust*. Springer, 2010, pp. 80–95.

[20] C. Baier and J.-P. Katoen, *Principles of Model Checking (Representation and Mind Series)*. The MIT Press, 2008.

[21] N. Piterman, A. Pnueli, and Y. Sa’ar, “Synthesis of Reactive(1) Designs,” in *Verification, Model Checking, and Abstract Interpretation*, ser. Lecture Notes in Computer Science, E. A. Emerson and K. S. Namjoshi, Eds. Berlin, Heidelberg: Springer, 2006, pp. 364–380.

[22] B. Kordy, S. Mauw, S. Radomirović, and P. Schweitzer, “Foundations of attack–defense trees,” in *International Workshop on Formal Aspects in Security and Trust*. Springer, 2010, pp. 80–95.

[23] S. Rass and Q. Zhu, “Gadapt: a sequential game-theoretic framework for designing defense-in-depth strategies against advanced persistent threats,” in *International Conference on Decision and Game Theory for Security*. Springer, 2016, pp. 314–326.

[24] T. Yadav and A. M. Rao, “Technical aspects of cyber kill chain,” in *Security in Computing and Communications*, J. H. Abawajy, S. Mukherjea, S. M. Thampi, and A. Ruiz-Martínez, Eds. Cham: Springer International Publishing, 2015, pp. 438–452.

[25] “Common Vulnerability Scoring System SIG,” https://www.first.org/cvss.

[26] M. Frigault, L. Wang, A. Singhal, and S. Jajodia, “Measuring network security using dynamic bayesian network,” in *Proceedings of the 4th ACM Workshop on Quality of Protection - QoP ’08*. Alexandria, Virginia, USA: ACM Press, 2008, p. 23.

[27] L. Muñoz-González, D. Sgandurra, M. Barrère, and E. C. Lupu, “Exact inference techniques for the analysis of bayesian attack graphs,” *IEEE Transactions on Dependable and Secure Computing*, vol. 16, no. 2, pp. 231–244, 2017.

[28] A. Kumar, V. Kavitha, and N. Hemachandra, “Finite horizon risk sensitive mdp and linear programming,” in *2015 54th IEEE Conference on Decision and Control (CDC)*. IEEE, 2015, pp. 7826–7831.