



PDF Download
310889.310919.pdf
22 December 2025
Total Citations: 571
Total Downloads: 8299

 Latest updates: <https://dl.acm.org/doi/10.1145/310889.310919>

ARTICLE

A graph-based system for network-vulnerability analysis

CYNTHIA A PHILLIPS, Sandia National Laboratories, New Mexico, Albuquerque, NM, United States

LAURA PAINTON SWILER, Sandia National Laboratories, New Mexico, Albuquerque, NM, United States

Open Access Support provided by:

Sandia National Laboratories, New Mexico

Published: 01 January 1998

[Citation in BibTeX format](#)

NSPW'98: New Security Paradigms Workshop '98

September 22 - 26, 1998
Virginia, Charlottesville, USA

Conference Sponsors:
SIGSAC

A Graph-Based System for Network-Vulnerability Analysis

Cynthia Phillips

Sandia National Laboratories, MS 1110

Albuquerque, NM 87105

505-845-7296

caphill@sandia.gov

Laura Painton Swiler

Sandia National Laboratories, MS 0746

Albuquerque, NM 87105

505-844-8093

lpswire@sandia.gov

ABSTRACT

This paper presents a graph-based approach to network vulnerability analysis. The method is flexible, allowing analysis of attacks from both outside and inside the network. It can analyze risks to a specific network asset, or examine the universe of possible consequences following a successful attack. The graph-based tool can identify the set of attack paths that have a high probability of success (or a low "effort" cost) for the attacker. The system could be used to test the effectiveness of making configuration changes, implementing an intrusion detection system, etc.

The analysis system requires as input a database of common attacks, broken into atomic steps, specific network configuration and topology information, and an attacker profile. The attack information is "matched" with the network configuration information and an attacker profile to create a superset attack graph. Nodes identify a stage of attack, for example the class of machines the attacker has accessed and the user privilege level he or she has compromised. The arcs in the attack graph represent attacks or stages of attacks. By assigning probabilities of success on the arcs or costs representing level-of-effort for the attacker, various graph algorithms such as shortest-path algorithms can identify the attack paths with the highest probability of success.

Keywords

Computer security, network vulnerability, attack graph

1. INTRODUCTION

Military, government, commercial, and civilian operations all depend upon the security and availability of computer systems and networks. In October 1997, the Presidential Commission on Critical Infrastructure recommended increasing spending to a \$1B level during the next seven years. The Commission recommended that this money be heavily focused on cyber-security research, including vulnerability assessment, risk management, intrusion detection, and information assurance technologies [16]. In this paper, we describe a systematic analysis approach that can be used by persons with limited expertise in risk assessment, vulnerability

analysis, and computer security to (1) examine how an adversary might be able to exploit identified weaknesses in order to perform undesirable activities, and (2) assess the universe of undesirable activities that an adversary could accomplish given that they were able to enter the network using an identified weakness.

Quantifying security risks in computer networks is very difficult. Ideally, a network-vulnerability risk-analysis system should be able to model the dynamic aspects of the network (*e.g.*, virtual topology changing), multiple levels of attacker ability, multiple simultaneous events or multiple attacks, user access controls, and time-dependent, ordered sequences of attacks.

Probabilistic Risk Assessment (PRA) techniques such as fault-tree and event-tree analysis provide systematic methods for examining how individual faults can either propagate into or be exploited to cause unwanted effects on systems. For example, in a *fault-tree* a negative consequence, such as the compromise of a file server, is the root of the tree. Each possible event that can lead *directly* to this compromise (*e.g.*, an attacker gaining root privileges on the machine) becomes a child of the root. Similarly, each child is broken into a complete list of all events which can directly lead to it and so on. Wyss, Schriener, and Gaylor [19] have used PRA techniques to investigate network performance. Their fault tree modeled a loss of network connectivity, specifically the "all terminal connectivity" problem. Since PRA methods can measure the importance of particular components to overall risk, it seems that they could provide insights for the design of networks more inherently resistant to known attack methods. These methods, however, have limited effectiveness in the analysis of computer networks because they cannot model multiple attacker attempts, time dependencies, or access controls. In addition, fault trees don't model cycles (such as an attacker starting at one machine, hopping to two others, returning to the original host, and starting in another direction at a higher privilege level). Methods such as influence diagrams and event trees suffer from the same limitations as fault trees.

A major advance of our method over other computer-security-risk methods is that it considers the physical network topology in conjunction with the set of attacks. Thus, it goes beyond the scanning tools. A seminal tool, SATAN (Security Administrator Tool for Analyzing Networks), checks a "laundry list" of services or conditions that are enabled on a particular machine [17]. For example, on UNIX systems SATAN checks for NFS file systems exported to unprivileged programs or arbitrary hosts, but gives little indication of how these items lead to system compromise. More recent scanners such as the Internet Scanner™ from Internet Security Systems (ISS) also attempt attack scenarios and provide information about potential vulnerabilities and how they can be exploited [7]. These scanning tools can provide a system

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, to republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee.
1998 NSPW 9/98 Charlottesville, VA, USA
© 1999 ACM 1-58113-168-2/99/0007...\$5.00

administrator with a set of items to patch or fix. However, these scanners do not verify that all conditions for a complete attack are met, or identify linked attacks potentially more harmful than individual attacks. Though they can suggest fixes for local potential problems, they don't consider the network as a whole, proposing a global set of cost-effective defenses designed to protect the network's most critical resources.

Intrusion detection systems such as Internet Security Systems' Real Secure™ form another class of network security tools. Intrusion-detection systems attempt to monitor abnormal patterns of system usage (such as suspicious configuration information changes) to detect security violations [4,9]. Our system would be complementary to an intrusion detection system. If an administrator does not want to pay the full cost (development cost or system-performance hit) of all possible intrusion-detection strategies, our system could suggest cost-effective subsets which focus on the most vulnerable system components.

Our approach to modeling network risks is based on an *attack graph*. Each node in the graph represents a possible attack state. A node will usually be some combination of physical machine(s), user access level, and effects of the attack so far, such as placement of trojan horses or modification of access control. Edges represent a change of state caused by a single action taken by the attacker (including normal user transitions if they have gained access to a normal user's account) or actions taken by an unwitting assistant (such as the execution of a trojan horse). Attack graphs will be presented in more detail in Sections 2 and 3.

The attack graph is automatically generated given three types of input: attack templates, a configuration file, and an attacker profile. *Attack templates* represent generic (known or hypothesized) attacks including conditions, such as operating system version, which must hold for the attack to be possible. The *configuration file* gives detailed information about the specific system to be analyzed including the topology of the network and configuration of particular network elements such as workstations, printers, or routers. The *attacker profile* contains information about the assumed attacker's capabilities, such as the possession of an automated toolkit or a sniffer as well as skill level. The attack graph is a customization of the generic attack templates to the attacker profile and the network specified in the configuration file. Though attack templates represent pieces of known attacks or hypothesized methods of moving from one state to another, their combinations can lead to descriptions of new attacks. That is, any path in the attack graph represents an attack, though it could be cobbled together from many known attacks.

Each edge has a weight representing a success probability, average time to succeed, or a cost/effort level to an attacker (edges with zero probability are generally omitted). In this paper we use success probability as the example of edge weight, but the edge weight could be any of the above metrics. This weight is a function of configuration and attacker profile. Furthermore, each node can have local "overwrites" of these files representing effects of previous attacker actions on configuration (e.g. severed network connections, or changes to file-access privileges) or acquired attacker capabilities. In Section 2 we discuss possible ways to estimate edge weights.

A short path in the attack graph represents a low-cost attack. Since edge weights will only be estimates, we consider the set of all near-optimal paths. If the edge weights are reasonably

accurate, this set as a group represents the most vulnerable parts of the network. If one can assume independence of success probabilities, the same (shortest-path) algorithms can find paths with high success probability. By having multiple weights on each edge, one can represent potentially-conflicting criteria (e.g. the attacker wishes to minimize both cost and probability of detection).

This system can answer "what-if" questions regarding security effects of configuration changes such as topology changes or installation of intrusion-detection systems. It can indicate which attacks are possible only from highly-skilled well-funded attackers, and which can be achieved with lower levels of effort. A business owner might decide it is acceptable to allow a relatively high probability of network penetration by a "national-scale" effort, but will tolerate only a small probability of attack from an "average" attacker. Government sites, which are attacked with much higher frequency¹, may need exceptionally low probability of success for a particular attacker level in order to expect few penetrations, and they may be more willing to pay the cost for that level of security.

Finally, this system can simulate dynamic attacks and use the results to test intrusion-detection systems. These analysis methods, as well as possible ways to calculate cost-effective defense strategies, are explained in more detail in Section 4.

This is not the first system to represent attacks graphically. For example Meadows [10] uses a graph representation to model stages of attacks, particularly attacks on cryptographic protocols. These visual representations resemble attack templates, but nodes in her graphs represent stages of the attack (a to-do list for an attacker) at a much higher level than we envision. Edges represent temporal dependencies. There is no tie-in to particular user level, machine, configuration, etc, and there are no weights. Meadows describes previous work that also breaks attacks into atomic steps.

Moskowitz and Kang [11] use a graph to represent *insecurity flow*. Edges represent penetration of a security barrier such as a firewall. Each edge is weighted with the probability of successfully breaching the defense. They want to compute the probability that *any* path exists from the source to the sink (i.e. any hole exists in the system). They give an exponential-time algorithm to determine a set of edge-disjoint paths that correspond to "reasonable" attacks. The resulting paths seem to have series-parallel structure which can then be exploited for computing the probability, assuming all edges fail independently.

The system we are proposing is closely related to that of Dacier et al. [3] although these systems were developed independently. Dacier et al. use a "privilege graph" which is similar to our attack graph, but seems to represent complex attacks with a single edge, and does not explicitly represent attacker capabilities. It is not clear how the privilege graph is generated, but they appear to use a scanning tool and static "average" costs. The authors transform the privilege graph into a Markov model and determine the

¹ The Defense Information Systems Agency reports that the Department of Defense is attacked 250,000 times a year. Los Alamos National Laboratories is attacked daily, with 22 proven outsider intrusions in the last five months. From "Security Measures," Albuquerque Journal, March 24, 1998, pp. B1-B2.

estimated mean time and effort to target by enumerating all searches in the privilege graph. The Markov model represents all possible probing sequences of a non-omniscient attacker. Ortalo et al. [13,14], present experimental results using this model, based on a privilege graph constructed from 13 major UNIX vulnerabilities. They conclude that Mean Effort to Failure (METF) is more valuable as a security metric than the single shortest path or raw number of paths to target. However, they were not always able to compute METF, even for fairly small graphs.

We can compute all near-optimal shortest paths much more efficiently than the enumeration required to compute METF. We believe that the set of near-optimal shortest paths provides a good measure of overall system security. We expect the set of paths to evolve appropriately with underlying changes in the system, but not to be unduly volatile. In addition, by modeling at a finer level, we can potentially discover new attacks, have more confidence in our cost metrics for common operations, and provide more informative output for system administrators with limited security experience. Our method is more comprehensive since it can model time dependencies, multiple attempts, and multi-prong attacks. Our edge costs are more customized to a particular network and attacker.

As an example of an attack with timing constraints not covered in standard tools, suppose an attacker can listen on a network link and detects a valid user initiating a telnet session. The attacker then crashes or disables the machine initiating the telnet session (e.g., using the "ping of death" or syn flooding) and hijacks the telnet session.

The remainder of the paper is organized as follows. Section 2 gives a more detailed description of attack templates, the configuration file, and attacker profile. Section 3 discusses attack-graph generation. Section 4 presents analysis methods. Section 5 discusses implementation issues, and Section 6 provides some concluding remarks.

2. CONFIGURATION FILES, ATTACKER PROFILES, AND ATTACK TEMPLATES

This section explains the inputs required for our method: configuration files, attacker profiles, and attack templates.

2.1 Configuration files

The configuration file contains information relevant to operating system, network type, router configuration, and network topology. More specifically, each **device** (i.e., workstation, printer, file server, etc.) should have the following information:

1. **Machine class:** workstation, printer, router, etc.
2. **Hardware type:** e.g., SUN SPARCstation™ 5
3. **Operating System**

- a. O.S. patches that have been installed.
4. **Users** (Initially just the classes of users, i.e. root, normal, privileged.)
5. **Configuration**
 - a. Ports enabled
 - b. Services enabled and privilege level on the services
 - c. Any intrusion detection applications installed
6. **Type of network(s)** the device is on (Ethernet, FDDI, ATM, etc.)
7. **Physical link** information such as type of communications media

A configuration file includes a graph of the topology of the network and can extend to other criteria such as information related to user behavior, like password implementation (i.e., are users required to change their password on a routine basis, do they pick their own password, is there periodic security training, etc.).

Building and maintaining configuration files by hand will be a tedious, time-consuming and error-prone task which could seriously limit the utility of the system. Therefore, we envision an automated tool to help generate and maintain this configuration file. For example, a root-level daemon on each network component can periodically send information to a central server. The configuration file could be based upon the information available from a tool like SATAN or the ISS scanner, augmented to match the conditions in the set of attack templates. We expect that we can add system topology information (e.g., from Cisco routers) and rlogin information across machines. Policy issues such as password policies will need to be entered manually, but won't change frequently. We hope the system administrator will have reasonable defenses in place to protect the system data when using an automated tool. For example, it may only be available online in one place while the administrator is running analyses.

2.2 Attacker Profiles

We do not expect to model human behavior at this point, however we do believe the system needs to incorporate attacker capability, as this can have a significant impact on security decisions. The attacker profile contains information about an assumed attacker's capabilities, such as the possession of an automated toolkit or a sniffer, access to supercomputing facilities or significant financial resources, physical access to a network or machine, etc. The attacker profile is used to determine the probability of success for particular attack methods. The attacker profile represents the initial capabilities of the attacker in the same way that the configuration file represents the initial state of the network. To assist the analyst, default profiles for various attacker skill levels such as novice vs. expert could be provided. The network owner's security policies and strategies can be guided by the level of attacker they wish to strongly deter and their available budget.

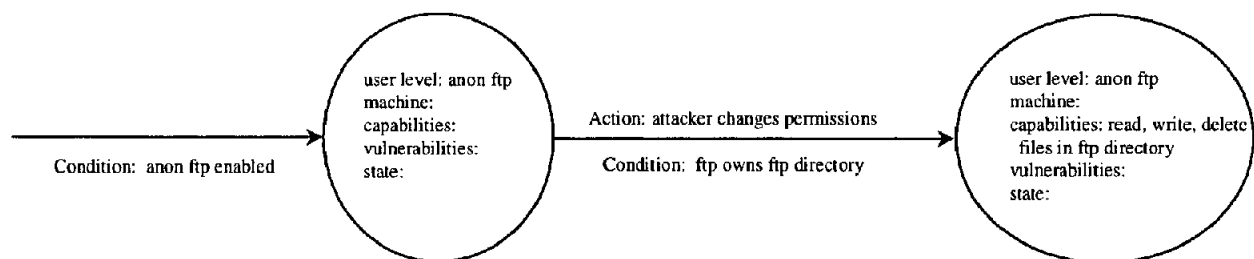


Figure 1. Example template for anonymous ftp attack

2.3 Attack template

Attack templates represent generic steps in known attacks, including conditions which must hold for the attack to be possible. Each node in the attack template represents a state of an attack, as detailed below. The nodes are distinguishable, and therefore, each edge represents a change in state on one or more devices. Examples of state changes are: a file was changed, a configuration setting was altered, an executable was run, an attacker gains root privileges on a machine, etc. An example of attack templates using the following definitions and fields is shown in Figure 1. Nodes have the following fields:

1. **User level:** Possible user levels include: none, guest (anonymous), normal user, privileged user, root, or system administrator. This could be one-time access.
2. **Machine(s):** This field could specify an individual machine or set of machines, all machines on a subnet, or all machines on multiple subnets. In the attack templates, this field contains placeholders (variables) that are instantiated in the attack graph.
3. **Vulnerabilities:** This field indicates changes to the original configuration caused by attacker actions. When building the attack graph, the vulnerabilities "overwrite" the relevant portions of the configuration file for a given node.
4. **Capabilities:** This field locally overwrites the attacker profile in the same way the vulnerabilities field overwrites the configuration file. Possible entries include physical access to part of the network, installation of a trojan horse, delivery of mail or an applet with executable content, or installation of a sniffer on an edge of the network. It can also indicate other programs that the attacker has successfully installed or has access to, such as crack programs, root kits, etc.
5. **State:** The state field breaks attacks into atomic pieces. An attack may require several steps, each of which could fail and none of which adds a new capability, vulnerability, etc. The states distinguish the nodes by indicating progress in the attack.

Edges in the attack template represent actions taken by the attacker or his/her victim/unwitting assistant. They can also indicate an event such as the detection of a particular type of packet on a network by some hardware and/or software under

attacker control. To allow maximum detection of new attack sequences, these events should be atomic and nontrivial (probability of success is strictly above 0). Probability-one edges must change the environment (introduce a vulnerability, change user level, etc.). Each edge has conditions on the users and/or machines. If all the conditions are met, the attack succeeds with a given probability and/or cost. The edges can be a function of configuration and attacker capability. If a user is only interested in viewing the possible universe of attacks regardless of cost/success probability, then these functions could be extremely simple. The probability-of-success numbers can be obtained from polling experts (assessing the best subjective judgments), from information about the frequency of attacks on certain kinds of networks [6], and from experimentation. Computer-security personnel can test various attacks. Furthermore, one can make increasingly-automated testbeds accessible from the internet and advertise them as challenges to the computer-security community, then gather statistics about success probability.

In the above paragraph, we use probability for edge weights, but one could also use other metrics such as time to success, effort required, or "cost" as an edge weight. The time to success can be an appealing metric, especially when network assets have a well-defined lifetime (i.e., password files or encryption keys changing regularly). Time as a metric also has a more obvious tie-in with intrusion detection. For example, if one can detect an attack step with a test, the test should be run more frequently than the average time to success of the attack.

A number of issues are not completely resolved. There is some flexibility in assigning conditions to the arcs (requirements for the attack) vs. the nodes (part of the state). For example, possession of a root kit may be required for a certain attack. It can be made a condition of the edge (hence the edge is not added to the attack graph unless the attacker possesses a root kit) or it can be made a state of the start node (thus the attacker must have a root kit in order for the node to be reached in the first place). In addition, one must carefully choose levels of machine aggregation. Generating nodes for all possible subsets of machines will be impossible even for small systems. However, we believe the design described above can model a wide variety of attacks. For example, we have developed a set of templates for several attacks in each of the following classes: sendmail, ftp, telnet, Windows NT, and Java. Furthermore, the system has sufficient flexibility to evolve smoothly as new, previously unanticipated modeling needs arise.

3. GENERATING THE ATTACK GRAPH

In this section we describe how one might generate the attack graph from a configuration file, an attacker profile, and a database of attack templates. In general the nodes of the attack graph look

like nodes of the attack templates instantiated with particular users and machines. Edges are labeled only by a probability-of-success (or cost) measure, and a documentation string for the user interface. For ease of exposition, for the remainder of this section, we will call the measure the *weight* of the edge. This weight is determined by an *instantiation function* associated with each edge of an attack template. This function accesses the configuration file and the attacker profile. If an edge goes from node u to node v , then we call node u the *tail* of the edge and node v the *head* of the edge.

We now describe how the attack graph could be generated by building backwards from a goal node. One could also build forward from a start node (to explore the universe of possibilities) or assume both a start and a goal node. We illustrate this description with the simple example in Figure 2. The attacker profile, which is not shown in Figure 2 for space reasons, assumes that the attacker has physical access to B and the boot CD. The goal state is to obtain user level access on machine M, and the start state(s) is nothing beyond the capabilities in the attacker profile. We maintain a queue of generated nodes which have not been processed. Initially this queue contains only the goal node and nodes are added as they are created.

Start with the goal node: achievement of user-level access on machine M. The graph generator checks the database of attack templates and identifies all edges whose heads match the goal node. Assuming this database contains only the two templates shown in Figure 2, we find two matches, namely the head of each attack template. Consider the first template for a rlogin attack. Machine M matches the variable M_2 in the template. The instantiation function can then generate the tail node (node N_1) by generating all (user, machine) pairs that meet the constraints (the user has an account on this machine and M, and an appropriate rlogin file on M). Note that if machine M has rlogin disabled, then node N_1 would not be generated. On the assumption that machines A and B can communicate with M (given the rlogin file), the probability of the edge from node N_1 to the goal is 1. Node N_1 is an OR node, meaning that achievement of any (user, machine) pair suffices.

The goal node also matches the last node of the second template for physical access. Machine M matches the variable X and the instantiation function creates node N_4 , which in turn generates N_5 . However, the attacker does not have physical access to M. Thus, the nodes N_4 and N_5 are marked with a dotted line to show that under existing conditions, they would not be reachable from the start state. There could be other attack templates which would lead to physical access to M, and then these nodes would be enabled. In this case, the capability of physical access to M is an addition (or overwrite) to the attacker profile.

Since there are no more matches for the goal, node N_1 is removed from the queue and matched against the database against both heads and tails. In principle, it can again match with the head of the rlogin attack. However, assuming transitivity (i.e. that a user has rlogin set up symmetrically for all his accounts), applying this edge again will give no new information. Recognizing and preventing this in all cases is still a research issue. Node N_1 also matches with the last node of the second template on physical access, which generates node N_2 .

Node N_2 matches the middle node of the second template. The attacker profile indicates that the attacker has physical access to

machine B, but not to machine A. Since N_2 is an OR node, it can be satisfied by the attacker becoming root on B. In this example, node N_3 is created with a subset of the machines in node N_2 . Alternatively, we could have generated an intermediate node for becoming root only on B rather than A or B. The advantage of this is that additional paths to the goal can pass through this intermediate node (i.e. a path unique to B cannot be built off a node which can be satisfied by either A or B). When both goal and start nodes are specified, either method is likely to work, since if this node is required for a path, it will be generated later. If only one of goal and start are specified, the more verbose method may be advantageous. We recognize node N_3 as a start node in this graph, and thus we do not try to match backwards from it. Although it is not shown, the attack graph would also contain a node for A similar to N_3 which, like nodes N_4 and N_5 , is unreachable because the attacker has no physical access to A.

When a node is matched with a template in the database, the other endpoint could either be generated as in the example above, or be a node already generated. Thus the generator must be able to efficiently search the nodes generated so far. Edges created between two nodes already generated can lead to interactions between attack templates and the “discovery” of new attack sequences.

There are a number of implementation issues which must be resolved when the system is tested on large datasets. These issues are presented in Section 5.

4. ANALYSIS METHODS

In this section we discuss analysis of the attack graph: determining a (set of) low-cost attack paths, finding a set of cost-effective defenses, and simulating dynamic attacks. A path from a start node to a goal node has a weight equal to the sum of the weights of the edges in the path. In the case where weights represent success probabilities rather than costs, we can convert to a problem of this form. By replacing each weight by its logarithm, the weight of the path (sum) now represents the product of the probabilities, and we wish to find highest-cost paths. Because the probabilities are all between 0 and 1, the logs are all non-positive numbers. Therefore, if we negate all the probabilities (i.e., multiply by -1), all weights become non-negative and the problem is converted from maximization to a minimization problem, that of finding the low-cost paths. The structure of the weights is critical for this conversion, because in general finding the longest paths in a network is NP-complete [5].

If one wishes to find only a single shortest path, representing the most likely or least-cost attack, from a start node to any number of goal nodes, then any standard shortest-path algorithm, such as Dijkstra's algorithm will suffice. Such codes are very efficient (near linear-time) and readily available [2].

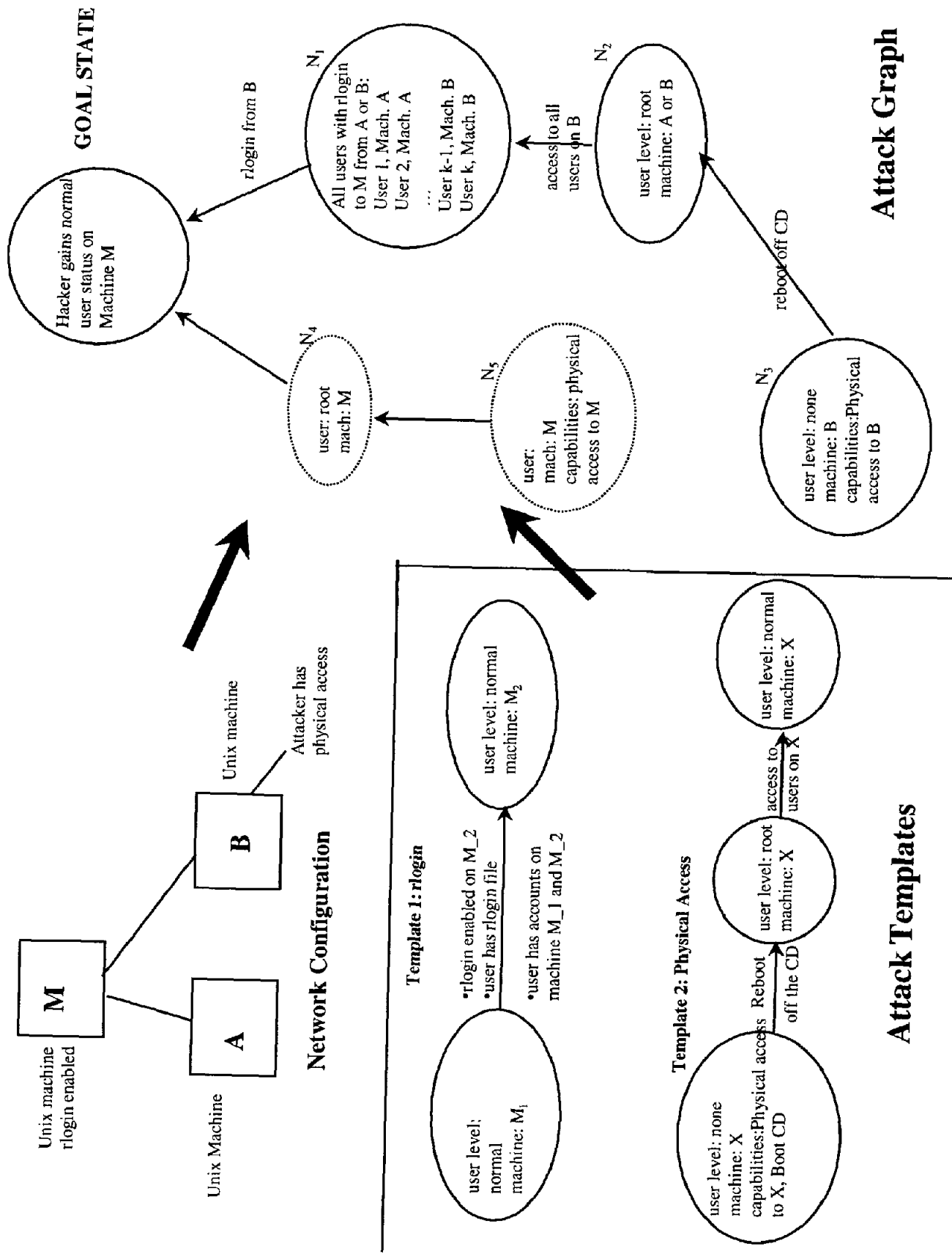


Figure 2. Graph Generation Example

However, the weights on the edges will almost surely not be sufficiently accurate to merit looking only at shortest paths. A better method is to use the technique of Naor and Brutlag [12]. Their algorithm computes a compact representation of all paths that are within δ of optimal for some given error parameter δ (the δ -optimal paths). For example, edges that are common to many δ -optimal paths are likely to represent vulnerable points. Their method applies to undirected graphs, and may need to be modified for directed graphs.

If edges have two weights representing different optimization criteria, bicriteria shortest-path algorithms compute a set of paths that are (near) optimal with respect to one weight while obeying a bound (e.g. a budget) on the second weight. Current (near) exact solution methods involve shortest-path computations in significantly expanded graphs. However, scaling provides a graceful tradeoff between approximation quality and the time and space needed to compute the solution [15]. Very recently, Tayi et al. [18] have shown how to compute all undominated (Pareto optimal) paths for multiple edge weights. Their algorithm runs in pseudo-polynomial time provided the number of criteria is bounded (i.e., the exponent in the running time depends on the number of criteria).

Given a set of possible defenses, each with a cost (financial, loss of service, etc.) and defense budget, we would like to compute a set of defenses to implement which will maximally decrease the probability of success (or increase attacker cost). Implementing a defense strategy on a particular machine could have a widespread effect on the attack graph, since it affects the weight on every edge involving that machine and an attack affected by the defense. In its most general form, this problem is NP-hard to approximate to within better than a logarithmic factor (by reduction from set cover). However, it is possible that attack graphs have special structure which makes the problem easier than this worst case.

A reasonable first question is to take the set of paths computed by the Naor-and-Brutlag algorithm and find a set of defenses that increases the cost of each of those paths above some threshold such as the value of the data stored in the system. The Naor-and-Brutlag algorithm also gives the number of δ -optimal paths. Therefore, one can use the following greedy algorithm: for defense d_i , compute the total gain g_i (increase in cost or decrease in success probability) over all the paths. Let c_i be the cost of defense d_i . Choose the most cost-effective defense (the one which maximizes (g_i / c_i)). Iterate until all paths are over the threshold. Alternatively, one can modify exact set-cover algorithms for this problem. Because one can model airline crew scheduling as a set-cover problem, there has been extensive work in (near) exact methods for this problem.

The unweighted version of this defense problem can model the placement of monitors for intrusion detection. The question becomes: choose a minimum number of monitor placements such that all the near-optimal attack paths are monitored at least k times. That is, any attempt to execute any of the attacks will potentially be observed by k (possibly nondisjoint) monitors. If monitoring of each edge or node in the attack graph were independent (i.e. we must pay for each monitor placed on any edge), we have the k -hurdle problem, which can be solved efficiently [1]. When sets of edges are affected by a single monitor placement, the problem is still theoretically as hard as set

cover (assuming no special structure). However, it will be easier than the weighted version in practice.

Even in the absence of automated defense-selection tools, however, the system can serve as a defense-selection tool. A network administrator can change the configuration file to reflect the placement of a set of defenses, and then run the shortest-paths analysis to determine their effect. Using global search techniques, this iterative procedure could be automated as well.

Alternatively, a system administrator could use the attack graph as the foundation for a simulation tool. The simulation could start from the node where the attacker breaks in or begins. The attacker could pick an edge (representing an attack), have the simulation “flip a coin” to see if the path is successful according to the edge probability, and if successful, the attacker continues down the path, otherwise, she backtracks. This kind of a model could represent the real behavior of attackers (going down one branch, figuring that it is too difficult to do something such as get root on a particular machine, so backing up and trying another method. This is one of the attacker models for which Dacier et al. compute METF). Another strategy would be that the attacker chooses his next attack edge based on configuration knowledge of all outgoing links, plus an estimate of the shortest path from neighboring nodes. The success probabilities used in the simulation can change dynamically to reflect the success/failure the attacker has had so far (i.e. as the attacker learns more about the particular system). This simulation technique would be appropriate for a graphical user interface which could show a network designer the paths the attacker is most likely to take (for example, by lighting up nodes with a green light as the attacker is successful, and displaying a red light where the attacker gets blocked).

5. IMPLEMENTATION ISSUES

There are a number of implementation issues which must be resolved when the system is tested on large datasets. For example, it may be useful to allow some hierarchy in the attack graph generation. If there is a common set of attack paths that allow an attacker to become root from a normal user account on the same machine, this could be a useful building block. If multiple machines have identical parameters, this subgraph need only be built once. It can be collapsed to one edge, with the option of expanding the graph for the system administrator via the user interface.

For each piece of the configuration or attacker profile files, it would be useful to maintain a list of edges whose probability was influenced by that attribute. This will allow quick recomputation of edge weights if a configuration or attacker parameter is changed. However, it is more challenging to leave such a “trail” for pieces that were missing in the configuration file or lead to edges not existing.

Instantiation functions could become quite complicated. For example, suppose one is searching for the universe of possible consequences from a break-in. In “spam” attacks on networks, an attack is replicated on many machines. If one wants to predict the number of machines compromised, the instantiation function must have an inclusion/exclusion calculation if the weights are probabilities.

The instantiation function may generate multiple nodes if reachability is a condition on an edge and there are multiple

routers between a pair of machines. The steps necessary for routing a message, telnet session, etc., are explicitly included in the attack graph because this access is an important security parameter. If a worrisome attack path involves going through multiple routers, the system administrator has the option of modifying the access-control tables to forbid the access.

There are two possible ways to represent the users and/or machines in a node: as an explicit list, or as a list of conditions (from edge conditions). Since each condition is associated with an instantiation function, one can go from condition lists to explicit user lists. Both representations could be used in different parts of the attack graph during generation depending upon the ways the lists will be refined. For example, the list-of-conditions method may be better for matching.

Another issue is how to model attacks that require access to two different user accounts possibly on two different machines. This could be done as a 2-step process in the attack template. However, in the attack graph, getting access to two users' accounts is highly correlated within the various attacks, and this correlation must be incorporated into both instantiation functions. Therefore, obtaining access to two or more accounts should probably be combined as a single atomic event. Since we expect most attacks to require access to only a small number of accounts simultaneously, this consolidation/duplication should not cause overwhelming graph expansion.

Matching methods will evolve experimentally. However, unification techniques used in logic programming languages are a natural starting place. It is possible that using lists of conditions, one can search the set of generated nodes efficiently using hashing techniques.

6. CONCLUSIONS

We have spoken with computer security experts, and the general consensus is that an attack-graph analysis could work well for modeling enterprise-level (commercial or military) network risks. We would like to take this work further and develop a robust tool with a graphical interface which is easy to use and which links to a large list of vulnerabilities, such as the databases that commercial vendors (i.e., Internet Security Systems' X-force database) have created or that CERT has compiled. We envision that the user could choose to view representations of all near-optimal paths, or individual high risk paths. He/she could examine edges of interest, obtain relevant topology or configuration information, or choose to ignore some vulnerabilities, recompute the graph, and review. In addition, the attack graph would allow system administrators to look at potentially high-risk paths, even if there are no vulnerabilities on individual portions of them.

This paper has presented a method for risk analysis of computer networks. The method is based on the idea of an attack graph which represents attack states and the transitions between them. The attack graph can be used to identify attack paths that are most likely to succeed, or to simulate various attacks. The attack graph could also be used to identify undesirable activities an attacker could perform once they entered the network. The major advance of this method over other computer security risk methods is that it considers the physical network topology in conjunction with the set of attacks. Thus, it goes beyond the scanning tools that are

currently available which check a "laundry list" of services or conditions that are enabled on a particular machine.

The method we have presented addresses many of the modeling issues that current scanning technology cannot. Specifically, our graph-based approach allows for modeling dynamic aspects of the network (this can be done by overwriting the configuration file as the attacker makes system changes). Our approach allows for several levels of attacker capability that can change dynamically. It allows for the modeling of user access levels and transitions between them, which are critical in network security. And it represents the time dependencies in sequences of attacks. We would like to examine the possibility of using the attack graph approach, especially the idea of attack templates, for testing intrusion detection systems. The attack graph could also be the basis for identifying the most cost-effective set and placement of defenses.

There are potential limitations with our method. We have not generated a realistic size attack graph based on 10 or 20 templates, and we have not resolved all of the issues associated with the matching of templates to configuration and attacker profile. Also, the existence of attack templates and of the configuration file could be another vulnerability in itself. If these got into the wrong hands, they would be very valuable tools for the attacker. However, we believe that the approach we have presented is an advance in network-vulnerability modeling and will ultimately help network security if implemented in a reasonable way.

7. ACKNOWLEDGMENTS

Timothy Gaylor, formerly at Sandia National Laboratories and currently at 3M, was instrumental in the development of the approach in this paper. The basic notion of an attack graph is due to Fred Cohen of Sandia National Laboratories. The authors also thank Stefan Chakerian, Greg Wyss, and John Howard of Sandia National Laboratories and Jean Camp at the Kennedy School of Government/Harvard University for helpful and insightful discussions. This work was supported in part by the United States Department of Energy under contract DE-AC04-94AL85000.

8. REFERENCES

- [1] Burch, C., Krumke, S., Marathe, M., Phillips C., and Sundberg, E. "Multicriteria Approximation Through Decomposition", submitted, 1998.
- [2] Cherkassky, B.V., A.V. Goldberg, and T. Radzik. "Shortest Paths Algorithms: Theory and Experimental Evaluation," *Math Programming*, **73**, pp.129--174, 1996. Web site: <http://www.neci.nj.nec.com/homepages/avg/soft/soft.html>
- [3] Dacier, M., Y. Deswarte, and M. Kaaniche. "Quantitative Assessment of Operational Security: Models and Tools." LAAS Research Report 96493, May 1996.
- [4] Denning, D. E. "An Intrusion-Detection Model." *IEEE Transactions on Software Engineering*, **13**(2), 1987.
- [5] Garey, M. R. and D. S. Johnson, *Computers and Intractability: A Guide to the Theory of NP-Completeness*, W. H. Freeman and Company, NY, 1979.
- [6] Howard, J. D. "An Analysis of Security Incidents on the Internet, 1989-1995." Doctoral dissertation, Carnegie Mellon University, 1997.

- [7] Internet Security Systems, Inc. 41 Perimeter Center East, Suite 550, Atlanta, GA 30346. Creator of the X-force database, accessed via <http://www.iss.net/xforce>.
- [8] Lundqvist, U. and E. Jonsson. "A Map of Security Risks associated with using COTS." *Computer*, 31(6): 60-66, 1998.
- [9] Lunt, T. F. "A Survey of Intrusion Detection Techniques." *Computers and Security* 12, pp. 405-418, 1993.
- [10] Meadows, C., "A representation of Protocol Attacks for Risk Assessment", *Network Threats*, DIMACS Series in Discrete Mathematics and Theoretical Computer Science, Vol. 38, R. N. Wright and P.G. Neumann editors, American Mathematical Society, pp. 1-10.
- [11] Moskowithz, I.S, and M. H. Kang, "An Insecurity Flow Model", *Proceedings of the Sixth New Security Paradigms Workshop*, Langdale, Cumbria, UK, September, 1997, pp. 61-74.
- [12] Naor, D. and D. Brutlag, "On suboptimal alignment of biological sequences," *Proceedings of the 4th annual Symposium on Combinatorial Pattern Matching*, Springer Verlag, 1993, pp. 179-196.
- [13] Ortalo, R., Y. Deswarte, and M. Kaâniche, "Experimenting with Quantitative Evaluation Tools for Monitoring Operational Security", in *Dependable Computing for Critical Applications 6 (DCCA'6)*, (M.Dal Cin, C. Meadows and W.H. Sanders, Eds.), Grainau, Germany, March 5-7 1997, Dependable Computing and Fault-Tolerant Systems, vol.11, pp.307-328, ISBN 0-8186-8009-1, IEEE Computer Society Press, 1998.
- [14] Ortalo, R., Y. Deswarte, "Quantitative Evaluation of Information System Security", in *Global IT Security, Proc. of the IFIP TC11 14th International Conference on Information Security (IFIP/SEC'98)*, (G. Papp, R. Posch, eds.), August 31 - September 4, Vienna-Budapest, Austria-Hungary, Austrian Computer Society, ISBN 3-85403-116-5, pp. 321-332, 1998.
- [15] Phillips, C. A., "The network inhibition problem," *Proceedings of the 25th Annual ACM Symposium on the Theory of Computing*, May 16-18, 1993, pp. 776-785.
- [16] Presidential Commission on Critical Infrastructure Protection. Commission Report "Critical Foundations: Protecting America's Infrastructures," October 1997. Available at: http://www.pccip.gov/report_index.html
- [17] SATAN. (Security Administrator Tool for Analyzing Networks) tool. SATAN's creators, Mr. Dan Farmer and Mr. Wietse Venema, made SATAN widely available over the Internet without cost starting April 5, 1995. It can be obtained from the web site: <http://142.3.223.54/~short/SECURITY/satan.html>
- [18] Tayi, G., Rosencrantz, D. and S. Ravi. "Path Problems in Networks with Vector Valued Edge Weights." Submitted for publication, October 1997.
- [19] Wyss, G. D., Schriener, H. K., and T. R. Gaylor (1996). "Probabilistic Logic Modeling of for Hybrid Network Architectures." Published in the Proceedings of the 21st IEEE Conference on Local Computer Networks.