Improving the Efficiency of Intrusion Detection Systems by Optimizing Rule Deployment Across Multiple IDSs

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Abstract: Intrusion Detection Systems (IDS) are strategically installed on specific nodes of an enterprise network to detect ongoing attempts to exploit vulnerable systems. However, deploying a large number of detection rules in each IDS may reduce their efficiency and effectiveness, especially when an IDS is monitoring high-speed data communication channels. Existing research on optimal IDS placement strategies does not address the problem at such a level of granularity. This paper proposes a novel approach for strategic rule deployment subject to various practical constraints. Attack graph-based modeling, along with knowledge of the network topology, is employed to identify the set of suitable rules for deployment on individual IDSs, and capacity constraints are considered to balance the load across IDSs. We provide a formal specification of the optimization problem and propose a practical heuristic solution based on a genetic algorithm.

1 INTRODUCTION

In today's cybersecurity landscape, a robust intrusion detection mechanism is necessary for any networked system to detect incoming attacks. In the last few decades, advanced persistent threat (APT) actors have developed highly advanced attack vectors that can bypass existing detection mechanisms. SolarWinds Supply Chain Attack (2020), Hafnium Exchange Server Exploits (2021), NOBELIUM Campaign (2021), Conti Ransomware Attacks (2021-2022) are examples of such attacks, which have targeted systems of importance to countries. Security researchers are working towards advancing intrusion detection technology using various mechanisms based on patterns, rules, and machine learning techniques (Liao et al., 2013; He et al., 2023; Chou and Jiang, 2021). Even after developing many defensive techniques like zero-trust architectures (Stafford, 2020) and security-by-design (Sequeiros et al., 2020), there are instances where sophisticated, persistent attacks can circumvent existing IDS mechanisms.

Although optimal IDS placement is a well-researched problem (Noel and Jajodia, 2008; Chen et al., 2010), current solutions do not provide directives for rule deployment. The placement of IDS rules is as important as sensor placement, as network throughput and security will depend on the number and appropriateness of the rules deployed. Usually, the rule deployment task is left to network security administrators, making it error-prone. In a networked system with multiple deployed IDS sensors, determining the optimal rule deployment based on the computational capacity of systems and the suitability of the rules requires an automated solution.

In this paper, we proposed an optimized IDS rule placement strategy based on attack modeling. Practical constraints like IDS capacity, traffic volume, and usefulness of the deployed rules are considered while formulating the rule placement strategies. The main contributions of this paper include (i) Leveraging attack modeling to identify sets of candidate rules to be deployed on each IDS to detect exploitation traffic traversing the IDS; (ii) modeling the rule deployment problem as an optimization problem aiming to maximize the number of detectable attack paths, subject to capacity constraints on each IDS; and (iii) a heuristic solution based on a genetic algorithm.

The rest of the paper is organized as follows. Section 2 discusses related research whereas Section 3 provides motivating examples. The formal problem statement is detailed in Section 4, along with its for-

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mulation as an optimization problem. Then, Section 5 presents a case study, and Section 6 discusses the heuristic solution based on a genetic algorithm. Finally, Section 7 presents the results, and Section 8 provides some concluding remarks.

2 RELATED WORK

Noel *et al.* (Noel and Jajodia, 2008) proposed a greedy algorithm for optimal IDS sensor placement using attack graph analysis. The approach in (Chen et al., 2010) used Multi-Objective Genetic Algorithms (MOGAs) for sensor placements meeting various security criteria. (Babatope et al., 2014) extended sensor placement models in Network-Based Intrusion Detection Systems (NIDS), accounting for diverse IDPS technologies.

Optimal detector placement for botnet mitigation has also been explored. (Venkatesan et al., 2015) used heuristic strategies based on centrality measures to identify key nodes for detector placement, aiming to disrupt botnet communication. (Albanese et al., 2018) introduced a monitoring approach based on moving target defense to identify and remove compromised machines. DeBot (Venkatesan et al., 2018) is a network-based scheme designed to detect exfiltration by persistent botnets, focusing on identifying suspicious traffic flows and demonstrating resilience against evasion techniques.

Despite extensive research on IDS placement, the deployment of IDS rules has received less attention. Optimal IDS rule placement can enhance detection efficiency by reducing redundant checks. Our work introduces an adaptive algorithm for optimizing IDS rule placement in a multi-IDS environment to improve network security.

As networks grow more complex, multi-hop attacks become more feasible, necessitating the use of attack graphs for vulnerability analysis and network hardening. Tools like Nessus, OpenVAS, Nexpose, and Burp Suite identify network vulnerabilities, which are categorized by CVE ID and CWE category. Detailed vulnerability information is available in the National Vulnerability Database (NVD). Tools like XploitMAP (Mukherjee et al., 2023), TVA (Jajodia and Noel, 2010), and Attack Dynamics (Sönmez et al., 2022) facilitate the generation of attack graphs.

3 MOTIVATING EXAMPLES

In Figure 1, a moderately complex enterprise network is shown. The network has internet-facing Web

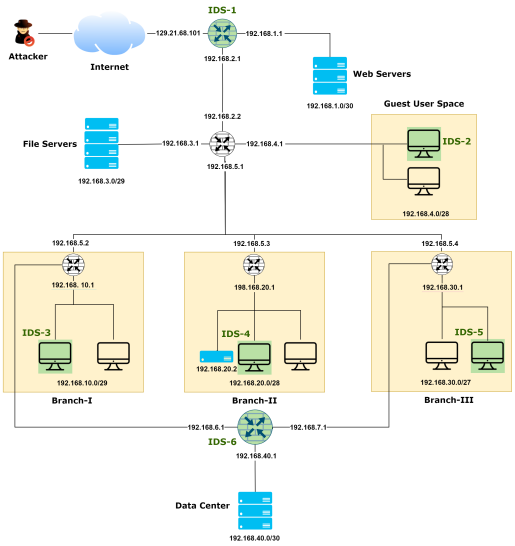


Figure 1: Example of network with multiple IDSs.

Servers, File Servers, and a separate sub-network for guest-user connectivity. Three separate branches of the network are shown. Branch-I and Branch-III are connected to the private Data Center. IPv4 address ranges are displayed for all sub-networks, with a few specific interface IP addresses explicitly shown. A few IDS instances are deployed, as shown in green. Some IDSs are installed within the sub-network, like IDS-2, 3, 4, and 5, and other IDSs are installed on routers connecting multiple sub-networks. IDSs within a sub-network can only observe traffic within that subnet, whereas an IDS deployed on a router can monitor the traffic across all connected subnetworks.

Applications on various network hosts may have exploitable vulnerabilities. Direct exploitation of vulnerabilities in the Data Center may be prevented by network traffic filtering. Thus, attackers must devise multi-hop attacks to reach their targets. In these scenarios, different IDSs will encounter different types of attack traffic. IDSs near the internet might detect initial stages of a multi-hop attack, such as phishing attempts, while an internal IDS might observe more advanced stages, like lateral tool transfers. Understanding the positions of IDSs and modeling multi-hop attacks can inform the development of an advanced and effective IDS rule placement strategy. When deploying IDS rules, various scenarios may arise, and our proposed solution aims to handle all such cases.

Scenario 1. Figure 2 illustrates examples of multi-hop attacks within a section of the network shown in Figure 1. These attacks are denoted with dotted curved arrows. An internet-based attacker might exploit a vulnerability in an internet-facing web server (e.g., a buffer overflow). After compromising the web server, the attacker can launch a second attack (e.g.,

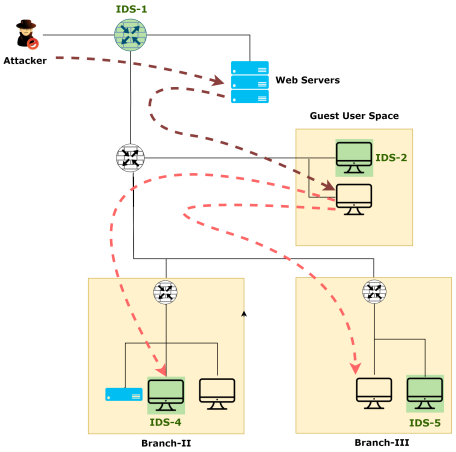


Figure 2: Scenario 1.

spearphishing) on a host in the guest user space. Suppose two Windows servers in Branch-II and Branch-III expose the same vulnerability (CVE-2022-29139: Remote Code Execution Vulnerability). An attacker with access to the guest user's machine can exploit this vulnerability in either branch.

The final phase of this multi-hop attack would start from the Guest User Space and target either Branch-II or Branch-III. The critical question is where to deploy the IDS rule to detect the exploit of vulnerability CVE-2022-29139. To ensure detection, the IDS rule should be placed either on IDS-2 alone or on both IDS-4 and IDS-5. The decision requires careful consideration of traffic volumes in different network sections. If the guest user network handles significant traffic, adding the rule to IDS-2 could strain computational resources. Conversely, deploying the rule on both IDS-4 and IDS-5 would increase maintenance costs. Deploying the rule on any other IDS would waste computational resources without improving detection capability. If the rule is deployed on both IDS-2 and IDS-4/IDS-5, it would result in redundant checks of the same traffic.

Scenario 2. Figure 3 shows an attacker using one of two multi-hop paths to reach the Data Center. The initial phase, exploiting a vulnerability in the File Server, is common to both paths. After this, the attack can proceed along two sub-paths, indicated by the orange (left side) and red (right side) dotted arrows.

To detect any attack directed at the Data Center, it is crucial to monitor all potential attack paths. This can be accomplished by deploying an IDS rule to detect the File Server exploit on IDS-1 or by ensuring detection on both alternative sub-paths. Detecting attacks where paths converge can minimize the number of IDS rules deployed but may overburden the IDS due to high traffic volumes. Typically, the traffic from the internet to the File Server is significant, so adding

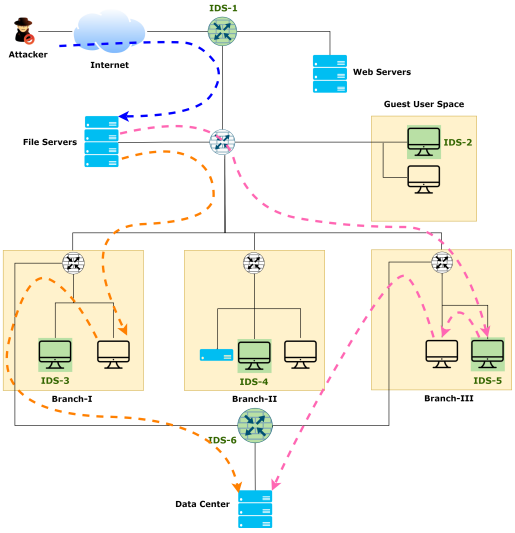


Figure 3: Scenario 2.

a rule to IDS-1 could heavily tax resources. The same issue arises if a rule is added to IDS-6 to detect attacks towards the Data Center Server. Alternatively, adding rules to IDS-3 and IDS-5 would distribute the load more evenly but would require rules on both IDSs to cover each attack path. This approach balances the use of computational resources, ensuring that detection is effective without overloading a single IDS.

4 PROBLEM STATEMENT

In this paper, we address the problem of optimally deploying intrusion detection rules on multiple Intrusion Detection Systems installed across a complex network. We model the network as a graph $G = (N, E)$ where N is a set of nodes representing hosts and routers and E is a set of edges representing connection between them. We use $R \subset N$ to denote the set of routers and $H \subset N$ to denote the set of hosts, with $R \cup H = N$ and $R \cap H = \emptyset$. A complex network is typically partitioned into multiple subnetworks connected by routers, with hosts in each subnetwork connected to one another through a local area network. The i-th subnetwork can be modeled as a graph $S_i = (N_i, E_i)$ where $N_i \subset N$ and $E_i = \{(u,v) | u,v \in N_i\}$, i.e., a subnetwork includes a subset of the nodes and the edges connecting them. Two or more subnetworks $S_1, S_2, \ldots, S_m$ can be connected through a router $r \in R$, such that $\{r\} = \bigcap_{i=1}^{m} N_i$, i.e, the router r is a node in each of the interconnected subnetworks.

Without loss of generality, we assume that for any two subnetworks S_i, S_j there is no more than one router connecting them, i.e., $|N_i \cap N_j| \leq 1$, and that every host $h \in H$ belongs to only one subnetwork. We

assume that intrusion detection systems are installed on a subset $D \subset N$ of the nodes, which may include both hosts and routers. An IDS installed on a host h in a subnetwork S_i can see all the traffic traversing that subnetwork, whereas an IDS installed on a router that connects subnetworks $S_1, S_2, \ldots, S_m$ can see all the traffic traversing any of those subnetworks.

Intrusion detection systems are equipped with sets of rules designed to identify attempts to penetrate and compromise networked systems. In particular, we are interested in deploying rules that are designed to detect attempts to exploit known vulnerabilities on any of the hosts in the network. To guide the optimal deployment of IDS rules, we need to map each IDS to the set of vulnerabilities such that an attempt to exploit one of these vulnerabilities results in network traffic that can be intercepted by that IDS. To this aim, we model an attack graph as a graph $A = (V, L)$ where V is a set of vulnerabilities and L is a set of edges representing dependencies between vulnerabilities in multi-step attacks, and we use a function $\gamma : V \to H$ to map each vulnerability $v \in V$ to the host $h \in H$ that exposes that vulnerability. An edge $(v_1, v_2) \in L$ represents an attack step and indicates that vulnerability v_2 can be exploited after exploiting vulnerability v_1. Let $\mathcal{P}$ denote the set of all attack paths over A. An attack path $a \in \mathcal{P}$ is a sequence of vulnerabilities $a = \langle v_{i_1}, \ldots, v_{i_n} \rangle$ s.t. $(\forall i \in [0, n-1])(v_i, v_{i+1}) \in L$.

An attempt to exploit v_2 will result in traffic from $\gamma(v_1)$ to $\gamma(v_2)$, traversing a sequence of subnetworks and routers $P(v_1, v_2) = \langle S_{i_0}, R_{i_1}, S_{i_1}, \ldots, R_{i_k}, S_{i_k} \rangle$, with $\gamma(v_1) \in N_{i_0}$, $\gamma(v_2) \in N_{i_k}$, and $R_{i_j} \in N_{i_{j-1}} \cap N_{i_j}$, where N_{i_j} is the set of nodes in subnetwork S_{i_j}, i.e., router R_{i_j} is the router connecting two consecutive subnetworks in $P(v_1, v_2)$, with the two vulnerabilities v_1 and v_2 being exposed on hosts in the first and last subnetwork respectively. Deploying an IDS rule for vulnerability v_2 on an IDS installed on any router or subnetwork in $P(v_1, v_2)$ will result in detecting an exploit of v_2. In the following, we will slightly abuse notation for the sake of brevity and use $P(v_1, v_2)$ to denote the following set of nodes, i.e., the set all nodes that can see traffic between $\gamma(v_1)$ and $\gamma(v_2)$:

$$P(v_1, v_2) = \bigcup_{j \in [0,k]} N_{i_j} \tag{1}$$

Let $\mathcal{R}$ denote the set of available IDS rules, and let $\delta : V \to 2^{\mathcal{R}}$ denote a mapping that associates each vulnerability $v \in V$ with a set of rules $\delta(v)$ that can detect an attempt to exploit v. A *rule deployment* is a mapping $\rho : D \to 2^{\mathcal{R}}$ that associates each IDS $d \in D$ with a set of rules $\rho(d)$ to be deployed on it. Based on these preliminary definitions and notations, we can now define the notions of attack step detection and attack path detection.

Definition 1 (Attack Step Detection)**.** *Given a network $G = (N, E)$, with an IDS deployed on each node in $D \subseteq N$ and an attack graph $A = (V, L)$, an attack step $(v_i, v_j) \in L$ can be detected if and only if $D \cap P(v_i, v_j) \neq \emptyset \wedge \exists d \in D \cap P(v_i, v_j)$ s.t. $\delta(v_j) \cap \rho(d) \neq \emptyset$, i.e., there is at least one IDS that can observe traffic between the hosts exposing vulnerabilities v_i and v_j and at least one IDS rule for v_j is deployed on at least one such IDS.*

Definition 2 (Attack Path Detection)**.** *Given a network $G = (N, E)$, with an IDS deployed on each node $D \subseteq N$ and an attack graph $A = (V, L)$, an attack path $\langle v_{i_1}, \ldots, v_{i_n} \rangle$ can be detected if at least one attack step $(v_{i_j}, v_{i_{j+1}})$ can be detected, formally if and only if $\exists j$ s.t. $D \cap P(v_{i_j}, v_{i_{j+1}}) \neq \emptyset \wedge \exists d \in D \cap P(v_{i_j}, v_{i_{j+1}})$ s.t. $\delta(v_{i_{j+1}}) \cap \rho(d) \neq \emptyset$, i.e., there is at least one IDS that can observe traffic between the hosts exposing vulnerabilities corresponding to at least one attack step $(v_{i_j}, v_{i_{j+1}})$, and at least one IDS rule for $v_{i_{j+1}}$ is deployed on at least one such IDS.*

Our objective is to determine a rule deployment ρ that maximizes the number of detectable attack paths. Section 4.1 formulates the optimization problem and proposes a solution based on a genetic algorithm.

4.1 Optimization Problem

Consider a set of start nodes $H_s \in H$ and a set of goal nodes $H_g \in H$. Our objective is to maximize the number of attack paths between H_s and H_g that can be detected, subject to capacity constraints on individual IDSs. Given a rule deployment ρ, consistently with Definition 2, the set of attack paths that can be detected by ρ is defined as follows:

$$\mathcal{P}_\rho = \{a \in \mathcal{P} \mid \exists j \text{ s.t. } D \cap P(v_{i_j}, v_{i_{j+1}}) \neq \emptyset \wedge \exists d \in D \cap P(v_{i_j}, v_{i_{j+1}}) \text{ s.t. } \delta(v_{i_{j+1}}) \cap \rho(d) \neq \emptyset\}$$

Let $c : D \to \mathbb{N}$ denote a mapping that associates each IDS with its capacity expressed as the number of packet inspections that the IDS can perform per unit of time and let $T : D \to \mathbb{N}$ denote a mapping that associates each IDS with the expected volume of traffic traversing it, expressed as the number of packets per unit of time. Each packet observed by an IDS d is matched against each of the rules deployed on that IDS, resulting in $T(d) \cdot |\rho(d)|$ inspections, which cannot exceed the capacity $c(d)$ of the IDS. This constraint can be formalized as follows:

$$(\forall d \in D)\ T(d) \cdot |\rho(d)| \leq c(d) \tag{2}$$

The optimization problem can then be formalized as:

$$\begin{aligned} &\text{Maximize} && |\mathcal{P}_\rho| \\ &\text{subject to} && ((\forall d \in D)|\rho(d)| \cdot T(d) \leq c(d)) \end{aligned} \tag{3}$$

We can represent a deployment $\rho(d)$ as a set $X = \{x_{ij}\}$ of binary decision variables, with $x_{ij} = 1$ if rule r_j deployed on IDS d_i, i.e., $r_j \in \rho(d_i)$. Thus, the constraints can be rewritten as follows:

$$\left(\forall i \in (1,|D|)\right) \sum_{j\in(1,|\mathcal{R}|)} x_{ij} \leq c(d_i)/T(d_i) \quad (4)$$

Let p_k denote the k-th attack path in $\mathcal{P}$, with $k \in (1,|\mathcal{P}|)$. Then, let $p_{km} = (v_{s_{km}}, v_{d_{km}})$ denote the m-th attack step of attack path p_k, with $m \in (1,|p_k|)$. We can now represent the mapping δ as a set of binary values $\{\delta_{jkm}\}$ with $\delta_{jkm} = 1$ if rule r_j can detect the m-th attack step of attack path p_k, i.e., $r_j \in \delta(v_{d_{km}})$. Let $o_{ikm} = 1$ if detector d_i can observe traffic corresponding to the m-th attack step of attack path p_k, i.e., $d_i \in D \cap P(v_{s_{km}}, v_{d_{km}})$. Thus, an attack path p_k can be detected if the following condition is satisfied:

$$\sum_{m\in(1,|p_k|)} \sum_{j\in(1,|\mathcal{R}|)} \left(\delta_{jkm} \cdot \sum_{i\in(1,|D|)} o_{ikm} \cdot x_{ij} \right) \geq 1 \quad (5)$$

Accordingly, $\mathcal{P}_\rho$ can be redefined as follows:

$$\mathcal{P}_\rho = \left\{ p_k \in \mathcal{P} \;\middle|\; \sum_{m\in(1,|p_k|)} \sum_{j\in(1,|\mathcal{R}|)} \left(\delta_{jkm} \cdot \sum_{i\in(1,|D|)} o_{ikm} \cdot x_{ij} \right) \geq 1 \right\} \quad (6)$$

Finally, the maximization problem defined by Eq. 3 can then be rewritten as follows:

$$\text{Maximize} \left| \left\{ p_k \in \mathcal{P} \;\middle|\; \sum_{m\in(1,|p_k|)} \sum_{j\in(1,|\mathcal{R}|)} \left(\delta_{jkm} \cdot \sum_{i\in(1,|D|)} o_{ikm} \cdot x_{ij} \right) \geq 1 \right\} \right|$$
$$\text{subject to } \left(\forall i \in (1,|D|)\right) \sum_{j\in(1,|\mathcal{R}|)} x_{ij} \leq c(d_i)/T(d_i).$$

5 ILLUSTRATIVE CASE STUDY

In the experimental setup in Figure 4a, virtual machines simulate the attacker machine, vulnerable hosts, and IDS devices. Open vSwitches (OVS) connect the IDS devices in the network using port mirroring. All four host machines run vulnerable applications. External attackers can reach vulnerable Host 1 and Host 2, as these are accessible from the internet. Due to traffic restrictions, Host 1 can only access Host 2 and Host 3, while Host 2 can access Host 3. The internal Host 4 is accessible only from Host 3.

Attackers can exploit host vulnerabilities to establish footholds for further attacks. Due to connection restrictions, attackers cannot directly exploit the vulnerability on Host 4 but can execute multi-hop attacks to reach it. As shown in Figure 4b, where $v_{i.j}$ represents the j-th vulnerability on the i-th Host, attackers may follow three possible attack paths to gain root access to vulnerable Host 4. The sequences of sub-networks and routers that the traffic will traverse during these multi-hop attacks are illustrated in Figure 4a, with different colors representing the sequence of subnetworks and routers for each attack path.

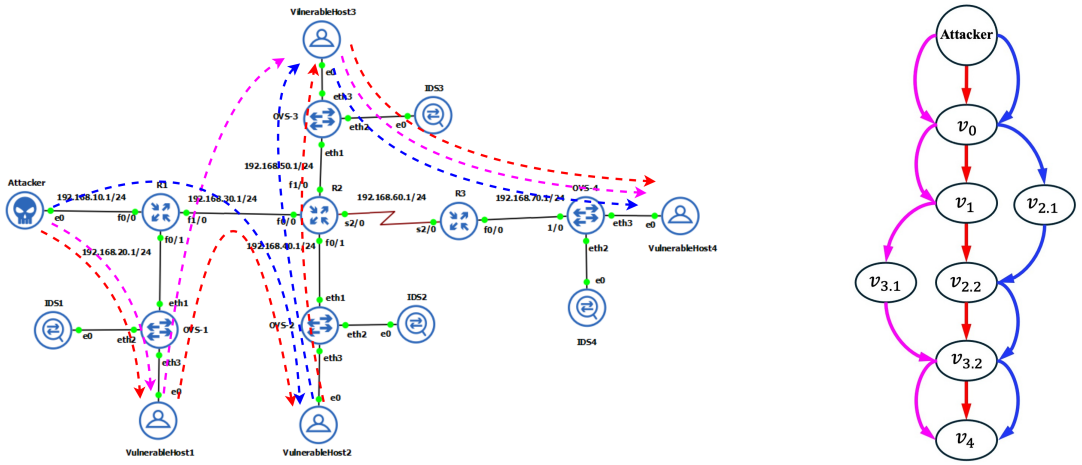
There are four IDSs strategically placed across the network. Our main goal is to deploy IDS rules to maximize detection of attack paths while keeping the load on any particular IDS within its capacity limit. Attack steps on all three attack paths – a_R (red), a_M (magenta), and a_B (blue) – are shown in Table 1. To ensure the security of Host 4, we need to detect at least one attack step per path (i.e., one per row).

None of the IDSs can observe all the attack traffic. For instance, when the attacker executes attack step (v_0, v_1), only IDS-1 can observe the attack traffic. The mapping between IDSs and observable attack traffic is crucial for IDS rule placement. Table 2 illustrates this mapping as a two-dimensional matrix. The appropriate rule for detecting an attack step can be identified based on the mapping in Table 3. The deployment of these rules across the four IDSs will determine the network's attack detection capabilities.

A possible deployment (Example I in Table 4) includes Rule C on IDS 1 and Rule B on IDS 2 to detect attack steps (v_0, v_1) and $(v_0, v_{2.1})$ respectively, thus detecting all attack entry points. Another possible deployment (Example II in Table 5) has Rule C on IDS 4 to detect the last attack step $(v_{3.2}, v_4)$. Security administrators must consider the capacity constraints of each IDS. If the traffic seen by IDS 1 and IDS 4 is too high for these IDSs to inspect all traffic, even for a single deployed rule, then IDS 2 and IDS 3, where traffic loads are lighter, can be utilized for detecting attacks, as shown in Table 6. Rule A on IDS 2 will detect attack steps $(v_{1.3}, v_{2.1})$ (part of path a_M) and $(v_{2.2}, v_{3.1})$ (part of paths a_R and a_B). Rule B on IDS 3 will detect attack step $(v_{0.1}, v_{1.2})$ (part of path a_R). This strategy ensures that critical attack steps are detected while meeting capacity constraints.

6 GENETIC ALGORITHM

As the objective function involves counting the number of attack paths satisfying certain conditions, it is not a simple linear function of the decision variables. Thus, direct methods like linear programming may not be applicable. Given the nonlinearity of the objective function and the binary nature of the decision variables, a heuristic or metaheuristic approach may be suitable for solving this optimization problem. One approach is to use a genetic algorithm (GA) to search for a solution that maximizes the objective function while satisfying the constraints. In a GA ap-



(a) Experimental setup showing all possible attack paths. (b) Attack Graph.

Figure 4: (a) Experimental setup showing all possible attack paths and (b) attack graph.

Table 1: Attack Path to Attack Step Mapping.

Attack Steps	v_0, v_1	$v_0, v_{2.1}$	$v_1, v_{2.2}$	$v_{2.1}, v_{2.2}$	$v_1, v_{3.1}$	$v_{3.1}, v_{3.2}$	$v_{2.2}, v_{3.2}$	$v_{3.2}, v_4$
Path a_R	1	0	1	0	0	0	1	1
Path a_M	1	0	0	0	1	1	0	1
Path a_B	0	1	0	1	0	0	1	1

Table 2: Mapping between IDSs and the attack steps they can observe.

Attack Steps	v_0, v_1	$v_0, v_{2.1}$	$v_1, v_{2.2}$	$v_{2.1}, v_{2.2}$	$v_1, v_{3.1}$	$v_{3.1}, v_{3.2}$	$v_{2.2}, v_{3.2}$	$v_{3.2}, v_4$
IDS 1	1	0	1	0	0	0	0	0
IDS 2	0	1	1	0	0	0	1	0
IDS 3	0	0	0	0	1	0	1	1
IDS 4	0	0	0	0	0	0	0	1

Table 3: Mapping between IDS rules and attack steps they can detect.

Attack Steps	v_0, v_1	$v_0, v_{2.1}$	$v_1, v_{2.2}$	$v_{2.1}, v_{2.2}$	$v_1, v_{3.1}$	$v_{3.1}, v_{3.2}$	$v_{2.2}, v_{3.2}$	$v_{3.2}, v_4$
Rule A	0	0	1	1	0	1	1	0
Rule B	0	1	0	0	1	0	0	0
Rule C	1	0	0	0	0	0	0	1

Table 4: Rule deployment: Example I.

Rules	Rule A	Rule B	Rule C
IDS 1	0	0	1
IDS 2	0	1	0
IDS 3	0	0	0
IDS 4	0	0	0

Table 5: Rule deployment: Example II.

Rules	Rule A	Rule B	Rule C
IDS 1	0	0	0
IDS 2	0	0	0
IDS 3	0	0	0
IDS 4	0	0	1

Table 6: Rule deployment: Example III.

Rules	Rule A	Rule B	Rule C
IDS 1	0	0	0
IDS 2	1	0	0
IDS 3	0	1	0
IDS 4	0	0	0

proach, each individual in the population represents a potential solution, and the fitness of each individual is driven by the optimization function. Selection, crossover, and mutation operators are applied to the population iteratively to generate better solutions over generations. The GA continues until a termination criterion is met, such as reaching a maximum number of generations or convergence to a satisfactory solution. Finally, the best solution found by the GA can be used as the solution to the optimization problem.

Initial Population. The initial population consists of a set of individuals, where each individual represents a potential solution to the optimization problem. In our case, each individual corresponds to a set of values assigned to the binary decision variables x_{ij}. To create the initial population, we can randomly generate binary vectors of length $|D| \cdot |\mathcal{R}|$, representing different configurations of deployed rules on IDSs,

ensuring diversity in the initial population to explore a wide range of potential solutions and ensuring that each solution satisfies the constraints.

Fitness Evaluation. The fitness score assesses the effectiveness of a solution in detecting attack paths. A few inherent factors characterizing the quality of a rule deployment are identified and utilized to formulate a fitness evaluation function.

Selection. After completing the fitness evaluation, solutions are chosen for the next generation of the GA. Solutions with higher fitness values are more likely to be selected for their potential to produce offspring of higher quality. For the present scenario, *steady-state selection* is used, which not only prioritizes solutions with higher fitness, but also allows some diversity by retaining a portion of less fit solutions.

Crossover. Crossover combines genetic information from selected parent solutions to create new offspring, mimicking natural reproduction by passing traits from both parents to the next generation. In this problem, we use a method called single-point crossover. This technique randomly selects a point along the solution and exchanges genetic information beyond that point between two parent solutions.

Mutation. Mutation introduces random changes in the genetic information of solutions to maintain diversity within the population. It prevents the GA from converging too quickly to a sub-optimal solution by exploring new regions of the solution space. A random percentage of genes in the solution are randomly flipped (mutated) from 0 to 1 or vice versa.

Termination. The termination criterion determines when the GA stops iterating and returns the best solution found. In our implementation, the termination criterion is defined as not satisfying the minimum required improvement in the solution between consecutive generations. This criterion ensures that the GA stops when it reaches a plateau and further iterations are unlikely to improve the solution significantly.

In our work, we used the Python library PyGAD (Gad, 2023) to solve the optimization problem.

6.1 Fitness Factors

Prioritizing the detection of frequently occurring attack steps is crucial for effective rule deployment, provided that the load constraints are met. The frequency score (FA) for an attack step represents the count of distinct paths containing that attack step. Additionally, if an attack step in an attack path is already detected, there's no need to detect another step of the same path. To account for this, the frequency of potential pairs of attack steps across various paths can be computed. A good deployment should avoid detecting attack step pairs that frequently occur together and prioritize those that rarely occur together. The frequency score (FP) for a pair of attack steps is the count of distinct paths containing that pair.

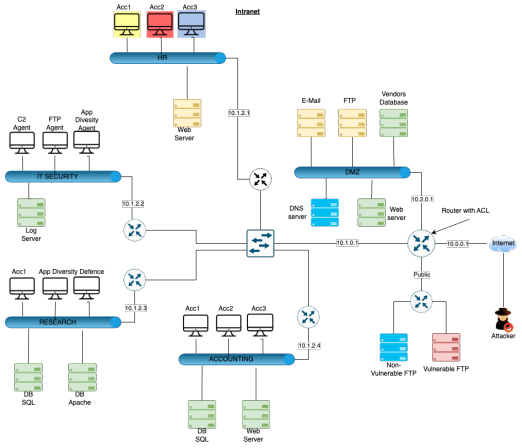


Figure 5: Example Enterprise Network.

Deploying a rule on an IDS that cannot observe the corresponding attack step's traffic adds to the IDS load without improving detection. We denote the count of such useless rules as CUD. The fitness of a solution, aiming to maximize the detection of attack paths, can be estimated using the equation:

$$f = \alpha_1 \cdot e^{DAP} + \alpha_2 \cdot \left(\sum e^{FA}\right) - \alpha_3 \cdot \left(\sum e^{FP}\right) - \alpha_4 \cdot CUD^{\alpha_5}$$

Here, DAP represents the number of distinct attack paths detected, while α_1 to α_5 are tunable parameters. Relying solely on the DAP value for fitness evaluation might lead to local maxima. To ensure the selection of optimal solutions across generations, it's crucial to factor in FA, FP, and CUD values. A higher FA value indicates a better deployment. This is captured by adding the weighted sum of e^{FA} for all detected attack steps to the fitness score. Conversely, a higher FP value indicates a poorer deployment. This is accounted for by subtracting the weighted sum of e^{FP} for all detected attack pairs from the fitness score. Additionally, penalizing the deployment of useless rules and increased IDS load is achieved by subtracting the weighted CUD value from the fitness score. The impact of FA, FP, and CUD diminishes as the DAP value becomes significantly high.

7 RESULTS & DISCUSSION

In Figure 5, a relatively large enterprise network is depicted. A total of ten potential attack paths are identified, comprising twenty-five distinct attack steps. Six IDSs are positioned within the network, each with identical traffic inspection capacity but varying traffic

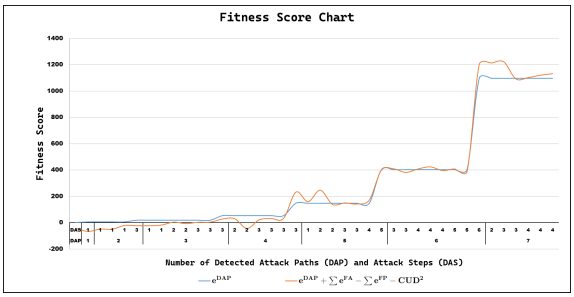


Figure 6: Comparison of fitness score only with *DAP* and fitness score with *DAP*, *FA*, *FP*, and *CUD*.

loads. Thirty different IDS rules have been identified for deployment across these IDSs. Experiments on a prototype implementation of our approach begin with an initial population of solutions. Steady-state selection is used to choose parents, while elitism is maintained by carrying the best solutions from the current generation to the next. As new solutions are generated, many exceed the IDS capacity and are replaced with elite solutions from the previous generation.

In Figure 6, the fitness score changes with the increase in the number of detected attack paths (DAP) in the larger example. If only DAP is used to compute the fitness score, it can lead to local maxima at the initial stages of the solution. However, incorporating other factors (*FA*, *FP*, and *CUD*) eliminates unpromising partial solutions. The figure plots the number of detected attack paths (major) and the total number of detected attack steps (minor) on the horizontal axis. Values are shown up to a DAP value of 7; beyond this, DAP becomes the dominant factor, and both fitness score equations produce similar results.

8 CONCLUSIONS

In this paper, we formalized the rule deployment problem within a multi-IDS environment, considering capacity constraints on individual IDSs. We proposed an effective strategy for rule deployment by leveraging both the attack graph and the network graph. With fixed IDS placements assumed, our aim was to maximize the detection of attack paths directed toward critical assets. We presented a genetic algorithm-based solution to identify IDS rule deployments.

While our focus was on fixed IDS positions, future plans include expanding this research to optimize both IDS positioning and rule deployment strategies concurrently. Given the growing importance of monitoring and early detection of attacks targeting critical assets, we plan to integrate the criticality of assets into our analysis. Additionally, future efforts will consider the possibility of attackers evading IDS detection, thus enhancing the robustness of our approach.

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