Selecting Countermeasures for ICT Systems Before They are Attacked

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Abstract

A countermeasure is any change to a system to reduce the probability it is successfully attacked. We propose a model based approach that selects countermeasures through multiple simulations of the behaviors of an ICT system and of intelligent attackers that implement sequences of attacks. The simulations return information on the attacker sequences and the goals they reach we use to compute the statistics that drive the selection. Since attackers change their sequences as countermeasures are deployed, we have defined an iterative strategy where each iteration selects some countermeasures, updates the system models and runs the simulations to discover any new attacker sequence. The discovery of new sequences starts a new iteration. The Haruspex suite automates the proposed approach. Some of its tools acquire information on the target system and on the attackers and build the corresponding models. Another tool simulates the attacks through the models of the system and of the attackers. The tool to select countermeasures invokes the other ones to discover how countermeasures influence the attackers. We apply the whole suite to three systems and discuss how the connection topology influences the countermeasures to adopt.

Keywords: Risk Assessment and Management; Countermeasures; Scenario; Monte Carlo Method.

1 Introduction

An intelligent attacker, or simply attacker, aims to acquire some access rights on an ICT system to exfiltrate or manipulate some information or to produce some unexpected behavior in a process the system controls. In general, the attacker collects these all these rights, its goal, through a sequence of attacks because one attack seldom grants all the rights of interest. An attacker selects the sequence to implement according to its priorities and preferences.

This paper introduces and applies a model-based approach to select countermeasures for an ICT system targeted by intelligent attackers. A countermeasure is any change to the system that reduces the success probability of one attack or guarantees its failure. The proposed approach introduces one model for the target system and one for each attacker. The system model describes attacks and their attributes such as the rights each attack grants and its success probability. An attacker model lists its goals and how it selects a sequence to these goals according to its priorities. The interaction between these models simulates the attacker behaviors. Since the output of each simulation strongly depends upon random events such as the success or the selection of attacks, we apply a Monte Carlo method and run independent simulations. Each simulation returns information on the attacker sequences, the goals they reach and the time this take. This defines a sample we use to compute the statistics to select countermeasures.

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Haruspex [1–3] is a suite of tools to increase the robustness of a system before or after its deployment. Some tools build the system model and those of the attackers, other build a statistical sample through an *experiment* that applies a Monte Carlo method with multiple simulations of a scenario where some attackers target the system.

Haruspex adopts a *divide et impera* strategy that only requires the probabilities of simple events such as the success of an attack. By collecting observations in multiple simulations, Haruspex tools return a statistical sample to compute global probabilities, such as the one that an attacker reaches a goal. The adoption of multiple simulations avoids the definition of a formal model that relates probabilities of simple events to the global ones. Being model based, the tools only require the models of the system and of the attackers and they can evaluate how countermeasures affect the probability that attackers reach their goals even before the system is actually deployed and attacked.

This paper is focused on the *manager*, the Haruspex tool to select countermeasures. This tool implements a first experiment to discover the attacker sequences. After selecting countermeasures for these sequences, it updates the system model and runs another experiment to discover the attacker sequences against the new system version. If the attackers still reach their goals, the *manager* selects further countermeasures, updates accordingly the system model, and it runs a new experiment till it discovers all the sequences.

After describing the *manager*, we present a case study that applies the whole suite to three systems and show how an increasing number of connections influences the countermeasures to deploy. The three systems do not actually exist but they merges features of real systems we have analyzed through the suite.

The paper is structured as follows. Sect. 2 briefly reviews related works on vulnerabilities, attacks, attacker, and attack simulation. Sect. 3 describes the building of the system model and of those of the attackers as well as the simulation of the attackers. Sect. 4 describes the *manager* and outlines how it iteratively selects countermeasures and evaluates their effectiveness. We compare the robustness of the alternative versions of a system the *manager* considers through the *security stress*. Sect. 5 defines this measure and then describes the case study. Lastly, Sect. 6 draws some conclusions and outlines some future works.

With respect to our previous works [1–4], this one is focused on the selection of countermeasures and it extends the one in the Parallel and Distributed Processing 2015 Conference [4] with a fully original case study to outline the relation between the selection of countermeasures and the connection topology. The original theoretical contribution of this work concerns the discussion of the problems posed by the adoption of countermeasures that reduce the success probability of attacks but do not guarantee their failure.

2 Related Works

We outline the contribution of the Haruspex suite by reviewing related works on attacks, plans, their description, and countermeasures.

[5–11] review the simulation of ICT attacks but do not adopt the Monte Carlo method. [12, 13] discuss intelligent, goal-oriented terrorists. The model of attack sequences in [14] is similar to the Haruspex one because it formally defines both pre and post condition of attacks but it does not discuss the probability of reaching a goal. [15] describes attack attributes and maps attacks into the proper countermeasures. [12, 16, 17] describe how the deployment of countermeasures affects the attackers. None of these work discusses attack sequences.

[18, 19] analyze attack simulation in the framework of game theory. In the same framework, [20] computes the best protection for alternative targets of an attacker. Instead, Haruspex focuses on an effective protection for a single target by reducing the probability that attackers reach their goals and not

by diverting them to a distinct target [21, 22].

[23, 24] review agent-based simulation [25–27] consider multi objective optimization that underlies the selection of sequences. [28] discusses the relation between planning and attack sequences under the assumption that accurate and complete information on the target system is available. [10] models attacker with partial information and [29] defines a notion of look-ahead but in a different perspective than Haruspex. Our attacker model is more general than those in these papers because we are not interested in the optimal sequence or in the optimal strategy to select a sequence [30]. Instead, we focus on an accurate modeling of how attackers:

- acquire information on the target system,
- select their sequence,
- change this selection because of countermeasures.

Most works on attack sequences do not discuss the selection of countermeasures. This is likely due to the lack of formal models to compute the success probability of a sequence. The taxonomy of attacks in [31] focuses on a series of security incidents. [32] proposes a classification to map each vulnerability into a distinct class. The theoretical approach in [33] analyzes attack sequences targeting distinct network nodes and it is focused on the compromised level of each node. This approach cannot discover all the sequences because they grow exponentially in the number of attacks. [34] describes the discovery of attack sequences and it computes the success probability of each one in isolation without considering that distinct sequences may be selected. [35–37] model the selection of countermeasures through attack graphs but they neglect the success probability of a sequence. [38] considers goal oriented attackers. [39] discusses a metrics to evaluate system robustness. [40, 41] discuss the measurement of the risk due to, respectively, ICT systems and software components.

Sequences of attacks also play a critical role in intrusion detection. [42–45] correlate, attacks or alerts from an intrusion detection system to discover attacks that belongs to the same sequence.

3 Haruspex Suite: Simulating a Scenario

The *builder*, the *descriptor*, and the *engine* are the suite tools that support the simulation of a scenario where some attackers target a system S. The *builder* builds the model that describes the vulnerabilities in the components of S and the corresponding attacks. Instead, the *descriptor* receives information about each attackers and it builds the corresponding model. Both tools minimize the complexity of model building to increase not only the accuracy of the simulation but also the complexity of the scenarios that can be analyzed. The *engine* uses the models built by the other tools to apply the Monte Carlo Method and run an experiment with multiple simulations. In this way, it returns a sample to compute the statistics to select and evaluate countermeasures. In the following, we use the acronyms in Table 1.

3.1 The Builder

The system model of S is modular as it decomposes S into some components, each defining some operations. Through the attacks enabled by the vulnerabilities in a component c, an attacker can illegally acquire some *access rights*, or *rights*, to invoke some operations. Vulnerabilities in c are either known or suspected. A known vulnerability is public when S is analyzed. Instead, suspected vulnerabilities may be discovered and become public in the future. Haruspex introduces these vulnerabilities to support a *what-if* approach that evaluates how some vulnerabilities affect the selection of countermeasures. As an

Table 1: List of Components and Attributes

S	the target system
n	a node of S
c	a component of S
op	an operation of a component
ag	an attacker
g	a goal of an attacker
at	an attack
v	a vulnerability
n_a	a node of an attack graph
ar	an arc of an attack graph
$r(n_a)$	the set of rights that n_a represents
$v(at)$	the vulnerabilities enabling at
$time(at)$	the time to execute at
$pre(at)$	the rights to execute at
$post(at)$	the rights acquired if at is successful
$succ(at)$	the success probability of at
$\lambda(ag)$	the look-ahead of ag
$na(ag)$	the number of attacks before a new selection
sa	a sequence of with l attacks
$sa(i)$	the $i-th$ attack of sa, where $i \leq l$
$succ(ag,g,sa)$	the probability sa enables ag to reach g
$p(sa,g)$	the plan corresponding to sa
$cont(at)$	a countermeasure for at
$cost(at)$	the cost of $cont(at)$
$lowrisk$	an upper buond on the success probability of ag

example, we can evaluate how a stack overflow attack against S influences the countermeasures to adopt. We pair a suspected vulnerability with the probability it becomes public at each time t.

Haruspex models an attacks at through a set of attributes. $pre(at)$, the pre condition of at, includes the rights an attacker needs to implement at. $post(at)$, the post conditions of at, includes any rights an attacker acquires if at is successful. $succ(at)$, the success probability of at, models the complexity of the actions of at as well as the likelihood of events enabling its execution. As an example, $succ(at)$ is close to zero if the attacker has to execute the corresponding actions in a small time window that it does not control.

The *builder* receives a database with the vulnerabilities in the nodes and the interconnection structure of S. If S already exists, this database is the output of a vulnerability scanning. The scanning of a node n discovers the components that n runs and returns a list of their public vulnerabilities. Also the interconnection structure components are scanned and their vulnerabilities added to the database.

If Haruspex is applied in the design of S, then the information in the database is deduced from public vulnerabilities in the components to be adopted.

The *builder* discovers attack attributes by classifying each vulnerability v in its input database into one of seven classes. Vulnerabilities in the same class enable attacks with similar pre and post conditions. As an example, one class includes all the vulnerabilities of n that only attackers with an account on n can exploit. The vulnerabilities that enable attacks that do not require an account on n belong to another class because these attacks have a distinct precondition. The classification of v is driven by the description of

the attacks that v enables. We use the description in the Common Vulnerabilities and Exposures (CVE), a *de-facto* standard for vulnerability description. The *builder* analyzes the CVE description of v and considers its Common Vulnerability Scoring System score [46] to compute other attributes of the attacks v enables such as their success probabilities and execution time. We refer to [2, 47] for a description of the *builder* implementation and an evaluation of the accuracy of the classification.

The attack surface of n is an important attribute of the model of S. This surfaces describes how an attacker sequence spreads among distinct nodes as it includes the attacks that other nodes of S can launch against n. To compute this attribute, the *builder* integrates the information on the attacks enabled by the vulnerabilities of n with the topology of the logical connections to/from n.

The *builder* stores the model of S in a database with the information previously described.

3.2 The Descriptor

An attacker ag owns the resources and the capability to violate the security policy of S to reach one of its goals. Each goal g of ag is a distinct sets of rights. To create the model of ag the user supplies to the *descriptor* information on the resources it can access to implement an attack and the operations ag is entitled to invoke by its initial rights. A further critical information is the strategy of ag to select a sequence of attacks according to its preferences and priorities [48]. We describe this strategy through $AttGr(S,ag)$, the attack graph of ag against S. $AttGr(S,ag)$, is an oriented graph that represents all the sequences of ag to reach g. Any node n_a of $AttGr(S,ag)$ represents a set of rights $r(n_a)$ and each arc ar is labeled by an attack $at(ar)$. If ar is an arc from n_s to n_d, then $r(n_s)$ includes $pre(at(ar))$ and $r(n_d)$ is the union of $r(n_s)$ and of $post(at(ar))$. If $r(n_i)$ is the initial set of rights of ag then n_i is the initial node of $AttGr(S,ag)$. A path from n_i to any node n_f where $r(n_f)$ is a goal of ag represents a sequence to reach the goal. Another notion of interest is the one of *plan*. A sequence of attacks to reach one of its goals is a plan if ag does reach the goal if it does not execute even one attack in the sequence.

If ag uses $AttGr(S,ag)$ to select the sequence to implement, it always selects a plan, i.e. a sequence without useless attacks. However, this is too complex for any real system because the time to build $AttGr(S,ag)$ is exponential in the size of S. As a consequence, ag builds and analyzes $subAttGr(S,ag,\lambda(ag),c)$ a small subset of $AttGr(S,ag)$. c, the initial node of the subset, is the *current* node of ag, the one that describes the current rights of ag. $\lambda(ag)$, the other parameter that define the subset is a natural number, the *look-ahead* of ag. If $\lambda(ag) = 0$, then $subAttGr(S,ag,\lambda(ag),c)$ only includes c and the arcs leaving it. Here, ag randomly selects one of these arcs and the corresponding attack. If $\lambda(ag) > 0$, then $subAttGr(S,ag,\lambda(ag),n)$ includes c and the paths of $AttGr(S,ag)$ from c with, at most, $\lambda(ag)$ arcs. If at least one of these paths leads to a goal, then ag ranks all and only the sequences paired with a path to a goal. Otherwise, it ranks all the sequences paired with a path of $subAttGr(S,ag,\lambda(ag),n)$. In both cases, the ranking considers the attributes of the attacks of each sequence. If no path in $subAttGr(S,ag,\lambda(ag),n)$ leads to a goal, ag may select a sequence with useless attacks. Hence, ag reduces the complexity of selection by analyzing a subset of $AttGr(S,ag)$ but, as a counterpart, it may select sequences with useless attacks.

To simulate in accurate way an attacker, we also consider how ag acquires the information to build $subAttGr(S,ag,\lambda(ag),n)$ through a vulnerability scanning. This scanning returns all the vulnerabilities of the components in the scanned nodes and it delays ag for a time depending on these nodes. ag is delayed to scan a node n only the first time it ranks a sequence with an attack enabled by a vulnerability of a component running on n. Hence, the collection overhead increases with the number of nodes ag scans for each selection that, in turn, increases with $\lambda(ag)$. This is another compromise between accuracy and overhead of a selection. We model insiders by pairing each attacker with the nodes it does not need to scan because it already knows their vulnerabilities.

The Haruspex model of *ag* can specify distinct selection strategies according to the priorities of *ag*. Among them:

1. random: returns any sequence with the same probability,
2. maxProb: returns the sequence with the best success probability,
3. maxIncr: returns the sequence granting the largest set of rights,
4. maxEff: returns the sequence with the best ratio between success probability and execution time.

None of these strategies neglects a sequence. As an example of a strategy that neglects a sequence, considers the one that never selects a sequence with an attack a where $succ(at) \leq \beta$. We discuss in the following how this impacts the selection of countermeasures.

ag invokes again its selection strategy after implementing $na(ag)$ attacks of the selected sequence. $na(ag)$ determines the compromise between the selection overhead and the ability of collecting more accurate information on $AttGr(S,ag)$ after some attacks. Furthermore, a low $na(ag)$ enables *ag* to exploit suspected vulnerabilities as soon as they are discovered.

3.3 The Engine

Using the model of *S* and those of the attackers in a scenario, the *engine* runs an experiment to analyze the scenario. An experiment includes a number of independent runs that simulate, for the same time interval, the discovery of suspected vulnerabilities and how each attacker selects and implements its sequence. Initially, the *engine* determines the attacks each attacker can implement according to the resource it can access. Then, at each time step of each run, first of all the *engine* determines the suspected vulnerabilities that are discovered. Then, it considers each attacker *ag* that still has to reach at least one goal and it is idle or it has just executed an attack. After building $subAttGr(S,ag,\lambda(ag),n)$, the *engine* applies the selection strategy of *ag*. If *ag* cannot select a sequence, then it is busy for the time to collect the information to build $subAttGr(S,ag,\lambda(ag),n)$ and then it waits for the discovery of a suspected vulnerability. If the strategy returns a sequence *sa*, the *engine* sequentially simulates the first $na(ag)$ attacks of *sa* and *ag* will be busy for the time to select *sa* and the sum of times to successfully execute these attacks. The *engine* repeats a failed attack for an user-defined number of times before selecting a distinct sequence. Anytime an attack is successfully, the *engine* checks if *ag* has reached a goal.

At the end of each run, the *engine* inserts into the output database one observation that records, among others, the sequence of each attacker, any goal it has reached, the time this has required. An observation also records information on *S* such as the number of successful executions and failures of each attack. Before starting a new run, the *engine* restores the initial state of *S* and of any attacker to guarantee run independence.

The observations in the database define a sample to compute statistics of interest. The number of runs in the experiment determines the confidence level of these statistics because each run returns one observation. The user can either choose the number of runs in an experiment or define the confidence level for some predefined statistics. In the latter case, *engine* starts a new run until reaching the required level.

The current version of the *engine* is coded in Java and it runs on a highly parallel IBM cluster with 96 cores. We exploit run independence to map distinct runs onto distinct cores. This results in a linear speed up.

4 The Haruspex Manager

This section describes how the *manager* selects countermeasures. For the sake of simplicity, we consider scenarios with just one attacker ag with just one goal g. Generalization to multiple attackers with some goals are straightforward. We also assume that the user of the *manager* specifies $lowrisk$, the highest probability it is willing to accept that ag reaches g. In the following, we do not discuss the implementation of $cont(at)$, the countermeasure for at, but only the decrease of $succ(at)$ that it produces.

4.1 Sequences and Their Success Probabilities

Countermeasures should reduce $succ(ag,g,sa)$, the probability ag reaches g through sa, for any sequence sa that ag may implement to reach g. $succ(ag,g,sa)$ increases with the probability that ag selects sa as well as with the success probability of sa. The former is related to the selection strategy of ag, while the latter increases with the success probabilities of attacks in sa. After running a Haruspex experiment, we approximate $succ(ag,g,sa)$ as the percentage of runs where ag implements sa and reaches g. We cannot approximate the probability that ag selects sa because ag may change its selection after some attack failures.

A countermeasure affects sa if it changes the success probability of at least one of its attacks. This change also affects the probability that ag selects sa. Hence, the countermeasure may also change $succ(ag,g,sqalt)$ where $sqalt \neq sa$ by changing the probability that ag selects $sqalt$. As an example, thi may happen if ag adopts the *maxProb* strategy. We have experimentally verified that a countermeasure may force ag to select plans with a better success probability that it neglects before the countermeasure is deployed. This extends to ICT security the Braess's paradox for traffic control [49,50]. While in traffic control the paradox is due to congestion, now ag neglects a plan with a better success probability because of partial information on S due to a low $\lambda(ag)$. Since we do not know them in advance, we can discover all the sequences a countermeasure affect and their success probabilities by updating the model of S and by running an experiment with the new model.

These considerations have led to the design of an iterative algorithm where the *manager* selects some countermeasures and runs a new experiment to discover any new sequences ag implements and their success probabilities. New iterations start till the overall success probability of ag is lower than $lowrisk$. The update of the model of S exploits at best the Haruspex model based strategy to discover the effectiveness of countermeasure before their actual deployment.

4.2 Mapping Sequences into Plans

To select cost effective countermeasures, the *manager* only deploys countermeasures for attacks that ag has to implement to reach g. To this purpose, it applies the *planner*, a tool that maps each sequence sa into the corresponding plan $p(sa)$ to each sequence that ag implements to reach g in a run. We describe now how the *planner* removes useless attacks through a backwards scans of sa.

Initially, the *planner* initializes $tp(sa,g)$, the current approximation of $p(sa)$, with the last attack of sa. The *planner* also initializes $useful$ to $pre(sq(n)) \cup (g - post(sq(n)))$. This variable is a set with the rights that ag should own before executing the current attack to reach g. Initially, this set includes the rights to execute $sa(n)$ those in g that $sa(n)$ does not grant.

The *planner* does not add $sa(j)$ to $tp(sa,g)$ if and only if:

1. no right in $post(sa(j))$ belongs to $useful$,
2. before executing $sa(j)$, ag already owns any right in $post(sq(j)) \cap useful$.

In 1), $sa(j)$ is useless because no right it grants belongs to g or to the precondition of a useful attack. Instead, in 2) $sa(j)$ is useless because it grants rights that ag owns initially or has already acquired through previous attacks.

If $sa(j)$ is useful, before analyzing $sa(j-1)$, the *planner* removes from $useful$ the rights in the post condition of $sa(j)$ and adds those in its pre condition.
At the end of the scanning, $p(sa) = tp(sa,g)$.

This algorithm is correct provided that ag only executes attacks that grant some rights it does not own. A problem is arisen if sa interleaves more than one plan because the algorithm returns just one of these plans. We handle an interleaving by mapping any permutation of sa that is also a sequence, i.e. where the first $j-1$ attacks grants the rights in the pre condition of the $j-th$ one.

After discovering any plan p, the *planner* computes $succ(ag,g,p)$ as the percentage of runs where ag reaches g through sequences mapped into p.

4.3 Selecting Countermeasures for a Set of Plans

We assume that we know at least one countermeasure for each attack. If no countermeasure for at is known, then $cost(at)$ is infinite. If some countermeasures for at are available, $cont(at)$ is the one resulting in the largest reduction of $succ(at)$. Ties are broken by selecting the cheapest one. As an example, if a patch for some vulnerability in $vuln(at)$ is known, then $cont(at)$ applies this patch and it guarantees the failure of at. Here, $cost(at)$ is the one of the patching. As an alternative, $cont(at)$ may replace the component affect by $vuln(at)$ with an equivalent one. An example where $cont(at)$ only reduce $succ(at)$ is the adoption of a longer encryption key or the adoption of an intrusion detection system.

The *selector* is the *manager* module that receives Sp, a set of plans of ag to reach g, and returns a set countermeasures to reduce the success probability of each plan in Sp. To minimize the number of countermeasures, the *selector* considers the attacks the plans in Sp share because $cont(at)$ affects all the plans that execute at.

Initially, we assume that $cont(at)$ guarantees the failure of at. Then, we discuss the general case.

4.3.1 Zero Success Probability

The *selector* computes the countermeasures for Sp by considering the coverages of Sp. A set of attacks is a coverage [51] of Spif the countermeasures for its attacks affects any plan in Sp. The cost of a coverage is the sum of the costs of the countermeasures for its attacks.

The *selector* computes all the coverages for Sp and it returns the cheapest one. When computing a coverage, the *selector* neglects an attack at_1 if all the plans that share at_1 also share another attack at_2 such that $cost(at_2) < cost(at_1)$. Furthermore, if some plans share more than one attack and their countermeasures have the same cost, the *selector* only considers the countermeasure resulting in the lowest success probability of the attack. The tool breaks further ties according to the ratio between the success probability of an attack and its execution time [34, 52, 53].

The execution time of the *selector* is acceptable even if the coverage problem is NP-Complete provided that Sp is small or its plans shares a large number of attacks. Instead, the execution time sharply increases if Sp is large and the plans share a low number of attacks. However, if ag can implement a large number of plans, the deployment of countermeasures cannot result in a large robustness that requires an extensive redesign of S.

If the *selector* returns a coverage with an infinite cost, then at least one plan only include attacks with no countermeasure. The success probability of this plan is a lower bound on the success probability of ag.

4.3.2 Non Zero Success Probability

If $cont(at)$ only reduces $succ(at)$ for at least one attack at, then we may have to select countermeasures for distinct attacks in the same plan. Obviously, this may reduce the success probability of ag only if sequences are not very short. As an example, a reduction of the success probability of each attack in a sequence with two attacks can stop an attacker only if there are strong constrains on the time to reach a goal. Here, a set of attacks is a coverage if the countermeasures for its attacks reduces at least of δ the product of the success probabilities of the attacks in each plan. δ is a constant value that the *selector* determines according to the number of attacks in the plan. The *selector* prefers coverages with countermeasures that guarantee the failure of attacks.

In the following, we discuss further differences arising in this case.

4.4 Reducing the Success Probability of an Attacker

The *manager* runs a first experiment and it enters a loop. At first, each iteration applies the *planner* to the output of the previous experiment to discover each plan p of ag to reach g and $succ(ag,g,p)$. Then, it invokes the *selector* to compute the countermeasures for these plans and it updates the model of S to model the deployment. Then, the *manager* runs an experiment with the new model to discover any plan ag successfully implements against the new version of S and its success probability. ag never executes these plans in a previous experiment because it selects them only when some countermeasures affect other plans. Only a new experiment can discover these plans because the simulation of the attacks of ag against the previous versions of S cannot return information to support their discovery. If, in the new experiment, the success probability of ag is still larger than $lowrisk$, the *manager* starts a new iteration. Otherwise, it terminates after returning the countermeasures deployed in the last version.

The number of countermeasures the *selector* returns at each iteration strongly depends upon the plans it receives. In a global approach, at the $i-th$ iteration, the *selector* receives a set Sp_i with the plans that ag implements in any iteration. Hence, at each iteration the *selector* may return a set of countermeasures that is disjoint from those it has returned in the previous iterations. In the incremental approach, instead, Sp_i only includes the plans ag executes in the $i-th$ iteration. Then, the *manager* extends the countermeasures previously deployed with those the *selector* returns.

A global approach minimizes the number of countermeasures because it considers the attacks some plans share independently of the iteration that discovers a plan. Instead, the incremental approach cannot anticipate the plans ag implements in the following iterations and the attacks they share with the previous ones. As a counterpart, this approach minimizes the number of plans that each iteration transmits to the *selector*.

The approach the *manager* adopts depends upon how countermeasures reduce the success probability of attacks.

4.4.1 Zero Success Probability

If any $cont(at)$ guarantees the failure of at, the output of the *selector* in an iteration guarantees the failure of any plan, even if differs from the one of the previous iteration. Hence, Sp_i includes all the plans the *selector* has received in the first $i-1$ iterations and a subset, Cp_i, of those ag executes in the $i-th$ experiment. We insert plans into Cp_i according to $succ(ag,g,p)$ and stop as soon as the sum of $succ(ag,g,p)$ for the remaining plans is lower than $lowrisk$. To reduce Cp_i when ag executes a large number of plans each with a low value of $succ(ag,g,p)$, we bound its size as a fixed percentage of successful plans in the $i-th$ iteration. This reduces the computational overhead of each iteration at the expense of the number of iterations because countemeasures may increase the success probability of some plans.

4.4.2 Non Zero Success Probability

If some $cont(at)$ only reduce $succ(at)$, the selection of countermeasures for distinct attacks in a plan may affect in an unexpected way the plan success probability. This may results in a loop where the *manager* alternatively selects one of two sets of countermeasures. To avoid this loop, the *manager* adopts an incremental approach. Since the *manager* may transmit the same plan to the *selector* in distinct iterations, it also transmits the countermeasures previously selected.

4.5 Exiting the Iterations

The *manager* executes a finite number of iterations anytime any $cont(at)$ results in the failure of *at* because each iteration discovers and stops at least one of finite number of plans. However, the number of iterations is unknown *a priori* because the *manager* discovers each plan as *ag* implements it in an experiment. Since the success probability of *ag* decreases in a way that is not monotone, the user can bound the *manager* execution time by bounding the number of iterations. When the *manager* reaches this bound, it returns the best version of S it has discovered, i.e. the one with the lowest success probability of *ag*.

If countermeasures only decrease the success probability of some attacks, then the incremental approach guarantees that the success probability of each plan steadily decreases because the number of countermeasures that affect a plan never decreases. However, since countermeasures may increase the success probability of *ag*, even now a bound of the number of iterations may be specified.

4.6 Avoiding Iterations

The *manager* can adopt a distinct algorithm if *ag* never neglects a plan. Hence, in distinct *manager* experiments, *ag* selects distinct sequences till it executes all those it can select. In this way, it implements the same sequences of an attacker that randomly selects its sequence. This implies that we can discover all the sequences of *ag* through one experiment that adopts the *random* selection strategy. Since no information is available on the sequence execution order, this solution may be adopted only if any $cont(at)$ results in the failure of *at*.

5 Case Study and Evaluation of Results

We have applied the Haruspex suite to for three ICT systems: sys_1, sys_2 and sys_3 with the same number of nodes but a different, complex, interconnection topology. Each ICT system has 24 subnetworks and a total of 36 distinct nodes running either Windows or Unix operating systems and provide a total of 175 services such as Telnet, SMB and Remote Desktop.

Fig.1, Fig.2 and Fig.3 show the three systems. Each figure shows the name of each subnet, the number of its nodes and the bidirectional, logical connections among subnets. The topology of sys_1 consists of 36 connections. sys_2 has four more connections that link, respectively, subnet E and subnet J, D and O, K and T, and N and U. sys_3 includes four further connections that link E and U, D and T, J and N, and K and O. There are 1848 vulnerabilities that affect the components of each system. The critical levels of these vulnerabilities ranges from critical to low.

Each system is the target of four attackers. Two attackers adopt the *maxProb* strategy, the other two the *maxIncr* one. The attackers with the same strategy have distinct λ values in the set $\{1,2\}$. Each attacker initially controls the node in the A subnet and it aims to reach the control of, or implement a denial the service against, the node in the X subnet.

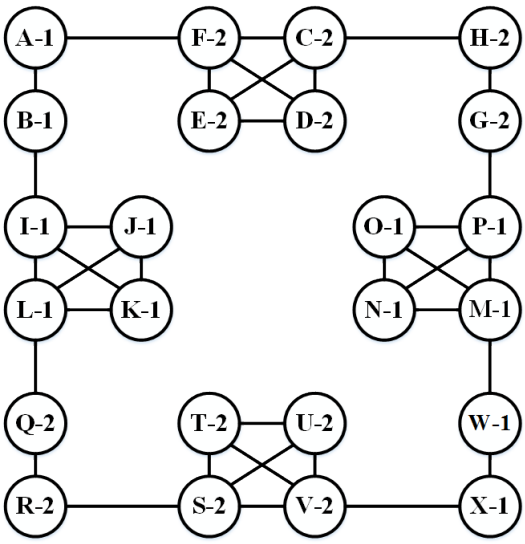

Figure 1: Topology of sys_1

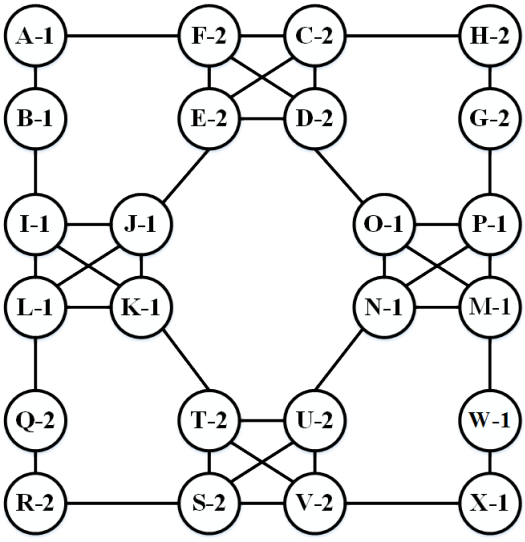

Figure 2: Topology of sys_2

In the following, we compare the various versions of each system that the *manager* considers through the security stress. The security stress is a synthetic measure we have defined to evaluate and compare the robustness of alternative version of a system. As a particular case, we apply it to evaluate the effectiveness of the countermeasures the *manager* selects. First of all we describe this measure and then the selection of countermeasures for the three systems.

5.1 Security Stress

The *security stress* is a synthetic evaluation of how a system resists to some attackers. Initially, we consider a single attacker and generalizes at the end of this section. If ag attacks S to achieve g, $Str^S_{ag,g}(t)$, the security stress of S at t, is the probability that ag achieves g within t. $Str^S_{ag,g}(t)$ evaluates the resistance of S to the attacks of ag as t increases. S cracks at t_c if ag always reaches g for times larger than t_c. The

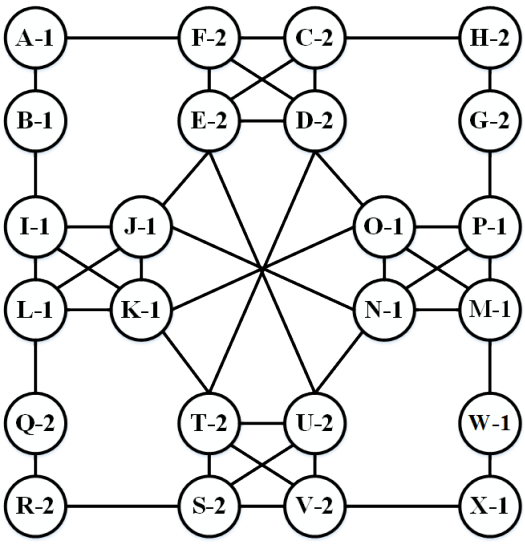

Figure 3: Topology of sys_3

resistance of S in a time interval decreases as the surface underlying $Str^{S}_{ag,g}(t)$ increases.

To explain why we use $Str^{S}_{ag,g}(t)$ to evaluate the robustness of S, let us considers two time under the assumption they both exist. t_0 is the lowest time when the success probability of ag is larger than zero while t_1 is the smallest time where this probability is 1. The value of $t_1 - t_0$ evaluates how long S, partially, resists to the attacks of ag before cracking. The attacks are ineffective till t_0. Then, they are more and more effective till S cracks at t_1 as ag is always successful for larger times. The values of t_0 and of t_1 depend upon both some properties of S, such as the attack attributes, and some properties of ag, such as the sequences it selects. In particular:

1. t_0 depends upon the length of these sequences and the time the time to execute their attacks ;
2. t_1 depends upon $succ(at)$ that determines the average number of times ag repeats at;
3. $t_1 - t_0$ depends upon the standard deviation of the length of the sequences of ag.

We approximate $Str^{S}_{ag,g}(t)$ as the percentage of the runs in an experiment where ag reaches g within t. To evaluate the effectiveness of some countermeasures, we compare the robustness of S against the one of S_c, the system that deploys the countermeasures. In general, $Str^{S_c}_{ag,g}(t)$ is lower than $Str^{S}_{ag,g}(t)$ in the time interval simulated in the Haruspex experiment. However, if some countermeasures forces ag to select shorter sequences to reach g, $Str^{S_c}_{ag,g}(t)$ may become larger than $Str^{S}_{ag,g}(t)$ and the two curves may intersect.

If any scenario with multiple attackers, we consider the largest stress curve among those of the attackers and denote the corresponding attacker as the most dangerous one. If no curve is larger than the other, we consider a weighted sum of the curves.

An alternative definition of stress considers $Str^{S}_{ag,g}(n)$, the success probability of ag after executing n attacks. This value includes both successful and failed executions and it evaluates both the effort of ag and the opportunities of S to detect the activity of ag.

5.2 Selecting Countermeasures: A Case Study

Any Haruspex experiment described in the following has been implemented by the *engine* and it uses the models returned by the *builder* and by the *descriptor*. Each experiment reaches a 95% confidence

level on the components that are the targets of the attacker. This results in about 50.000 runs that our multicore architecture executes in about 10 minutes.

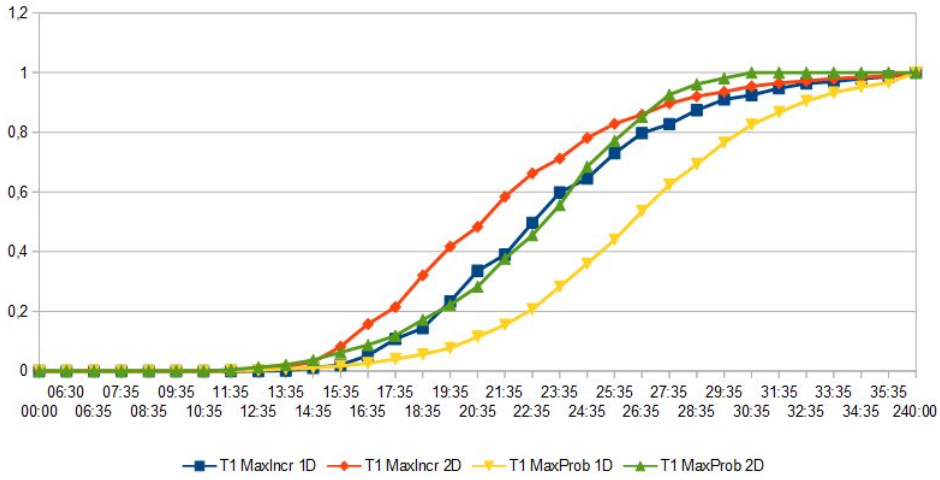

Figure 4: sys_2: Stress Curves of the Four Attackers

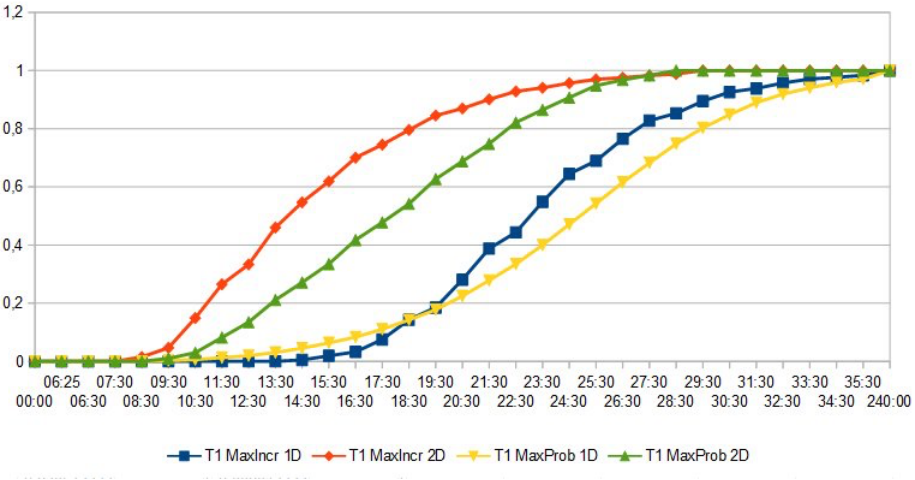

Figure 5: sys_3: Stress Curves of the Four Attackers

Fig.4 and Fig.5 show the stress curves of, respectively, sys_2 and sys_3 for each of the four attackers. We do not show the corresponding curves for sys_1 as they always overlap the x axis because no attacker reaches its goal.

Fig. 6 shows the stress of sys_2 due to the four attackers in terms of the number of attacks. This curve shows that the success probability of attacker is larger than zero after, at least, 14 attacks. Fig. 7 shows the corresponding stress for sys_3. When targeting sys_3, an attacker can reach its goal after, at least, 5 attacks, while the most powerful attacker always reaches its goals after 39 attacks.

The stress curves for sys_2 shows that there is not a most dangerous attacker. The stress curve of the one that adopts the *maxIncr* strategy with $\lambda = 2$ dominates the other ones for most of the time but the first curve that reaches 1 is the one of the attacker with *maxProb* strategy and $\lambda = 2$. In the following, we do not introduce a weighted sum of the curves of these two attackers and discuss each attacker independently.

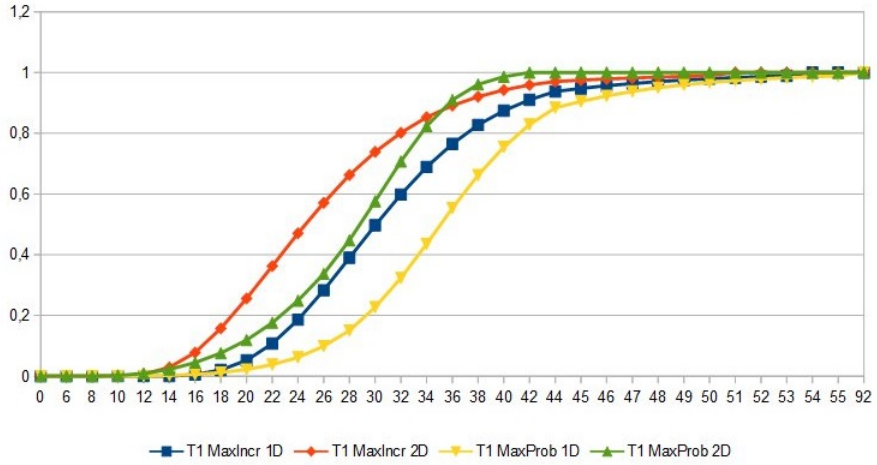

Figure 6: sys_2: Stress Curves of the Four Attackers using Attacks

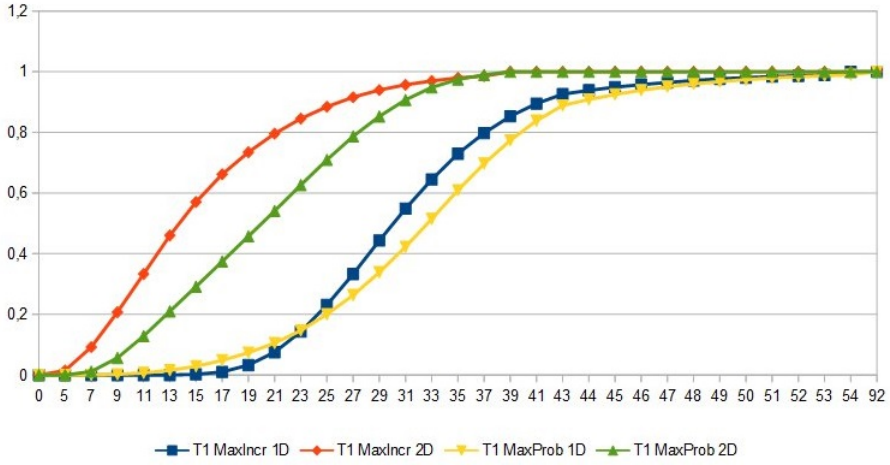

Figure 7: sys_3: Stress Curves of the Four Attackers using Attacks

The stress curve of the *maxIncr* attacker with $\lambda = 2$ shows that sys_2 starts to crack after about 14 hours of attacks and it completely cracks after about 36 hours. Even the *maxProb*attacker with $\lambda = 2$ starts to crack sys_2 after about 14 hours of attacks but it completely cracks sys_2 after about 30hours. The least dangerous attacker against sys_2 adopts the *maxProb* strategy with $\lambda = 1$. This attacker starts to crack the system after about 15 hours and it is always successful after 240hours.

The stress curves of sys_3 show that most dangerous attacker adopts the *maxIncr* strategy with $\lambda = 2$ and the least dangerous one is, for most of time, the one that adopts *maxProb* with $\lambda = 1$. The most dangerous attacker starts to crack sys_3 only after 7 hours while its attacks are always successful provided that it has about 29 hours available. The least dangerous attacker completely cracks the system after 240 hours and starts to reach its goals after about 12 hours.

These curves show that a richer topology strongly may reduce the complexity of attacking a system. In fact, when passing from sys_1 to sys_2, the number of connections increases of about 11% and this enables any attackers to reach its goal. The same increase when passing from sys_2 to sys_3 reduces the shortest time to reach a goal from 14 to 7 hours.

We have applied the *manager* to compute the countermeasures for sys_2 and for sys_3. The *manager*

adopts a global approach because countermeasures guarantee the failure of attacks. To avoid trivial solutions, we have assumed that there is no countermeasures for attacks that may be the first or the last ones of a sequence. These attacks are those the attacker can implement from the node it initially controls and those against the attacker goal, the subnet X node.

With respect to sys_2, we have applied the *manager* to each of the two attackers with $\lambda = 2$ and that adopt, respectively, *maxProb* and *maxIncr*. The *manager* returns for both attackers the same set with 7 countermeasures that guarantees that they cannot reach their goal. Three of these countermeasures concern the vulnerabilities on the SSH protocol in the nodes in the subnets M, T, and U. 3 further countermeasures patch 3 weakness of the Telnet, Samba and SSL protocols in the subnet M node. The last countermeasures changes a default password in subnet U node. By deploying countermeasures for less than 1% of vulnerabilities, the *manager* stops all the plans of these attackers but, since they never neglects a plan, the set of countermeasures also stops attackers that adopt distinct selection strategies.

The *manager* computes the countermeasures for the *maxIncr* attacker in 3 iterations while it computes the same set in 4 iterations for the *maxProb* attacker.

Fig. 8 and Fig. 9 show the stress values of the versions of sys_2 that the *manager* considers in its iterations for the two attackers. The curve of the last version is not shown as it overlaps the x axis.

It is worth noticing that Fig. 9 shows an instance of the Braess's paradox. The robustness of the version at the third iteration is lower than the one at the second iteration because the countermeasures that the *manager* selects in this iteration force the attacker to select longer sequences but with a better success probabilities. This increase in the success probability of the attacker is revealed by an intersection between the stress curves of the two versions. In this example, the attacker implements 412 distinct plans against the first version of sys_2, 443 against the second version and 438 against the third one. As previously discussed, the attacker initially neglects some plans because of partial information on sys_2 due to its λ.

The most dangerous attacker against sys_3 adopts the *maxIncr* strategy with $\lambda = 2$. Fig. 10 shows the stress curves of the versions of sys_3 that the *manager* produces. The *manager* selects the same set of countermeasures it computes to stop both attackers against sys_2. These countermeasures are effective even for sys_3 because they prevent the most dangerous attacker to exploit the new connections that sys_3 offers. This shows that a richer topology may not increase the complexity of defending a system because the *manager* computes the countermeasures for sys_3 in 3 iterations. However, this happens only when the *manager* exploits at best shared attacks among plans. As an example, this may not occur if an incremental approach is adopted. Even for sys_3, the deployment of countermeasures for less than 1% of all the vulnerabilities stops all the attackers.

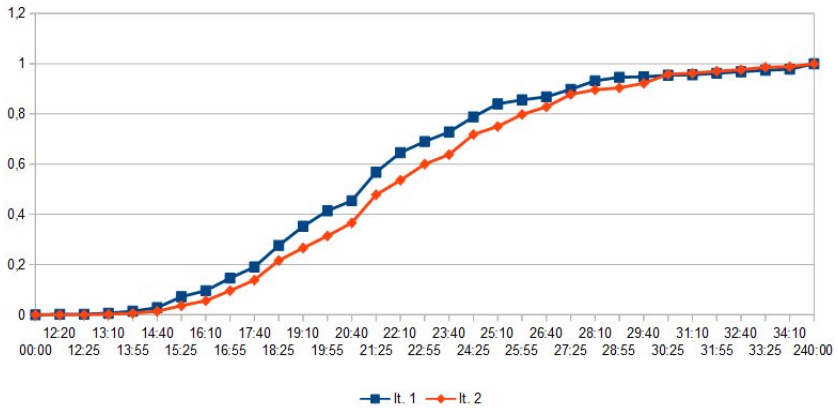

Figure 8: sys_2: Stress Curves at Distinct Iterations, *maxIncr* Attacker

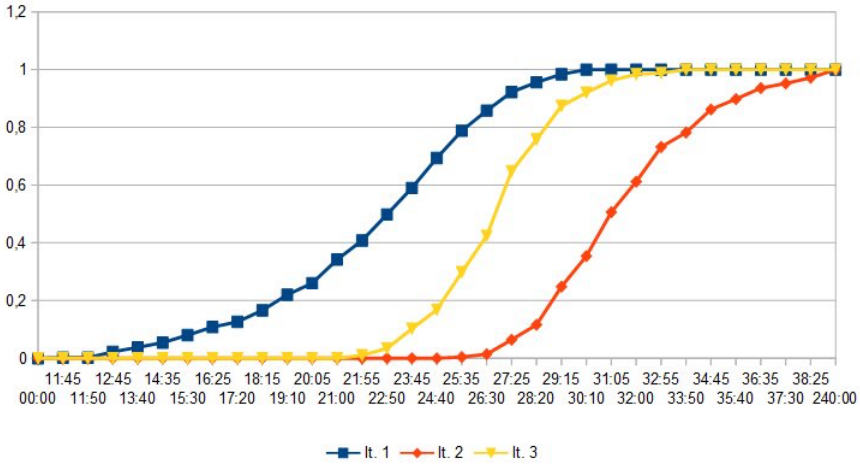

Figure 9: sys_2: Stress Curves at Distinct Iterations, *maxProb* Attacker

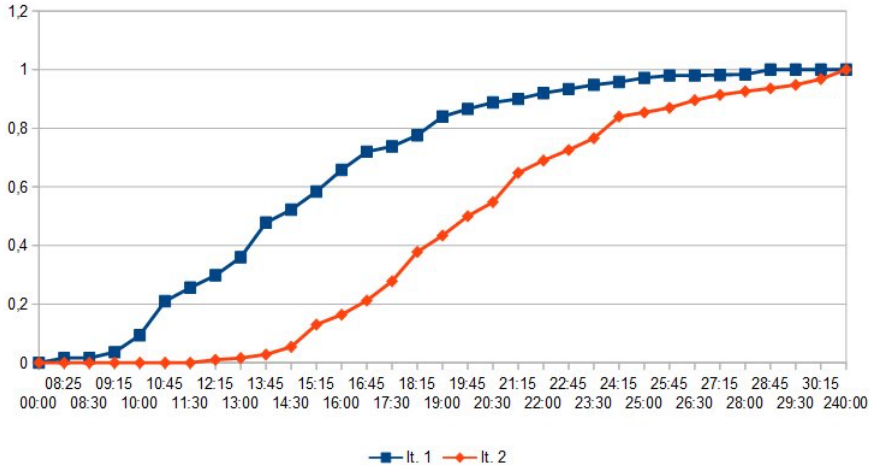

Figure 10: sys_3: Stress Curves at Distinct Iterations, *maxIncr* Attacker

We have also consider the deployment of countermeasures that only reduce the success probability of attacks. As an example, by deploying a host intrusion detection system on each node that is the target of one plan of the attacker, we reduce the success probability of the most dangerous attacker against sys_3 to 0.4 under the assumption that the false negative rate of the detection system is, at most, 1%.

6 Conclusion

This paper has discussed how the Haruspex suite supports the selection of countermeasures for intelligent attackers. These attackers aims to reach some predefined goals by composing the attacks enabled by the system vulnerability into sequences. In Haruspex, two tools cooperate to discover an effective set of countermeasures: the *manager* and the *planner*. These tools implement an iterative process where each iteration implements a Haruspex experiment to discover how attackers changes their sequences as countermeasures are deployed. This take into account that an intelligent attacker can select and implement new sequences as old ones are affected by some countermeasures. We have presented a case study that

applies the suite to select countermeasures for three systems where the complexity of interconnection topology increases. In this way, we have experimentally evaluate the influence of a richer topology on the complexity of countermeasure selection. Our experiments show some cases where the complexity of selecting a set of countermeasures does not increase with the number of connections provided that the selection considers the attacks that distinct plans share. We have also shown an example where the deployment of countermeasures increases the success probability of an attacker.

Future developments of the Haruspex suite concern the definition of more sophisticated models for the attackers and for the system and the modeling of computer worms.

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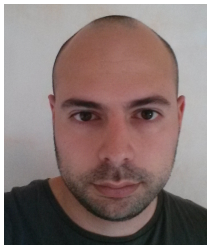
Alessandro Bertolini has a master's degree (109/110) in Computer Science. Now he works in the "Haruspex Project", a software dedicated to create models about real computer network systems and do risk assessment by simulating various attacks with intelligent and goal-oriented agents. Before, he worked in 2008 for six months in I.T. department of Lucchini (Piombino, Li, Italy), then he collaborated with M.A.I.O.R. Srl to realize "TTDAlgo", a new tool based on algorithms of Operational Research to create an optimized time-tables for the urban public transport. He was born on May 13rd, 1981, he live and he also studied until high school in Piombino. Then, he studied Computer Science at University of Pisa.



Roberto Bertolotti has a master's degree (106/110) in Information Security. He wrote the thesis on "Simulazione di attacchi scontro infrastrutture ICT" that won the international competition "Shared University Research Grant" of IBM Corporation. He was born in La Spezia on April 26th, 1985, where he also studied Applied Informatics and Informatics Security. He is the person who has installed and mainteins the server multi-host that permits to use Haruspex (the program that generates million of parallel simulation).