Collaborative Defense Against Zero-Day and Polymorphic Worms: Detection, Response and an Evaluation Framework

By

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M.S. (University of California, Davis) 2004

DISSERTATION

Submitted in partial satisfaction of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

Computer Science

in the

OFFICE OF GRADUATE STUDIES
of the
UNIVERSITY OF CALIFORNIA
DAVIS

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2007

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To my Parents

Contents

Acknowledgements

I would first like to thank my mentor Jeff Rowe without whom I would not be writing this dissertation. He has been an eternal source of ideas and practical advice through out the course of my doctoral research. A person of great kindness who tolerated all my follies and continued to teach and guide me. Next, I would like to thank my advisor Karl Levitt who has been more than a research advisor to me. He has been a great friend who stood by me through thick and thin the past six years at school as well as in my personal life – a wedding, a child birth and three funerals. I'm yet to meet a kinder person than these two.

I would always cherish the inspiring discussions I had with John-Mark Agosta at Intel. I thank him a lot for reading the numerous drafts of ideas, papers and this dissertation with a fine comb and providing his insightful and thought-provoking comments over the past three years. I thank Felix Wu and Todd Heberlein for those numerous inspirational chats and putting graduate school in perspective. I thank Matt Bishop for reading drafts of this dissertation and providing timely feedback.

Life would have been much harder without my dear friends at the Security Lab, Ebrima Ceesay, Denys Ma, Lynn Nguyen, Marcus Tylutki, Tufan Demir and Allen Ting who formed a great group to share all the fun and frustrations of graduate school. I have to thank the American education system and UCDavis for providing me this great educational and cultural immersion that I never imagined possible before coming to Davis.

Finally, I thank my family – partiularly my father who weathered the numerous misfortunes single-handedly all the way across the seven seas and let me carry on with my graduate school.

Abstract

Computer worms present a grave concern to the common man, and a challenging problem to the computer security community. Worms' abilities have precluded human intervention. Fast worms can be too fast to respond to. Slow worms can be too slow to be noticed. Zero-day and polymorphic worms can look like ordinary traffic to evoke any suspicion until they cause large scale destruction. This demands not just automated response but automated and intelligent response. This dissertation presents such an automated and intelligent means of detecting and responding to zero-day worms that could possibly be polymorphic in a signature independent fashion.

Worms are detected cooperatively using a novel distributed application of the long-established Sequential Hypothesis Testing technique. The technique developed here builds a distributed worm detector of any desirable fidelity from unreliable anomaly detection systems. Tracking anomalies instead of signatures enables detection of zero-day and polymorphic worms. Cost-effective responses in the face of uncertainty about worms are selected automatically using Dynamic Programming. Responses are selected based on the likelihood of a current worm attack, and the relative costs of infection and responses, while minimizing the operating cost over a period of time. This technique uses information about anomalous events, potentially due to a worm, observed by cooperating peers to choose optimal actions for local implementation.

In addition to developing the above techniques, this dissertation also presents a generic testing framework based on the Emulab network testbed to evaluate these and other such worm defense models, and provides a detailed survey of the research done so far in worm defense.

Chapter 1

Introduction

Computer worms are a serious problem. Over the decades, it has transformed from being an useful tool for distributed computing to a lethal tool chest of cyber criminals and one of the worst nightmares for legitimate computer users. Worms could be used by attackers and terrorists to launch various kinds of attacks such as denial-of-service, massive identity theft, and to scout for unguarded computers that can be subscribed to botnets. These can later be used for nefarious activities such as spam campaigns, phishing attacks, and illicit international financial transactions among others.

Tremendous progress has been made in the past decade to deal with worms. Worms manifest themselves through some of their activities which are anomalous with the usual operations or through damages they cause. They are then captured, analyzed manually and appropriate techniques are engineered and deployed to mitigate their ill-effects. However, given the speed with which they can spread, such manual analysis is too slow and the battle is lost even before it is fought. Worms can also spread so slow that any ill-effects they cause seem as isolated incidents rather than correlated events. Worms could also be programmed not to reveal themselves until all susceptible computers are infected, and then unleash their lethal force all at once at a pre-determined time or upon receipt of a commands. Such dangerous potentials of worms render manual intervention ineffective and warrant a timely and automatic detection of, and response to, worms.

One technique that has wide-spread prevalence and exemplary commercial success is traffic filtering based on signatures of worms. A signature is any string in the body of the worm that is unique to it; unique in the sense, that there is no other known worm with the same string. This method exploits the fact that a worm is after all a sequence of bits, and

a regular expression can be developed for a pattern unique to each worm. All traffic that enters a network or a machine, or crosses any boundary of interest, is compared against this regular expression. If there is a match, the given response action is taken. A typical response would be to drop the connection and inform the responsible authority about the incident. If there are multiple worms to be guarded against, multiple regular expressions are used. Sophisticated algorithms, including proposals to incorporate them in hardware, are used to perform this pattern matching at high speeds to keep up with the ever-increasing performance of network devices delivering more volume of traffic in lesser time.

This technique naturally does not work against unknown worms and polymorphic worms. Unknown worms also known as Zero-day worms use novel attacks or exploit hitherto unknown vulnerabilities. Polymorphic worms, on the other hand, change their appearance while preserving the semantics each time they spread from one victim to another. Techniques such as encryption and instruction re-ordering are used to achieve this polymorphism making their identification with pattern matching or signature matching ineffective even if the worm's details and mode of operation are known. Together, zero-day worms and polymorphic worms present a great challenge for computer and network administrators as well as researchers. Despite huge strides during the past few years, dealing with these two are still active research topics.

Once an outbreak of a worm has been detected, responding to it becomes trivial – shutdown services until a suitable solution is worked out . There is no point in continuing service without adequate safety guards when it is clear that infection is imminent. Suitable solutions could be automatic or manual distribution and installation of patches, signatures or both, or any other such strategies. However, one cannot really wait until a worm is authoritatively detected. There is a need to take evasive actions even while the detection process is in progress. Shutting down the service completely is definitely one such candidate response. Alternatively, a reduced service can be provided by scrutinizing every service request for infection attempts by a worm. Choosing whether or not to take evasive actions becomes challenging as the costs of such actions in response to false alarms must be balanced against the costs of infection.

The novel ideas for detecting zero-day worms explored in this dissertation deal with these two kinds of worms from a signature-independent perspective. This dissertation develops methods to detect worms in a distributed and collaborative fashion by exchanging and corroborating reports about anomalous events. Current anomaly detectors are prone

to high false positives. The methods developed here use a distributed version of a statistical tool called Sequential Hypothesis Testing [113] to build a strong distributed worm detector from imperfect or weak anomaly detectors as the building blocks. Chapter 3 details the algorithm and the protocols used to detect zero-day worms.

This dissertation also develops a control-theoretic approach for optimal cost response to events that are possibly due to a worm. This approach uses dynamic-programming techniques to generate a table of rules that can be looked-up during operation to determine the optimal-cost action to take in response to possible worm-events. The details of this idea is developed in chapter 4.

Apart from these two techniques, chapter 2 develops an evaluation framework that makes it easy to test these and other such new methodologies on an isolated network testbed such as Emulab or DETER. The next chapter, presents a overview, and a brief history of worms and an overview the latest technologies that are being developed and used in the worm research field.

1.1 Contributions

This dissertation makes several contributions to the field of worm research.

- First and foremost it develops holistic solutions to the worm problem, detection as well as response, from a content-independent perspective and making use of anomaly detection. This is a paradigm shift from the current solutions that look for certain patterns in the worm content called signatures. This is a major contribution as it is very difficult, if not impossible, to generate and detect new high speed worms or polymorphic worms with signature-specific approaches.

- An important contribution of this dissertation is that it moves away from a centralized control element that is a requirement in most of the other systems proposed so far and thus providing fault-tolerance to the system.

- This dissertation builds an evaluation framework which can be used to quickly and easily deploy and test new worm defense systems. This framework consists of the necessary software infrastructure to conduct experiments in the EMULAB [120] and DETER [16] network testbeds to evaluate new algorithms against worms.

- A high fidelity distributed worm detector is developed in this dissertation using imperfect and unreliable components such as anomaly detectors that have high false positive rates. This has been achieved using a novel distributed application of a statistical technique called Sequential Hypothesis Testing(dSHT) .

- This dissertation develops a control-theoretic approach to response, independent of any particular worm. The response mechanism is designed to make use of the dSHT developed here to detect the worm and apply Dynamic Programming techniques to choose the appropriate response from a give set of responses.

Chapter 2

An overview of Worm Research

There is a vast literature detailing the history, evolution and mechanics of worms [33]. In this chapter, we will present a quick overview of these aspects first in Sec. 2.1, and devote the rest of the chapter to present more detailed discussions on the current paradigms that govern the state-of-the-art in prevention, detection, and response and mitigation techniques against worms.

The problem of worms can be partitioned into several sub-problems and each one is currently being addressed from several perspectives using a variety of tools from mathematics to machine learning to software engineering. Sec. 2.2 of this chapter presents this overview of the problem space. The two sections following that delve deeper into the work done so far by the research community to address two of the sub-problems, viz-a-viz, detection and mitigation. The last section talks about evaluation systems that can evaluate these research efforts – including new worms, detection and response. This chapter also sets up the stage for the rest of this dissertation by identifying the gaps in the current research.

2.1 An overview of worms

This section provides a very basic understanding of a worm for the uninitiated and then puts that in perspective by providing a few examples of old as well as hypothetical worms. It also gives an overview of the various algorithms that can be used by worms to look for new victims.

2.1.1 Hello Worm!

A computer worm is an extremely handy tool to perform a particular task in a distributed fashion or repetitively on several machines. Unfortunately, it can also be used as a weapon. For example, consider a computing task that takes several days to perform on a single machine. It can be done much quicker if it can be broken down to several smaller and simpler sub-tasks that can be done in parallel on several machines. A parallel processing machine will be very useful for this purpose. However, such a machine is usually very complex, expensive and not very versatile. Instead of designing such a complex parallel processing machine, we can design a comparatively simple tool that can assign sub-tasks to capable idle machines and collect and compile the results. Such a tool is a worm.

When used properly a worm tries to hop on from one idle host to another carrying with it a sub-task in search of computing power to accomplish its tasks and return the results to the parent process that waits for the results on a different machine. A classic example is the worm program that Shoch and Hupp used at the PARC to make use of idle computing power of computers of several employees after regular office hours [97].

The most important requirement for a worm to perform a sub-task on a idle machine is, obviously, permissions to execute programs on it. In cases where prior permissions are granted on various machines, the task is simple. In cases where permissions are not granted the worm may try to force his or her way into other peoples' computers. This can be done by remotely exploiting one of the vulnerabilities that exist in those computers. When a worm does this, it transforms from being an useful tool into a malicious software (malware). When there is a particular vulnerability on many hundreds of machines spread across the Internet, the Internet becomes a happy hunting ground for anyone that can exploit that it. In fact, a vulnerability gives certain capabilities called *primitives* to the attacker. For example, improper bounds checking in an array operation or an input operation is a vulnerability that can give an attacker the ability to overwrite the return pointer on the stack – also called *smashing the stack* [87]. The attacker can then use this *primitive* to write several exploits.

2.1.2 Worm Examples

Morris Worm: This was the first popular worm(released 1988). This worm located vulnerable hosts and accounts, exploited security holes on them to transfer a copy of the worm

and finally ran the worm code. The worm obtained further candidate host IP addresses to infect by examining the current victim's */etc/hosts.equiv* and */.rhosts* files, user files like *.forward* and *.rhosts*, dynamic routing information produced by the *netstat* program and by randomly generating host addresses on local networks. It penetrated remote systems by exploiting the vulnerabilities in either the *finger daemon*, *sendmail*, or by *guessing passwords* of accounts and using the *rexec* and *rsh* services to penetrate hosts that shared the same account [50, 95, 101].

Code Red: On June 18th 2001 a Windows IIS vulnerability was discovered. After about a month a worm called Code-Red that exploited this vulnerability was released. It was buggy and did not spread much. About a week after that, a truly virulent version was released. This worm worked as follows. On each machine the worm generated 100 threads. Each of the first 99 threads randomly chose an IP address and tried to set up a `http` connection with it. If the connection was successful, the worm would send a copy of itself to the victim to compromise it and continue to find another one. If the `http` connection could not be set-up within 21 seconds, another random IP address was generated and the entire process repeated. The worm's payload was programmed to launch a denial-of-service attack against the White House web-site at a pre-determined time. However, once the worm was detected the attack was thwarted by the White House system administrators by moving the target web-site to a different IP address [8, 32, 77, 124].

Slammer: The Slammer worm [82], also known as the Sapphire Worm was the fastest computer worm in history. It began spreading throughout the Internet at about 5:30 UTC, on January 25 2003, and doubled in spread every 8.5 seconds. It infected more than 90 percent of vulnerable hosts within 10 minutes. Although very high speed worms [105] were theoretically predicted about a year before the arrival of Slammer, it was the first live worm that came any closer to such predicted speeds.

Slammer exploited a buffer overflow vulnerability in computers on the Internet running Microsoft's SQL Server or MSDE 2000. This vulnerability in an underlying indexing service was discovered in July 2002. Microsoft released a patch for the vulnerability before it was announced but many system administrators around the world didn't apply the patch for various reasons. The following were some of the reasons. The patch was more difficult to install than the original software itself. They were afraid that applying the patch might

disturb their current server settings while it was always not trivial to tune a software to the required settings and performance. Many just weren't ready to spend much time to fix this problem. Instead they were waiting for the next release to replace the entire software instead of applying patches. Some were just ignorant or lazy to apply patches.

Ironically, Slammer didn't even use any of the advanced scanning techniques that were hypothesized by Staniford et al. [107] to choose a worm's next victim. It was a worm that picked its next victim randomly[1]. It had a scanner of just 404 bytes including the UDP header in contrast to its predecessors Code Red that was 40KB and Nimda that was 60KB. The spread speed of Slammer was limited by the network bandwidth available to the victim. It was able to scan the network for susceptible hosts as fast as the compromised host could transmit packets and the network could deliver them. Since, a scan packet contains only 404 byte of data, an infected machine with a 100 Mb/s connection to the Internet could produce $\frac{100\times10^6}{404\times8} = 3\times10^4$ scans per second. The scanning was so aggressive that it quickly saturated the network and congested the network.

This was by far one of the most destructive worms whose ramifications rendered several ATMs unusable, canceled air flights and such. Peculiarly, this worm did not even have a pay load. All the damages were just out of sheer volume of traffic generated by the worm.

Polymorphic and Metamorphic Worms: Unlike where any two copies of a worm look alike, polymorphic and metamorphic worms differ in the physical appearance for each copy. Polymorphic worms use encryption techniques while metamorphic recompile themselves differently each time they try to spread make it difficult to detect.

Hypothetical Worms: Say a worm author collects a hit-list of a few thousand potentially vulnerable machines, ideally ones with good network connections. When released onto a machine on this hit-list, the worm begins infecting hosts on the list. When it infects a machine, it divides the hit-list into half, communicating one half to the recipient worm and keeping the other half. Such a worm is called a *Warhol Worm* and such a scanning technique *hit-list scanning* [107]. An improvised worm called a *Flash Worm* divides the list into n blocks instead of two huge ones, and infects one victim with a high bandwidth from each block and passes the block to the victim to continue infection from that list. Such a

[1]Scanning techniques are discussed in section 2.1.3.

worm if spread at the maximum possible rate could infect all the vulnerable machines on the Internet within a second [105, 107].

Though *Flash Worms* can propagate with high speed such that no human mediated efforts would be of any use, we could devise automatic means of detecting and stopping them. On the other end of the spectrum are *stealth worms* that spread much slower, evoke no peculiar communication pattern and spread in a fashion that makes detection hard [107]. Their goal is to spread to as many hosts as possible without being detected. Given Code-Red's final target of launching denial-of-service attacks against the White House web-site, the authors must have intended to make the spread stealthy. However, it spread too fast not to attract attention. However, once such a worm has been detected, manual means of mitigation are possible as was the case with Code-Red.

These worms usually do not cause any obvious damage to any system, for if they did, they would be detected easily. Some subtle uses of such worms are to plant Trojan Horses and 'time bombs', and to open back doors for future attacks.

2.1.3 Scanning algorithms

The propagation speed of a worm is generally limited by how quickly new potential victims can be discovered. For the purpose of this discussion, we define scanning to be the process of finding new potential victims. Without any clues, random scanning seems obvious. However, with some clever insights, new victims can be found much quicker. Some of the scanning techniques are discussed below.

Topological Scanning: This technique uses information contained on the victim machine to select new targets. A popular example that uses this technique is an e-mail virus. It uses the address book of the victim host. Another classic example is the *Morris worm* which made use of the entries in the `.rhosts` file to select new targets.

Sub-net Scanning: Sub-net scanning has been used by the Code Red and Nimda worms [116]. This involves scanning for vulnerable hosts in the same sub-net in preference to scanning for victims in the Internet. This usually increases the number of infected machines quickly. Once the worm penetrates the gateway of an organization it can quickly infect all the other vulnerable hosts behind that gateway as the security restrictions within an organization is usually relaxed.

Hit-list Scanning: New victims are probed or infected from a list built beforehand by the worm author. This list is usually built using slow and stealthy scans over a long period of time such as not to raise any suspicion. Alternatively, publicly available information is used to build this list. It could take several weeks or even months to build this list by which time the vulnerability might be fixed. So, this technique is effective only for exploiting unknown vulnerabilities and zero-day worms.

2.1.4 Scanning Constraints

Some interesting problems arise for the worms that try to spread fast. Their ability to scan the network are usually constrained by either bandwidth or latency limits [82].

Bandwidth Limited: Worms such as the Slammer that use UDP to spread face this constraint. Since there is no connection establishment overhead, the worm can continue transmitting packets into the network without expecting an acknowledgment from the victim. Modern servers are able to transmit data at more than a hundred Mbps rate. When data generated by the worms exceed the bandwidth of the network connection, a worm is said to be bandwidth limited.

Latency Limited: A worm that uses TCP to spread is constrained by latency. These worms need to transmit a TCP-SYN packet and wait for a response to establish a connection or time-out. The worm is not able to do anything during this waiting time and is called latency limited. To compensate, a worm can invoke a sufficiently large number of threads such that the CPU is kept busy always. However, in practice, context switch overhead is significant and there are insufficient resources to create enough threads to counteract the network delays. Hence the worm quickly reaches terminal spread speed.

2.2 Problems, Paradigms & Perspectives

There are several sub-problems to the problem of worms. A worm is after all a program that remotely exploits a vulnerability in some application and hijacks the control flow of that application. So, the genesis of the problem is in the vulnerability that can be remotely exploited. So, **prevention** of such vulnerabilities in the first place and then the attacks that exploit them form the first problem to be addressed.

However, there is a large legacy of programs already in use that cannot be discarded or relieved of such vulnerabilities overnight. Given that there are also several undiscovered vulnerabilities in extant programs, it is fair to assume that exploits will be written for them by attackers who find them. So, **detection** of these attacks forms the second problem to be addressed.

Detecting and dealing with known attacks is fairly straightforward. The vulnerabilities these attacks exploit can be patched thwarting the attack itself. Detecting attacks that exploit unknown vulnerabilities is a hard problem and any solution to it is bound to be imperfect. So, we need a way to **mitigate** and **respond** to those attacks that have defied detection. This forms the third set of problems to be solved.

There have also been some efforts at **predicting** the next worm by studying the current threat environment on the Internet. The threat to any particular service or application is estimated based on the volume of scans such applications receive on the Internet. This helps system administrators to be ready for the predicted worm either by pro-actively patching the corresponding vulnerabilities or with other suitable mitigating strategies [9]. Researchers also **study the behavior** of worms through *forensic analysis* of old worms such as Morris worm [50,95,100], witty worm [71,96], slammer [82], Code-Red [8], etc., *modeling* of both old worms such as code-red [124] and hypothetical worms such as Warhol [107], Flash worms [105, 106] and smart worms [29], and through *simulations* of various worm scenarios [119] and defense [27]. These studies instruct researchers on ways to devise appropriate defensive strategies for future worms.

Each of these problems is addressed from various perspectives using various paradigms, techniques, and tools drawn from several fields such as AI, statistics, and software engineering (sandboxing, honeypots). The rest of this chapter explores the above mentioned problems and current solutions.

2.3 Modeling of worms

A good mathematical model helps us understand anything precisely. The same applies to computer worms. Computer viruses spread have been studied extensively. Fred Cohen was the first to give a theoretical basis for the spread of computer viruses [38]. Kephart and White later drew an analogy between the spread of biological and computer viruses based on epidemiological models [66]. Staniford *et al* came up with the well-known

logistics equation to model Code-Red worm [107]. This was later shown to be insufficient due to the effects of counter-measures such as patching, filtering, etc and an alternative *two-factor* model matching the observed Code-Red data was proposed [124].

Noijiri *et al.* propose a generic model for a co-operative response against worms including a back-off mechanism [48]. This response model also seem to follow the typical sigmoidal curve for a worm suggesting that a co-operative strategy against worms effectively produces a 'white worm' effect. This also suggests that if this 'white worm' can propagate faster than a malicious worm, a large number of vulnerable machines can be protected from infection.

Simple, deterministic models can accurately describe scanning and bandwidth-limited worms such as the Slammer and Witty. Such models consisting of coupled Kermack-McKendrick equations [67], captures both the measured scanning activity of the worm and the network limitation of its spread. The model was shown to fit the available data for Slammer's spread [68].

Crandall *et al.* propose a novel Epsilon-Gamma-Pi model to describe control data attacks in a way that is useful towards understanding polymorphic techniques. Control data is data such as *program counter*, *stack pointer*, etc., that control the execution of a program. This model encompasses all control data attacks, not just buffer overflows. Separating an attack into ϵ, γ, and π, enables us to describe precisely what we mean by polymorphism, payload and 'bogus control data' [43].

Such models of worm help us to better understand any given worm which in turn helps us to better devise automated means of tackling them.

2.4 Prevention

There are two different approaches to prevent worm attacks. One is to prevent vulnerabilities. Two is to prevent exploitation of vulnerabilities. Such prevention not only guards against worms attacks but intrusions of any kind.

2.4.1 Prevention of vulnerabilities

Secure Programming languages and practices: Most, not all, vulnerabilities can be avoided by good programming practices and secure design of protocols and software architectures. No matter how good software systems are, untenable assumptions and betrayed

trusts will make them vulnerable. Protocols and software architectures can be proved or verified by theorem provers such as HOL [4] but there is always a chance for human error and carelessness even in the most careful of programmers. Also, C [93], the most common language with which critical applications are programmed due to the efficiency and low-level control of data structures and memory it offers, does not inherently offer safe and secure constructs. Vulnerabilities such as buffer overflows in C programs are possible, though caused by human-errors, because it is legitimate to write beyond the array and string boundaries in C. Thus there is a need for more secure programming and execution environments. Fortunately, help is available for securing programs in the form of

1. *Static analysis* tools which identify programming constructs in general that can lead to vulnerabilities. Lint is one of the most popular such tool. LCLint [53,75], is another one. MOPS [35, 36] is model checking tool to examine source code for conformity to certain security properties. These properties are expressed as predicates and the tool uses model-checking to verify conformation. Metal [51,52], and SLAM [19,20] are just a two examples of many other such tools.

2. *Run-time checking* of program status by use of `assert` statements in C, but they are usually turned off in the production versions of the software to avoid performance degradation [63].

3. *A combination* of both of the above. Systems such as CCured [84] perform static analysis and automatically insert run-time checks where safety cannot be guaranteed statically. These systems can also be used to retro-fit legacy C code to prevent vulnerabilities.

4. *Safe Languages* offer the most promise. These languages such as Java and Cyclone [63] offer no scope for vulnerabilities. Cyclone, a dialect of C, ensures this by enforcing safe programming practices – it refuses to compile unsafe programs such as those that use uninitialized pointers; revoking some of the privileges such as unsafe casts, `setjmp, longjmp`, implicit returns, etc., that were available to C programmers; and by following the third technique mentioned above – a combination of static analysis and inserting run-time checkers or assertions.

However, Java's type-checking system can itself be attacked exposing Java programs and Java virtual machines to danger [45]. Moreover, high level languages such as

Java do not provide the low-level control that C provides. Whereas, Cyclone, provides a safer programming environment by a combination of static-analysis and inserting run-time checks, yet maintaining the low-level of control that C offers to programmers.

Secure execution environments: A secure execution environment can also make sure that there are no vulnerabilities. A straightforward approach to provide a secure execution environment is to instrument each memory access with assertions for memory integrity. Purify [60] is a tool that adopts this approach for C programs. However, it has a high performance penalty that prevents it from being used in the production environment. It can however be used as a debugger.

There have been attempts to secure the process stack to prevent buffer overflow vulnerabilities. Notable amongst them are Stackguard [40] and efforts to patch Linux making the stack non-executable. Stackguard prevents buffer overflows on the stack by one of two methods: guard the function return address with canaries or make the location read-only temporarily. Designing a non-executable stack is non-trivial as an executable stack is required for signal-handling, and run-time code generation amongst others. However, these techniques still do not address the problems of buffer overflows on the heap, and register springs.

2.4.2 Prevention of exploits

Though a long list of mechanisms is available for prevention of vulnerabilities, no single tool's or mechanism's coverage is complete. Moreover, some of the tools are hard to use or have severe performance penalties and are hence not used in production environments. Therefore, software continues to be shipped with vulnerabilities and attackers continue to write exploits. Even if all future systems ship without any vulnerabilities, there is a huge legacy of systems with vulnerabilities. Preventing exploits of those vulnerabilities, both known and unknown, is thus expedient. There are several perspectives from which this is achieved.

1. *Access Control Matrix and Lists (OS Perspective):* Traditionally, the responsibility for preventing mischief, data theft, accidents and deliberate vandalism and maintaining the integrity of computer systems has been taken up by the operating system. This responsibility was satisfied by controlling access to resources as dictated by the Access

Control Matrix [73, 74]. Each entry in this matrix specifies the set of access rights to a resource a process gets when executing in a certain protection domain. On time-sharing multi-user systems such as UNIX, protection domains are defined to be users and the Access Control Matrix is implemented as a Access Control List. This is in addition to the regular UNIX file permissions based on user groups, thus allowing arbitrary subsets of users and groups [57].

2. *Firewalls and IPS (Network Perspectives)* - Another way to prevent exploits is to filter exploit traffic at the network level based on certain rules and policies. Such traffic filtering is implemented mostly at the border gateways of networks and sometimes at the network layer of the network protocol stack on individual machines. An example policy may be to never accept any TCP connections from a particular IP address. Another example may be to drop connections whose packet contents match a certain pattern. The former is usually enforced by software called a firewall; example netfilters' iptables [94]. The latter is enforced by Intrusion Prevention Systems based on signatures; example Snort-inline [6]. There is another class of closely related software called Intrusion Detection Systems which we will talk about shortly.

3. *Deterrents(Legal Perspective):* Several technical and legal measures have been undertaken to deter mischief mongers from tampering with computer systems. Enactment and enforcement of laws in combination with building up of audit trails [80] on computers to serve incriminating evidence have contributed in a large measure to securing computers.

2.4.3 The Diversity Paradigm

Prevention of both vulnerabilities as well as exploits focus on solving the problem on individual machines. By ameliorating the circumstances that lead to intrusions on individual machines, computer worms are thwarted as a side-effect. A little insight into the operation of a worm leads us to a new paradigm of preventing worms in spite of presence of vulnerabilities and exploits for individual machines.

Most exploit code of a worm are injected into the vulnerable process memory as a sequence of machine instructions. Such exploits need to work on all vulnerable machines or at least as many machines as possible for the worm to have an impact. This piece of code needs to know the exact memory locations of the native library functions it uses. When

several identical machines (same versions of Operating Systems) run the same version of a vulnerable application, the memory map of the process is bound to be same and hence, so are the location of the library functions. Worm authors use this insight to design worms that will have the maximum impact. The diversity paradigm breaks this assumption by randomizing the base address of each library on each machine using on a unique key for each machine. The same concept may also be applied to the system-call table, instruction set, etc. [24, 46, 65, 121]. While these involve rewriting the application executable (binary-rewriting), and are subject to brute-force attacks, more comprehensives solution have been proposed by randomizing more than just base addresses of libraries - code section and data sections are relocated and their relative distances randomized. Such techniques offer better protection and complete source-to-source transformation compatible with legacy C code [25].

2.5 Detection Systems

Early intrusion detection systems were programs that laboriously checked the configuration of the system(a single computer or a network) at regular intervals to identify any unauthorized changes to files and resources critical to the security and integrity of the system [17, 23, 47, 54, 69, 122]. These detections were usually after the attack had taken place. These can still be useful in case of worm attacks as the information thus gained can be used to protect other systems that have not yet been infected by the worm.

However, with the advent of high speed networks and sophistication of attackers, detection systems have also evolved. This section will talk about some of the sophisticated worm detection systems that have been developed recently. 'Worm detection' in this section as well as through out this dissertation refers to detection of zero-day worms that uses an unknown exploit of some known or unknown vulnerability in existing services.

Worm detection systems have primarily used two basic approaches:

1. Analysis of network traffic.

2. Run-time analysis of applications.

Most worm detection systems proposed so far primarily focus on characterizing the worm by developing some kind of a signature for the worm and then propose distributing the signature to other vulnerable systems to contain the worm. Though there is some amount of response

element in such proposals, all aspects of response are not considered and hence we classify them as primarily detection systems with the exception of a few. The next two sections analyze some of the systems developed so far that fall into the two categories mentioned above. Some of the other approaches to worm detection include using honeypots [42, 102].

2.5.1 Network Traffic Analysis

Given that a worm by definition is a program that replicates itself over the network it is only prudent that the network is the first place to look for worms. There is a vast literature on novel approaches to worm detection including those that use collaborative techniques. This section provides a brief summary of a select few.

Autograph [70] proposes a distributed content-based payload partitioning method to identify worms and their signatures. The authors propose multi-casting information about suspect port-scanners to all participants in the distributed detection. Polygraph [85] is a system that can produce signatures for polymorphic worms. They claim that for a real-world exploit to function properly, multiple invariant sub-strings must be present in all variants of a polymorphic worm. And that these invariants correspond to protocol framing, return addresses and poorly obfuscated code.

Earlybird [98] is a very promising approach toward identifying and generating signature for zero-day worms. It uses content prevalence and dispersion of participating addresses. Nevertheless, it needs to be installed at a high-visibility site where large amounts of network traffic can be monitored. Monitoring at the border may be infeasible for some sites. Both of the above use Rabin fingerprints to characterize the suspicious traffic.

Zou et al. [123] present an algorithm for early detection of worms using a network of monitors employing Kalman filters and an aggregator that digest the observations sent by them. Their model suffers from single point failures and demands that observations be immediately available to the aggregator even in presence of a worm. These shortcomings make it difficult for deployment in production environment whereas our approach is completely distributed and there is no single point failure.

Columbia University's [114] uses its predecessor PAYL [115] to profile normal data and flag any data that does not match this profile. It first uses ingress/egress correlation. If there is a suspicious anomaly, it then tries to correlate that with one another site. If there is a match, a worm is declared and the correlated string is used as a worm signature. But

this minimalist correlation is fraught with high false positives.

Cai et al. [30]propose a collaborative worm containment technique. It needs to be deployed on edge-networks and requires high processing power and careful manual oversight owing to its high-visibility location on the network. Furthermore, their work is also supported by simulations only.

Dash et al. [44] extend collaborative anomaly detection to corroborate the likelihood of attack by random messaging to share state information amongst peer detectors. They show that they are able to enable a weak anomaly detector to detect an order-of-magnitude slower worm with fewer false positives than would be possible by that detector individually. Both this and the work presented in Chapter 4 is distinguished from all of the other work described above in that we do not need a monitor at a high-visibility location on the network such as the border gateway or at the DMZ. While Dash et al.'s local detectors analyzes outgoing traffic, the work presented in this dissertation analyzes the incoming traffic. Both leverage relatively simple and weak IDSes on individual end-host computers and make high confidence distributed correlations using simple anomaly vectors. Distributed detection also avoids single points of failure. Dash et al. support their performance results by extensive discrete-event simulation experiments. Complementing their work, we evaluated the system in an emulated test-bed environment and have demonstrated the efficacy of our system using real software components that run on real operating systems.

GrIDS [104], Graph-Based Intrusion Detection System, is a general purpose large-scale malicious attack detector that can be used to detect worms too. It collects data about activity on computers and the network traffic between them. It aggregates this information into activity graphs which reveal the causal structure of network activity. This allows large scale automated attacks to be detected in near real-time.

ButterCup [88] uses a range of return addresses to detect polymorphic buffer overflows thus enabling detection of polymorphic worms. The return address checking can be easily done using any of the signature based network IDS such as SNORT which the authors used themselves. This idea is very unique since the signature used here is one of vulnerability's than that of the exploit. Thus, all worms written for the same vulnerability can be detected with the same signature.

2.5.2 Run-time Program analysis

Proposals using this technique usually run on a single machine and look for anomalies in control flow, taint in control data, violation of invariants etc in the target application. We provide brief summaries of representative systems that use this idea.

Vigilante [39] tracks the flow of data received in input operations. It blocks any attempts to execute or load that data into the program counter, thus preventing execution of any remotely loaded code. This has been implemented by rewriting the binary at load time and instrumenting every control transfer and data movement instruction to keep track of dirty registers and pages. This response part of this proposal includes automatically generating a machine verifiable proof of vulnerability called a *Self Certifying Alert(SCA)* which is distributed to other machines by flooding it over a secure structured overlay network. The recipients then verify this SCA and choose appropriate local responses. TaintCheck [86] uses the same principle as Vigilante but performs the binary rewriting at run-time.

The same concept was earlier used by Minos [41], a micro-architecture that implements Biba's low-water-mark integrity policy on individual words of data. A Pentium-based emulator implemented for Red-Hat Linux 6.2 and Windows has stopped several actual attacks. Contrary to the other two techniques mentioned above, Minos does not modify the address space of the vulnerable process and so a more precise analysis of the attack is possible [41].

Sidiroglou et al. [103] uses sand-boxing techniques to analyse the applications and also generate patches for the vulnerable applications. This is more of an automated response system than a detection system and will be discussed in the next section.

Property-based testing is a technique that instruments the source code to verify that the executing program satisfies particular invariants. The instrumented program outputs changes of state that affect conformance to the invariant, and a separate program, called the test execution monitor, inputs those changes to verify that the program satisfies the invariant throughout is execution [56, 59].

2.6 Response Systems

Broadly, they attempt to contain the spread of worms. Moore *et al.* [83] describe general parameters required in any worm containment system: reaction time, containment

strategy and deployment scenario. Hitherto, three broad classes of response systems in decreasing order of aggression have been proposed.

1. The most aggressive one generates a patch for the vulnerability being exploited by the worm and distributes it to machines having this vulnerability. The machine using the patch are said to be no longer vulnerable [103]. Sidiroglou et al. [103] approach the problem with end-point solutions. They use sand-boxing techniques to automatically generate localized patches to prevent worms from infecting production systems. However, they leave identifying worms to other third party systems like honeypots and IDSes.

2. The second idea is to generate, in co-operation or isolation, and distribute a signature for the worm to other co-operating vulnerable machines which then filter traffic matching this signature. In this class of response systems, several machines co-operate in a federation to exchange information about anomalies, or infection attempts to take reactive actions against worms thereby preventing infection [13,48]. Chapters 4 and 5 of this dissertation details a distributed and co-operative worm detection and response system that work independent of content-based signatures respectively. Distributed algorithms and cooperative systems have been shown to better balance effectiveness against worms with reduced costs in computation and communication in the presence of false alarms, and robust in presence of malicious participants in the federation [14].

3. The most defensive but a drastic class of approach is to shut down the vulnerable service completely or partially to a certain black-list of customers (IP addresses) and wait for further human intervention, or automatically throttle [111] the amount of traffic going in and out of the network.

The last two approaches can be applied to anomalies also without complete knowledge about the worm. A more aggressive but unrealistic idea, both technically and legally, is to launch a *white worm* to go after the infected systems and clean them [107].

The most important consideration in any response is that the response itself should cause less harm than the intruding worm itself. Any harm could be measured or expressed as a cost to the system. Primitive response systems that ignore the cost of intrusion and response could end up causing more harm [18]. So, the key here is intelligent selection of the available responses for application based on the costs of the intrusion and response.

2.6.1 Response Selection

Though there has been quite few research efforts to respond to worm attacks as mentioned in the previous section, none of those have proposed a strategy to choose an optimal response from a give set of responses. However, there are proposals to choose optimal responses for intrusions [18] in general that are discussed later in this section.

Intrusion and Response Taxonomy

Past research in the area has stressed on the need for a taxonomy of intrusions and responses to produce an effective response. Fisch [49] proposed a intrusion response taxonomy based on just 2 parameters: the time of intrusion detection(during or after attack) and the goal of the response(damage control, assessment or recovery). Carver [31] claims that this is not sufficient and proposes a 6 dimension response taxonomy based on the following:

1. timing of the response (preemptive, during or after the attack)
2. type of attack (DOS, integrity or confidentiality attack)
3. type of attacker (cyber-gangs, economic rivals, military organizations, automated attacks or computer worms)
4. degree of suspicion (high or low)
5. attack implications (critical or low implication)
6. environmental constraints (social, ethical, legal and institutional constraints)

For a comprehensive digest of attack taxonomies refer to Carver and Pooch [31]. Some of the approaches proposed for response selection using these taxonomies are based on:

- dependency trees that model the configuration of the network which then give an outline of a cost model for estimating the effect of a response [110]. A response with the minimum negative impact on the system is chosen from a set of alternatives. Possible responses include re-configuring firewalls, controlling services' and users' accesses to resources.

- grouping intrusion into different types so that cost measurement can be performed for categories of similar attacks [76].

In their proposal, Lee et al. classify each intrusion successively into sub-categories based on the intrusion results, techniques and finally based on the targets [76]. They assign fixed costs to damages and responses to each category of attacks relative to each other. Their response model tempers responses based on the overall cost due to damage caused by the intrusion, response to the intrusion and the operational costs. In short, for a true intrusion, response is initiated only when the damage cost is greater than or equal to the response cost. The shortcoming of their approach to response is that they consider only individual attacks detectable by IDSs. They cannot detect attacks that are a composition of several smaller attacks but have a cost that is more than the sum of costs of the smaller attacks. Given that most IDSs detect an attack after the fact, any response to that attack alone doesn't help much. At best it could serve as an automated means of restoring sanity to the system.

Specification-Based IDS Response

Balepin [18] proposes an automated response strategy by combining response with a host based specification based IDS. They describe a map of the system and a map-based action cost model that gives a basis for deciding upon the response strategy. They also show the process of suspending the attack to buy time to design an optimal response strategy even in the presence of uncertainty. However, this scheme is purely only for a host. This doesn't address the issue of enterprise wide response.

Feedback Control Response selection

Survivable Autonomic Response Architecture(SARA) [99] and Alphatech's Light Autonomic Defense System(αLADS) [15] are two feed-back control based automated response frameworks. The term autonomic response is analogous to the autonomic nervous system, which automatically controls certain functions of an organism without any conscious input.

Tylutki [112] proposes another response system that is based on policy and state-based modeling and feedback control. This provides a general response model capable of using low-level response systems in order to address a wide range of response requirements

without any scope restriction. Thus, enlarging the collective scope of several existing automated intrusion response paradigms. EMERALD [90] and CSM [58] are some of the other response strategies that this model can use.

2.7 Evaluation Systems

Any evaluation of a new idea, algorithm or technique to detect worms or respond to them falls into one of the following four categories:

- Internet deployment,
- Experimentation in controlled environment,
- Simulation, and
- Mathematical Proofs.

In general, these methodologies in the order listed lend decreasing credibility to the new proposal respectively. Most recent research in worms try to produce a defense that in real time can detect a worm and quarantine sites that are not yet infected [48,118]. One major deficiency in most of the research is that the claims are not supported by realistic tests. Most claims are supported by theoretic models or simulations only.

Deploying an implementation of a new idea on to the Internet or operational environment for testing purposes is infeasible due to two factors. One, the inherent dangers of launching a worm to test the newly built system. Two, the elaborate amount of work involved in setting up such an experiment including setting up security measures to prevent leaking the worm to the Internet. So, most research on worm defense and quarantine strategies have relied on simulations to validate the algorithms [10, 27, 48, 118]. It is the easiest way to demonstrate a technique.

2.7.1 Simulations

Simulations, however, cannot effectively capture insights related to systems variability, network characteristics, worm behaviors, and other operational details that it abstracts. There are efforts to capture some of these characteristics in certain simulation tools such as SSFNet [7] which tries to simulate the network stack behavior also. Such

tools have been used to simulate realistic worm traffic for testing defenses by Liljenstam et al. [78]. However, in general, all these simulations are based on formal models and cannot fully represent some of the network and malware behaviors that are more difficult to model mathematically. For example, it is generally very difficult to simulate "smart" worms that exploit various network evasion techniques [29, 92].

While operational testing is infeasible, simulations and mathematical models are not sufficient, a promising approach, and maybe the only one that is viable, is to test a worm defense in an isolated or controlled environment otherwise known as a testbed. This methodology is also known as emulation because, the controlled environment is isolated and emulates the real environment as much as possible. The next section details this technique.

2.7.2 Emulation on Testbeds

One major difficulty with this approach is that a large number of test machines have to be configured and managed efficiently. Also care should be taken that the malcode used for testing doesn't leak into the real Internet. Another great difficulty is the task of assembling huge volumes of hardware to reflect the Internet or even an enterprise network. It is clearly impossible. So, we need some way of representing large networks with smaller networks. While Weaver et al. [117] have shown that worm propagation on small networks or scaled-down networks do not match the observations on the real Internet, Psounis et al. [91] have shown that by carefully scaling-down networks some of the network characteristics such as queuing delays and flow transfer times can be extrapolated. Such management of large numbers of machines, scaling down of networks are challenging tasks.

One example of emulation is a testbed developed by Lippmann et al [79] in order to accurately model a government enterprise network and evaluate real intrusion detection systems off-line. That was in 1998. There have been developments since then.

Network infrastructures developed later such as EMULAB [120] and DETER [16] offer the capability to emulate any kind of live network environments. These are resource and time shared, remotely accessible networks[2] that provide hundreds of end-host systems, with remotely configurable operating systems, that can be operated and managed individually or collectively in several groups. The topology of the network to which the end-hosts

[2]The former is located at the University of Utah, Salt Lake City while the latter is spread over two locations, University of California, Berkeley and University of Southern California, Los Angeles.

participating in an experiment are connected and the traffic flowing into and out of these networks can also be fully controlled. These capabilities make such infrastructures ideal testbeds for network security experiments as opposed to PlanetLab [21] where the experimenters do not have complete control over the end-hosts participating in the experiment.

Carefully designed emulations on testbeds such as EMULAB can fully capture the heterogeneity of the network and worm characteristics that simulations cannot do accurately. There are projects that have used EMULAB and DETER but unfortunately, they have not used these infrastructures effectively. Weaver et al [118] use DETER but as a parallel processing environment to run their simulation quickly rather than as an emulator.

The EMIST [2] project provides various tools to ease using the DETER testbed. Penn State University's EMIST ESVT [1] provides a GUI package for topology creator and generator, traffic and experiment interfaces and visualization tools. ESVT does not provide experiment synchronization and automation. EMIST Tool Suite from Purdue University, on the other hand, provides a Scriptable Event System(SES) [3] for synchronization and automation for individual nodes in the experiment. The EMIST Tool Suite, however, does not provide any tools for topology utilities and worm specific tools. Finally, both tools do not support real applications such as IDS and firewalls that are crucial to worm experiments. They also do not provide any methods to integrate additional components, such as real worm codes, real defense strategies, and live background traffic. Addressing these issues form the contents of the next chapter.

Chapter 3

A framework for worm-defense evaluation

3.1 Introduction

Given the difficulty of reproducing live environments for worm-defense research, most researchers resort to simulations. Since simulations are insufficient to capture all aspects of worm and defense behavior, there is a great need for a way to faithfully reproduce live environments for worm- and worm-defense research. In this chapter, we develop a framework making use of a network testbed called EMULAB [120] to satisfy this need. We describe an implementation of the framework and use it to evaluate an example defense strategy, but emphasize that the framework can support many different defense strategies. The framework is encapsulated in an API. This API accepts a topology description and a description of the defense system, and evaluates the defense system against worms. The worms can be characterized by a specification or operationally by a worm program.

The next section provides the motivation for this framework. Section 3.5 shows how a defense strategy [33] previously developed by the author can be evaluated using this framework; previously, this worm defense system was evaluated using a simulation, and this present work confirms the results of the simulation but in a more realistic setting. Finally, section 3.6 shows future directions to pursue.

3.2 Motivation

EMULAB [120] and DETER [16] are network testbeds that can be used for network security research offering a low cost option to operational testing. As already mentioned in Sec. 2.7.2, they provide hundreds of end host systems[1] and with various popular operating systems that can be brought up in a matter of minutes, saving both equipment and maintenance expenses. Virtual nodes are also supported on each physical node, thereby multiplying the effective number of nodes that can be used for our experimentation. Network topologies of experiments and the OS on the participating nodes can be remotely configured. These capabilities and their similarity to the typical size of real-world enterprise networks make them a perfect theater for worm-in-enterprise research.

However, a large scale worm experiment is very difficult to setup. It typically takes a new user only a few hours to run the first "Hello World" experiment but several weeks to run the first worm-defense experiment. Also, simulating Internet size phenomenon in a smaller environment tends to produce skewed results due to the stochastic nature of the processes, such as worms, involved [117]. This is called the scale down phenomena. Hence, we need to repeat the experiments numerous times to get results that can be meaningful interpreted. However, while working on an evaluation of collaborative worm containment strategy [108], we discovered that the set-up time for each experiment is significantly higher than the experiment duration itself. It usually takes ten to fifteen minutes to set up an experiment depending on the size of the topology that runs for two to three minutes. Also, worm experiments require a large number of nodes that are not always available on the testbed. Hence, setting up the testbed for such numerous experiments manually becomes infeasible. We need a way to set up the testbed automatically and perform experiments in batches.

To facilitate this, the testbed offers features such as synchronization servers, program objects and group event control systems. However, it requires very careful programming of these sub-systems to repeatedly reproduce test environments. During our efforts to evaluate *The Hierarchical Model of Worm Defense* [33], we had developed several programs and scripts to automate these processes. Also, experience shows that the event system set-up doesn't differ much from one experiment to another. Hence, we reasoned that we could package and parameterize these scripts to be used by other users through a simple

[1] The terms 'end-host systems', 'end-node systems' and 'nodes' are used interchangeably here.

interface, thus taking the testbed one step closer to the community.

Nevertheless, using EMULAB, people can evaluate their worm defenses without using this API, but it is a very exacting task. The other, easy, end of the spectrum would be a command line or point and click tool. This tool would have a set of pre-programmed defense schemes that can be executed with a few pre-determined parameters to evaluate which scheme is best for their enterprise. However, this would not be as flexible as using EMULAB directly. Hence, we try to find a sweet spot in between these two extremes that would make life of researchers easy as well as provide them a framework with enough flexibility to tweak and tune their schemes.

3.3 The Framework

This section describes the components of the framework. Figure 3.1 shows the interconnections between these components (shown within the box in broken line). The NS [5] to NS-testbed compiler generates user defined topologies for the testbed. After proper topology configurations, the Pseudo Vulnerable Server and Event Control System integrate user-supplied defenses and worms and conduct experiments for a certain number of iterations predetermined by the user. The 'Data Analysis Tools' collect various data about the experiments and generates evaluation statistics. These modules are transparent to the users, creating an appliance approach to worm defense experiments.

3.3.1 NS to NS-testbed compiler

The NS to NS-testbed compiler in the API, takes the user's NS file and compiles it to format suitable for the testbed. Apart from the usual tasks of specifying the OS to load, the routing protocol and assigning IP addresses to the nodes, the compiler does the following two important tasks.

First, set up a synchronization mechanism for the experiment. This can be done by specifying a node as the synchronization server and using the testbed's `sync_server` tool. This is required so that we can make use of the batch processing feature of the testbed. As mentioned in section 3.2 batch processing is the only practical way of running large experiments.

Second, set up 'Program Objects' and 'Event Groups' appropriately. The users' defense programs and the 'Pseudo Vulnerable Servers', called pseudo-servers for short, are

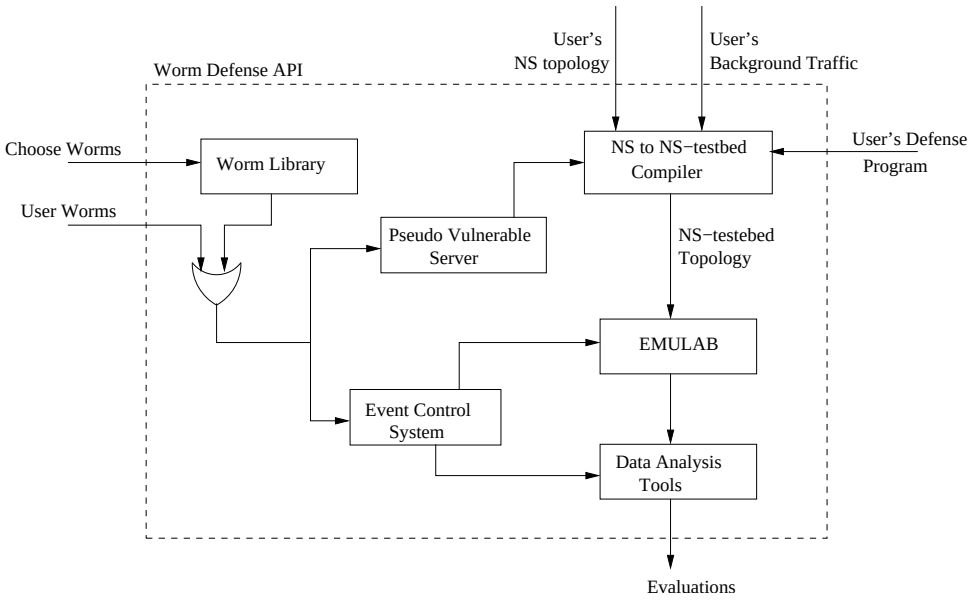


Figure 3.1: Design of the Worm-Defense Evaluator.

inserted into the appropriate event groups, such as, *defense event group* and *vulnerable event group* respectively. This grouping is required so that the pseudo-servers and the defense programs can be restarted from a single `tevc` command in the 'Event Control System'. This helps us to bring the testbed to a clean state instantaneously without swapping out and swapping in experiments saving about 10–15 minutes. A clean state of the testbed is the state when all experiment nodes are just booted up and no user processes are running, and all changes made to the routing tables, firewall rules, IDS signatures, etc., during the last run of an experiment are erased. Such a state is required for each run of an experiment. A typical worm experiment series has about 1000–1500 experiments lasting two minutes each on an average. This step helps complete a series in about 36 hours that would otherwise take about twelve days. That is a huge saving!

3.3.2 Pseudo Vulnerable Servers

The 'Pseudo Vulnerable Servers', pseudo-servers for short, listen for traffic on a certain port. Once they are receive a packet of a specified type, a worm packet, they mark themselves as infected, save a time-stamp of the infection and spawn off a worm in their own node. This relieves us of the task of writing a worm that exploits some vulnerability.

By deploying our own pseudo-servers for vulnerable servers, we are also able to make use of them as data acquisition tool.

This doesn't compromise the experiment in any way. These pseudo-servers are a valid abstraction of vulnerable servers because we don't know how the real servers would be attacked. Even if we write our own exploit for a real server, it will not reflect reality as a real worm's exploit is bound to be very different than the one we devise for our experiments. Rather, we are more interested in worm spread models and ways to mitigate the repercussions. Pseudo-servers accomplish these tasks effectively. We also note that, these servers don't take much time to spawn off a worm once they are infected. This is not very different from real exploits which spawn off a worms in a victim machine rather instantaneously.

As a pleasant side-effect, we end up with safe worms; worms that cannot spread out on the Internet where these *pseudo-servers* are not installed.

3.3.3 The worm library

The framework has a very flexible built-in worm generator. This worm generator can generate several families of worms based on the scanning pattern, transport protocol used, and speed at which it scans for new victims. A worm in this library is specified by the context-free grammar,

$$G = (V, \Sigma, R, \langle \text{WORM} \rangle),$$

where the set of alphabets, Σ and the set of variables, V are respectively,

$$\Sigma = \{0, \ldots, 100, \text{tcp, udp, random, topological}\},$$
$$V = \{\langle \text{TRANS\_PROT} \rangle, \langle \text{SPEED} \rangle, \langle \text{NUMBER} \rangle, \langle \text{SCAN\_ALGO} \rangle, \langle \text{SCANOUT\_RATIO} \rangle\}$$

and the rules, R, are:

$$\begin{aligned}
\langle \text{WORM} \rangle &\longrightarrow \langle \text{SCAN_ALGO} \rangle \langle \text{TRANS_PROT} \rangle \ \langle \text{SPEED} \rangle \\
\langle \text{SCAN_ALGO} \rangle &\longrightarrow \text{random} \mid \text{topological} \ \langle \text{SCANOUT_RATIO} \rangle \\
\langle \text{TRANS_PROT} \rangle &\longrightarrow \text{tcp} \mid \text{udp} \\
\langle \text{SPEED} \rangle &\longrightarrow \langle \text{NUMBER} \rangle - \{0\} \\
\langle \text{SCANOUT_RATIO} \rangle &\longrightarrow \langle \text{NUMBER} \rangle \\
\langle \text{NUMBER} \rangle &\longrightarrow \{0, \ldots, 100\}
\end{aligned}$$

The available scanning patterns are random and subnet scanning. Either TCP or UDP transport protocol can be selected and the scan speed is chosen as a number of scans per second. SCANOUT_RATIO gives the ratio of scans that go out of the sub-net for a topological worm. The worm can be built with any given random string to act a payload. However, this payload is discarded by the pseudo-server. So, a TCP sub-net scanning worm that looks for a victim five times a second and send one out of every 10 scans out of the sub-net can be specified as "`topological 10 tcp 5`".

The worm itself has been implemented as a tight loop that sends out a message every $\left(\frac{1}{\text{scan rate}}\right)$ seconds, to the *pseudo-server* chosen according to its scanning algorithm. The implementation provides for inserting any other third-party scanning algorithms into the worm.

3.3.4 The Event Control System

The Event Control System(ECS) runs on the synchronization server of the experiment. It controls the start and stop of the experiment run, triggering the data analysis tools and rotating the log files.

This is a script that was hand-coded originally to help in evaluating our earlier defense models. Now, we have parameterized this script so that others can also use it. The parameters to the ECS are the worms that need to be launched, and the names of the event groups generated by the compiler. These values are passed on to this component internally transparent to the user.

When an experiment needs to be run, ECS starts all the program *event groups*. Given the worm's characteristics, the ECS bootstraps a worm on one of the pseudo-servers, thereby creating victim 0. This starts the worm outbreak. The ECS keeps track of the progress of the experiment by counting the time-stamps of the infections from the pseudo-servers. (Since the same home directory is mounted on all experiment nodes all data is written to the same directory and hence counting the time-stamps becomes easy as does the final data processing). Once the worm count reaches a stable value the ECS deems that the experiment run is complete. A worm count is considered stable if it does not change for over a minute. The collected data is stored in a retrievable fashion. The *event groups* are restarted and the next worm is launched. This is repeated for several pre-determined iterations. Once the entire experiment series is complete data analysis programs are run on

the collected data to give us the evaluations.

3.3.5 Data Analysis Tools

The pseudo-servers write all data on the user's home directory. Current implementation collects infection time and alert time, the time when defensive responses kick in. Tools are provided that chart the infection trace, the total number of nodes infected during each experiment run and the time taken to stop the worm from spreading. The users are welcome to do their own analysis of the data. In case, the user needs more data, the defense programs need to be programmed appropriately to collect necessary information.

The next section presents an implementation of the framework which is encapsulated in an Application Programming Interface(API).

3.4 The API

The framework described above has been implemented and a programming interface has been provided. This API takes in three parameters, a network topology in NS [5] format, a defense program and a worm. It returns a thorough analysis of the proposed defense strategy based on various parameters. Some of these parameters are the total number of nodes infected, the time taken to stop the worm from spreading, the effects on the network such as latency, bandwidth occupied by the defense vs the worm vs the normal traffic, the effects of false alarms on the normal operational efficiency and the recovery time. Recovery time is the time taken for the network to return from a defensive posture during worm attack to its normal state of operation. This is a very important factor in real-world networks because there is a cost involved when the network is not operating in its usual fashion.

Figure 3.1 on page 29 gives a design diagram for this API. At the outset, we can see that user specifies the above mentioned three parameters apart from the ability to play background traffic using some third party tool. The following sub-sections describe the user-inputs required and the various components of the framework.

3.4.1 User Inputs

This sub-section describes the various user parameters and their specifications. These are the topology specification, the worm parameters and the user's defense program and optionally a background traffic generator.

The topology specification

The user specifies the topology of the test network as an NS2 file. This would represent the enterprise network of the user. The NS2 language was chosen because it lets us specify exactly various network parameters like the network bandwidth, latency, etc., and also allows for traffic shaping information. This topology information should also include the location of various servers, gateways, routers, firewall, IDSes, etc., in the enterprise.

One can reconfigure the interconnection of the experiment nodes in EMULAB by feeding it a script written in NS-testbed, an extension of the NS language. This extension contains several commands that are specific to the testbed. These commands control the event groups and program object sub-systems, the routing protocol used, the synchronization sub-system, etc. The user's topology is transformed into NS-testbed by the compiler in our framework. This compiler will be discussed in the next sub-section.

The defense program

The API provides an interface to attach the users' defense program to the framework. Since users' home directories are auto-mounted on all experiment nodes, there is no need for any special installation procedures for these programs. It is sufficient if they are available in the user's execution path and the user just has to provide the program name. Our compiler picks up this defense program and inserts it to the NS-testbed script thus registering it with the testbed.

By providing such an interface, we allow for maximum flexibility for the user to implement their own defense and response mechanisms. The programs could be anything from worm detection algorithms using correlation, decision trees, Bayes Net techniques to automatic signature generation to response mechanism using firewalls, IP black-listing, or any other novel technology that the users' want to evaluate. This is the parameter of the API for which we expect the user to spend the most effort and rightly so because this is the program we are evaluating.

Since the defense program is already included in the *defense event group* by our compiler, it would be called at the appropriate time from the *Event Control System* of our tool. Ideally, we expect the user to design their defense program as a server that responds to events, typically events that are symptoms of worm activity. Hence, the most propitious time to start up these defense programs would be at the beginning of the experiment.

If the defense programs use any tools or programs that are not available by default on the experiment nodes, these have to be installed manually and a disk image made prior to starting the experiment. Then this image can be specified in the NS-testbed file to be loaded on to the experiment nodes.

Worms Parameters

Our API by default provides a very parameterized worm generator. The parameters are as follows:

1. **Type of connection:** UDP or TCP.
2. **Speed of worm:** The number of scans per second.
3. **Scanning method:** Random or subnet scanning. If subnet-scanning is specified the user could also specify *pods*, the desired Percentage of Out-of-Domain Scanning. If no *pods* is specified we use *pods* from 10 to 100 with step size of 10. In fact, at 100 *pods*, the worm becomes a random scanning worm.
4. **A payload to the worm:** This could just be a random text. This is only to analyze the effect of payload size on the worm dynamics and network bandwidth rather than anything else. If it is a malicious function to be executed on the testbed, the user should also provide the vulnerable servers along with the topology specification. However, we discourage this, as this worm can get out of control and doesn't add any value to the experiments.

The users can choose one or more worms and parameterize them to be deployed against their defenses. Alternatively, the API also provides hooks to hang the users own scanning method for the worm. For example, a hit-list scanner, or a real Code-Red, Slammer, etc. These user scan functions need to be added into the framework's worm library beforehand. Then the API should be instructed to use this users' worm function while choosing the 'Scanning method' mentioned above.

After all, the users can just ignore all of these and provide their own worm programs and corresponding vulnerable servers.

Background Traffic Generator

The users can replay their normal enterprise traffic in the background on EMULAB while testing their defense policy. The background traffic can be played using tools like TCPOpera [62] or NTGC [109] depending on whether the users want the traffic to be source or trace parameterized. This may also depend on the defense strategies. If the defense contains signature matching, the user may want to replay raw traces.

3.5 An Example - The Hierarchical Model of worm defense

To demonstrate the effectiveness of this tool, we consider a worm-defense model called, *The Hierarchical Model of worm defense* that was developed in [33].

Briefly, this model assumes that all participating nodes are arranged in a tree structure. The leaves are vulnerable but run some sort of an IDS system to detect attacks and have some tunable firewall capabilities. The non-leaves are invulnerable to attacks and run the worm-defense programs. Once a leaf detects an attack, it send a message to its parent. In essence, this message would contain the suspicious packets. Once the parent receives a threshold number of messages from unique children it takes two actions. One, it instructs all its children to turn on responses to this attack. Two, it sends a message to its own parent about the infection. Needless to say, for each non-leaf its threshold should be lesser than its number of children to get any benefit from this scheme. Thus the information about the attack travels up the tree and the instructions to respond percolates down the tree. Intuitively, the lower the threshold, better the defense.

3.5.1 Modeling the system

The topology specification: This model attempts to reflect a real enterprise network as closely as possible. The root node would be entry point to the enterprise. The leaves would be end-nodes, users machines and servers that are vulnerable to attacks. The non-leaf nodes are routers or gateways to individual departments inside the enterprise.

Our experiments contained 4 levels in the hierarchy, representing the UCDavis's

College of Engineering network. Going down from the root to the leaves, each level represents, Gateway for the College of Engineering, the departmental gateways, research lab routers and then finally the individual machines, in that order. This model consists of pseudo-servers at the leaves running host based firewalls and IPSs that can be tuned upon receiving instructions from their parents. All the non-leaves nodes run the defense program. These nodes are called controllers because they control the defense. We also assume that they are invulnerable to attacks.

This model is so simple that it can be represented by just the number of levels in the hierarchy, the number of children and threshold of the nodes in each level of the hierarchy. We hand-rolled a program that would read this specification and give us a NS-testbed script. However, when we finally release the full implementation of this API, this program would be a more versatile compiler to handle NS scripts.

The defense program: The defense program is run on all the non-leaf nodes. Upon a worm infection, the infected server would alert its parent. Once the threshold is reached, the parent sends a similar alert to its own parent. In addition, it also extracts a signature from the suspicious packets received from its children. This signature is then sent to its children including the infected ones, and instructs them to block traffic matching this signature. Refer to [33] for further details of this model on back-off mechanisms, handling false positives, etc.

The worm program: Our experiments used the default worms provided by the framework. UDP random and sub-net scanning worms were deployed against our defense using a simple text string as the payload. No malicious programs were on the payload.

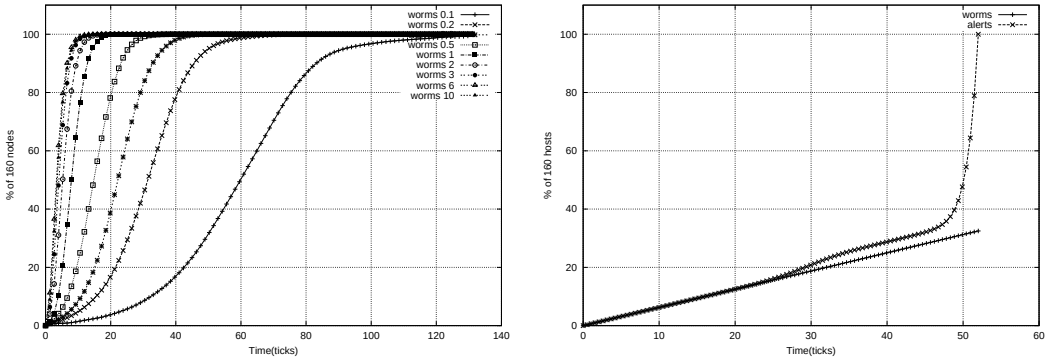
3.5.2 The experiment

All our nodes in the experiment ran FreeBSD 4.10 Jails. The controllers copied the payload string into the signature distributed to the pseudo-servers. The latter in turn implemented the defenses using a combination of firewall and IPS. “ipfw” was the firewall of choice. This helped to divert packets arriving at a certain port to a program that could examine them for the malicious signature. “snort_inline” was the IPS of choice to examine the packets and drop packets that matched the signature provided by the controllers.

Our tool ran the experiments with 160 pseudo-servers and 21 controllers in tree

topology with three layers. Each layer from the root of the tree contained one, four and sixteen controllers respectively. We used both random scanning and sub-net scanning worms with *pods* of 10–100. In fact, a subnet-scanning worm with pods of 100 is the same as a random scanning worm. Each experiment was conducted with a worm of a particular scanning speed. Different experiments were conducted with worms with different scanning speeds in the range 0.2 to 100 scans per second. Each experiment was run for ten times, to reduce the stochastic effects. This is not a large number but it did gave us better results. Thus, ten different worm kinds at nine different speeds ran for ten repetitions making for 900 experiments. It took about 18 hours to complete it. This is where the diligence of this tool comes to the fore. For sake of clarity, we only present the results of experiments with *pods* of 30, 60 and 100.

First we corroborated our worm spread pattern with no defense to the mathematical models and simulation results [33]. The results of this run is shown in Figure 3.2(a). This means that our worm program and the framework work as expected. Then we turned-on the defense mechanism. Figure 3.2(b) shows how the defense overtakes the worm spread. To recollect, the messaging protocol used here is hierarchical. Each node that sees a infection attempt sends an alert to its parent. Once the parent collects enough alerts to cross a threshold, the alert is escalated to its parent. This continues all the way up to the root node. We used a worm with a speed of 2 scans/second.



(a) Random scanning worms with no defense

(b) Alerts are distributed faster than the worms

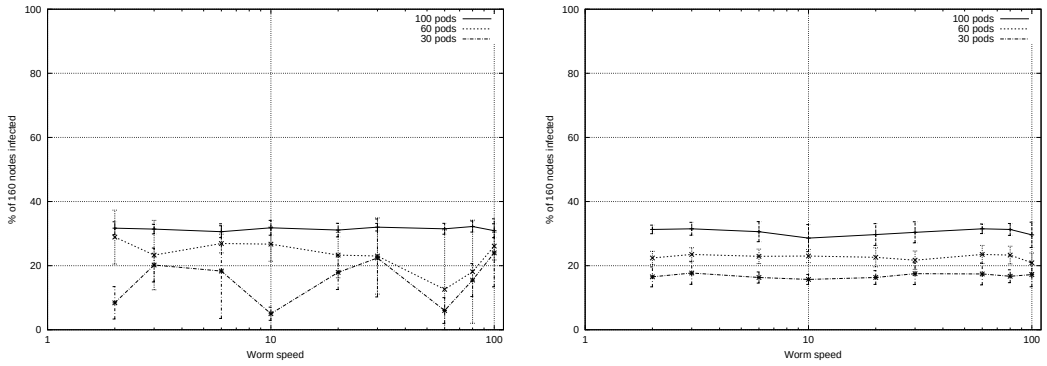
Figure 3.2: Notice the characteristics *S-curve* in Figure (a) on the left being flattened out in Figure (b) on the right when the defense is turned on.

3.5.3 Results

With the current set of experiments and the data analysis, we were able to draw several insights into the hierarchical defense strategy. These are:

1. The root node alerts all of its children to turn on defenses within a definite time from the first infection. All the experiments ran to completion. This shows that the system is convergent and does not run-away due to any feed-back effects. This verifies the mathematics given in Cheetancheri [33].

2. No matter how fast a worm spreads, this model of defense stops the worm with a constant upper limit on the number of infections. This lets us decide the threshold parameters at the controllers based on our tolerance for infections. Figure 3.3(b) shows this result. Each data point shows the average number of infections and the standard deviation.



(a) Only 5 iterations

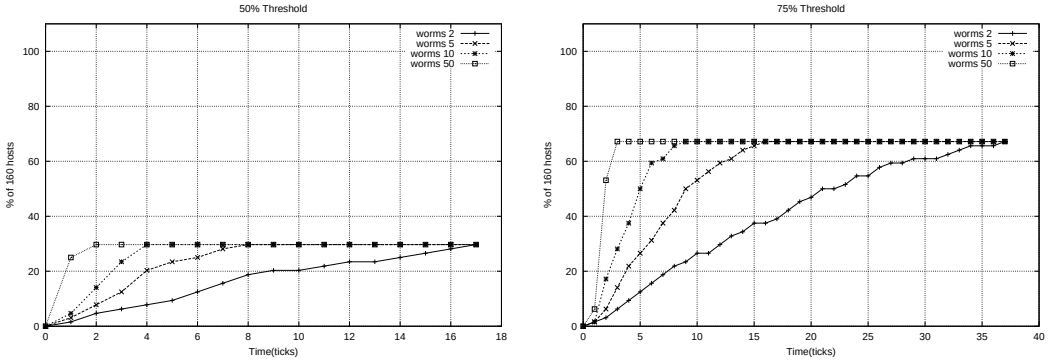
(b) Increased to 10 iterations

Figure 3.3: The stochastic effects due to random variables are considerably less when the number of iterations are increased.

3. The experiments showed us that this scheme works better for suppressing subnet-scanning worms that are more biased towards scanning within the subnet than those that scan outside the subnet. This also means this scheme performs poorly against random scanning worms. Figure 3.3(b) shows this feature of the model. This is obvious once we realize that alerts go out of the subnet faster than the subnet scanning worms.

4. **Scale down factors:** Figure 3.3(a) and 3.3(b) together show that the stochastic effects of scaling down of networks can reduced by increasing the experiment repetitions. The experiment originally carried out with just 5 iterations gave us large standard deviations, whereas the one with 10 iterations gave a considerably lower deviations from the average value.

5. It is only the threshold levels that makes or breaks the network. A low threshold helps to save a lot of machines but in reality it might help raise several false positives. Figures 3.4(a) and 3.4(b) show the effect of different thresholds.



(a) Worm Containment with 50% Threshold (b) Worm Containment with 75% Threshold

Figure 3.4: These two graphs show the relative performance of the defense for different thresholds. Each node escalates an alert to its parent, when a certain percentage of its children raise an alert.

3.6 Future work

Currently, the data analysis tools only analyze the kinematics of worms. We need to design and implement the traffic analysis tools. As mentioned earlier, the effects on the network such as latency, bandwidth occupied by the defense vs the worm vs the normal traffic, the effects of false alarms on the normal operational efficiency needs to be analyzed. For this, we need to design program stubs to be inserted at the appropriate locations on the testbed.

In this chapter we presented only an operational work-around to counter the scale-down effects on worm experiments. Two solutions to overcome this are to increase the ex-

periment size and increase the number of iterations. Obviously, we can't emulate the entire Internet and we also can't repeat experiments indefinitely. We need to find a compromise between these two for our framework to be applicable to Internet wide worm problems.

We also want the users to be able to choose different kinds of networks from a library. The library would provide a set of environments like university, a commercial organization or a defense network. There are differences between these networks. University networks usually tend to be quite open with little or no firewalls enforced. It usually tends to have several web-servers hosted by individual departments as well as individuals. A commercial environment tends to be quite hardened on the outside but highly interconnected on the inside. Companies also have trusted connections with their suppliers. A defense establishment's network tends to be highly compartmentalized with rigid firewalls on the perimeter as well between different departments.

Chapter 4

A Distributed Worm Detection System

4.1 Introduction

Monitoring for and responding to security incidents in large-scale, complex enterprise networks requires a new approach to security incident management. Security reports indicating a policy violation, come from a heterogeneous collection of components, such as intrusion detection sensors, firewall access policy violations or anomalous network traffic loads. Protecting against attacks currently in progress or eliminating a new vulnerability involves the reconfiguration of several different types of devices, such as firewalls, border gateways, software updates, and even host-based wrappers.

The challenge is to collect all information from the numerous data sources and to decide on appropriate actions for each reactive component. Simply forwarding all reports to a central location will not scale to large networks. Local decision making, however, may lack the global view necessary to thwart large-scale attacks.

Defending against worms, particularly day-zero worms, is perhaps the most pressing challenge for a large enterprise. Such a worm can have a devastating impact as it automatically propagates itself to all vulnerable machines on a network. Defending against worm attacks, for which no pre-existing attack signature is available, requires the automation of tasks that current system administrators must perform manually. These include: automatic aggregation and correlation of security reports to detect activity at a local site,

automated short-term defensive actions to stop local worm infections, cooperative alert sharing across administrative boundaries to protect sites not yet infected, and automated back-off when a worm is contained or in the event of a false alarm.

4.2 A Distributed Collaborative Defense

As a complement to centralized cyber-security defensive systems we have developed and evaluated cooperative defensive schemes. Centralized systems are designed primarily to protect enterprises by monitoring aggregate traffic at fixed locations in the network and responding by blocking or delaying observed malicious behavior. In some circumstances, however, such centralized systems may not be suitable; organizations may not have the resources to acquire and manage a large system, there may not be sufficient trust between sub-domains to accept a centralized protection policy, and large numbers of mobile nodes may exit and enter the network leaving them temporarily without protection.

Previous work by us and others [13,26,28,48] have developed cyber-defenses based upon collaborative alert-sharing as a way to detect and react to large-scale distributed attack such as Internet worms. Evaluation of these schemes is usually done both analytically and through simulation. Assumptions regarding false positive rates and other environmental aspects are idealized abstractions due to the lack of a realistic testing and evaluation framework. Emulations on DETER and Emulab testbeds were used for this work.

4.2.1 Collaborative Distributed Attack Detection

In this chapter we describe and evaluate a scheme for distributed attack detection using cooperating end-hosts. In this system, all events are generated using software detection agents on individual end-hosts. Currently, we monitor inbound and outbound network traffic at the host and detect local anomalies in traffic features. Due to the limited view of these detectors, however, isolated end-hosts alone would serve only as low-quality (high false positive or high false negative) detectors of distributed attacks. Our goal is to cooperatively share information such that the aggregation of end-host alerts produces a high-quality (low false positive and low false negative) global attack detector. We accomplish this by implementing a distributed version of the sequential hypothesis test(dSHT) used successfully in centralized detection schemes [64]. With this method, all collaborating sites maintain a decision table constructed using the ratio of the likelihood that the features

are a good indicator of the current worm attack to the likelihood for the features to occur at random. When the likelihood of observed behavior exceeds a predetermined threshold, enough evidence has been accumulated to reach a correct decision with high probability.

This work was inspired by the Jung et al.'s algorithm for quick port-scan detection [64]. While they use Sequential Hypothesis Testing to identify malicious port-scanners, we adapted the principle to detect worms. In this formulation, let H_1 and H_0 be the hypotheses that there is and is not a worm respectively. Let Y_i be the random variable that says there is evidence of an attack or not at site i. This represents the weak local end-host detector at site i.

$$Y_i = \begin{cases} 1 & \text{if there is evidence of an attack;} \\ & \text{this could be either an attack or a false positive with probability(fp)} \\ 0 & \text{if there is no evidence of an attack;} \\ & \text{this could either be an attack or a false negative with probability(fn)} \end{cases}$$

By definition,

$$\mathrm{P}[Y_i = 0|H_1] = \mathrm{fn}; \quad \mathrm{P}[Y_i = 1|H_1] = (1 - \mathrm{fn})$$

$$\mathrm{P}[Y_i = 1|H_0] = \mathrm{fp}; \quad \mathrm{P}[Y_i = 0|H_0] = (1 - \mathrm{fp})$$

The observation vector $\vec{Y} = \{Y_1, Y_2 \cdots Y_n\}$ then is the set of measurements obtained by n conditionally independent end-hosts. Each end-host contributes one y_i to the vector and passes the vector to another end-host as dictated by the messaging protocol in effect at that time. Sec. 4.2.2 details the messaging protocol we used in this study. We now define, $P[\vec{Y}|H_i]$ to be the likelihood that the given observation $\vec{Y}$ was made because the hypothesis H_i is true. Therefore the ratio,

$$\mathrm{L}(\vec{Y}) = \frac{\mathrm{P}[\vec{Y}|H_1]}{\mathrm{P}[\vec{Y}|H_0]},$$

gives the Likelihood Ratio that the sequence of events observed are a good indicator of the current worm to the likelihood for the observation to occur at random. Further assuming all Y_i's are conditionally independent measurements, we have,

$$\mathrm{L}(\vec{Y}) = \frac{\mathrm{P}[Y_1|H_1] \cdot \mathrm{P}[Y_2|H_1] \ldots \mathrm{P}[Y_n|H_1]}{\mathrm{P}[Y_1|H_0] \cdot \mathrm{P}[Y_2|H_0] \ldots \mathrm{P}[Y_n|H_0]}$$

for a sequence of n local detectors sampled. Then if vector $\vec{Y}$ has a 1's and b 0's, the Likelihood ratio is,

$$\mathrm{L}(\vec{Y}) = \frac{(1 - \mathrm{fn})^a * \mathrm{fn}^b}{\mathrm{fp}^a * (1 - \mathrm{fp})^b}$$

Using this we compute a table of the outcomes of many random walks through a collection of local detectors. For example, entry (5,2) would contain the likelihood ratio of finding two alerts after sampling five independent sites.

The strength of the desired global detector, then, is specified by two quantities: desired detection rate, DD, and desired false alarm rate, DF. DF, in other words, is the maximum acceptable failure rate of the global detector. Using these, one can calculate thresholds in the table of likelihood ratios:

$$T0 = \frac{1 - DD}{1 - DF} \quad \text{and} \quad T1 = \frac{DD}{DF}$$

Each host, then, implements a global intrusion detector that makes decisions as follows: if, after including the local detector state, the calculated likelihood ratio, $\mathrm{L}(\vec{Y})$, is less than $T0$, accept the hypothesis that there is no worm (H_0) and halt the query. If $\mathrm{L}(\vec{Y}) > T1$, accept the hypothesis that there is a worm (H_1) and raise a global alarm, otherwise continue the random walk among end-hosts. This defines upper and lower blocks in the decision table as a region likely to have been produced by an attack and a region likely to come from normal behavior. By independently sampling weak local end-host detectors with given *fp* and *fn*, one can achieve a strong global detector if enough sites are traversed.

4.2.2 Cooperative Messaging Protocols

In the scheme described above, the method for obtaining random samples from cooperating end-hosts is left unspecified. In the case of Internet worm attack, our initial tests were performed using an epidemic spread protocol. Cooperating hosts contain a random subset of the addresses of all nodes in the collection. Nodes with new alerts from their local detectors choose m other end-hosts at random and send the message "{1, 1}", which means, "one site has reported one alert". Hosts receiving this message add their local information (e.g. it would generate a "{2, 1}" if had not seen the activity, and a "{2, 2}" if had) and attempt to arrive at a decision based upon the table of likelihood ratios. If no decision is reached, m new sites are selected at random and the message propagates. In this manner multiple SHT sequences(chains) of evidence are spread randomly across cooperating end-hosts. If "normal behavior" decisions are reached in any chain, that chain halts. If a "likely worm attack" decision is reached at any point, a global warning is broadcast to all nodes. Figure 4.1 shows an example message chain with a fan-out, $m = 2$. Preliminary experiments on Emulab [120] and DETER [16] testbeds have led us to conclude that messaging overheads

for protocols with $m > 1$ provide little benefit in early detection and result in needless communications in the presence of local false positives. During times of widespread attacks multiple query chains are initiated by local detectors, forming an ever-increasing number of independent queries.

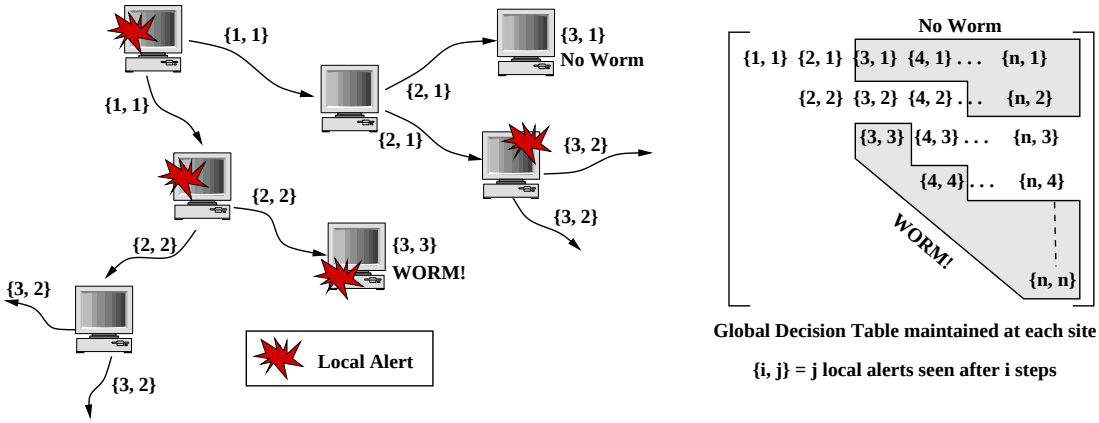


Figure 4.1: Diagram illustrating the co-operative messaging protocol and the decision table used in dSHT used to generate a global worm detector

4.3 Evaluation on an Emulated Test-bed

One major difficulty in testing any large-scale defensive systems is that a large number of test machines have to be configured and managed efficiently. To accomplish these tasks, we used the Emulab and DETER testbeds along with evaluation framework developed in the previous chapter. Instead of the native worm libraries and pseudo-server(Fig. 3.1) we used a more powerful worm simulation engine called *WormSim* [81] and its companion XML worm-specification library.

4.3.1 Experimental Setup

The goals of our experiments are to evaluate our algorithms' effectiveness in identifying worm outbreaks, to determine its robustness against false alerts and to measure the network overhead of the cooperative protocol itself.

The major components of our current experiment setup are:

- A worm simulator engine(*Wormsim*)

- A local intrusion detection system (IDS) to generate low level sensor inputs.
- A global detection algorithm and protocol implementing dSHT.
- The evaluation infrastructure including the network test-bed itself and instrumentation tool-kits.

We describe these components briefly.

Wormsim To test distributed defenses in the presence of realistic worm attacks without installing vulnerable software, we developed the Wormsim worm emulation framework. The goal of this framework is to generate network traffic patterns that mimic, as closely as possible, the patterns generated if malicious code had actually existed on the end hosts. Rather than executing malicious binary instructions that govern worm propagation, *Wormsim* agents interpret XML specifications written to emulate the same behavior. Agents accept and parse messages in an XML format and then, based upon the specification, connect to other "victim" hosts, sending them the same XML worm instructions. The targets are identified based upon the parameters in the XML worm specifications. Some other features that can be specified are the scan method, the transport protocol to use, the scan rate, etc. Each *Wormsim* engine can be remotely configured to be either vulnerable or not vulnerable to a particular worm.

A Local IDS In tune with our philosophy of achieving high-confidence correlations from weak detectors, we implemented a very weak end-node IDS. The IDS would raise an alarm to trigger dSHT whenever there is a connection attempt to an un-serviced port. The reasoning is that, a legitimate connection attempt usually never goes to a host that does not service it. On the contrary, automated attacks such as worms, ignoring sophisticated ones that have information from prior reconnaissance, try to make connections indiscriminately. Thus, those nodes that service a certain port have no protection and do not trigger the SHT. However, IDSes used in practice are much better than the one we use and will help in detecting a more sophisticated attack. This will enable even the vulnerable nodes to participate in the protocol.

Since *Wormsim* knows the vulnerability status of the host at a certain port, it can easily use the event of receiving XML specifications on a non-vulnerable node to trigger the detection algorithm. Hence this IDS was implemented as a patch to *Wormsim* itself.

Global Detection Algorithm As a message propagates, each detection agent adds one to the number of nodes queried and one to the number of positives if it has seen a similar alert locally. At this time, we assume there is only one alert that can be raised and hence no information about the kind of attack is passed along. However, we envision using an anomaly vector in future to describe the event so that stronger correlations can be made.

The SHT parameters *DD* and *DF* were set to 98% and 2% respectively(sec. 4.2.1). We consider these values to be within reasonable tolerance. The local IDS miss rate, *fn*, was set at 1%. Their false alarm rate was the independent variable and chosen as described in the next section. The fan-out, m, for the co-operative alert protocol (sec. 4.2.2) is set to 1. With each new infection, one new SHT sequence is created. After the first few infections, there are multiple parallel global alert chains propagating simultaneously. Each member propagates an alert by sharing it with another randomly chosen member. Besides satisfying a basic requirement for the SHT algorithm, such random selection defends the protocol from the following two attacks. One, malicious members gaming the protocol. Two, clever or hit-list worms, or a combination of both, circumventing our protocol by targeting only those nodes that will not be chosen to share the alert.

Evaluation Infrastructure The experimental test network was configured with 100 PCs, a mixture of Pentium IVs and 64-bit Xeons randomly assigned by the testbed, running FreeBSD 4.10. All nodes were assigned to a single LAN, though we emphasize that we could have used several thousand machines. Each one of them can be as far away from each other on the Internet and only connectivity amongst the nodes matter. We also emphasize that we are not trying to save the entire Internet from the worm attack. We are only interested in an early detection for this particular federation of willing participants.

A 1Mb LAN was used so that test machines on different switches could be assigned to our experiment. This speeds up node assignment on the testbed to our experiment without significant changes in experimental results since our cooperative protocol was not expected to consume much of the total bandwidth.

4.4 Experimental Results

To evaluate our system we focused upon three primary properties: the ability of the algorithm to detect worms, the likelihood of generating a global worm alert for a given

level of local false alarms, and the messaging overhead of the system under various false alarm conditions.

4.4.1 False Alarm Experiments

We wish to answer the following two questions in these experiments:

1. How many simultaneous false alarms generated by the local IDS are required to wrongly choose hypothesis H_1, a global false alarm?

2. What is the network bandwidth overhead during normal operating conditions?

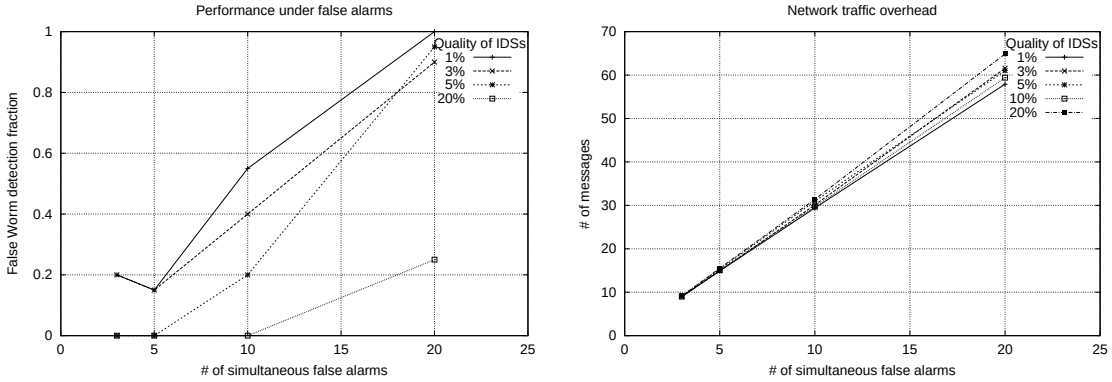
Wrong Choice: The answer to first question is important due to the following reason. Since, the local host IDS operates on a very naïve principle, we expect to initiate cooperative chains conducting the SHT quite frequently and even when there are no worms. Each and every local false alarm, or even a malicious port scan, will initiate a query sequence. To answer this question we set-up the following experiment.

Each local IDS was assigned a certain false alarm rate *fp* denoting its quality; (i. e) for each IDS, a certain n alarms out of every 100 was considered to be spurious. This property of the IDS forms an input to constructing the the decision table used by each participant. We set $n \in \{1, 3, 5, 10, 20\}$. n takes one of these five values for each experiment. An IDS with $n = 1$, or equivalently $fp = 0.01$, is said to be of high quality while one with $n = 20$ is considered to be poor.

It would be impractical to use the false alarm rates, configured as a parameter of the local detectors, to generate sensor events in the test-bed experiment. If we were to wait for, say, five simultaneous false alarms, most of the experiment time would be spent in simply waiting for this rare event. Alternatively, we selectively generate the rare events themselves and record the effects of these events on our SHT algorithm. The goal here is to generate simultaneous false-alarm conditions so that a SHT sequence has multiple members that have seen a local false alarm. We use the Event Control System (ECS) of the emulab test-bed to trigger false alarms in a number of participants(m) simultaneously. We set $m \in \{3, 5, 10, 20\}$. m takes one of the four values in each experiment described below. The results can then be applied to systems with a given quality of IDS.

Thus, we have a family of 20 experiments with different configurations (m simultaneous false alarm conditions times n local IDS quality levels) to run. We repeat each

experiment 20 times to reduce the effects of random fluctuations. These experiments were conducted with the detection system running on all 100 nodes. *Wormsim* did not have to generate any worms during these experiments.



(a) H_1 chosen wrongly due to false alerts

(b) Total number of messages required before dSHT chooses one hypothesis over the other

Figure 4.2: False alarms experiments

Fig. 4.2(a) shows the number of local false alarms needed to generate a global false alarm. It shows the fraction out of 20 repetitions of the experiments the dSHT wrongly chose hypothesis H_1. Naturally the the incidence of this mistake goes up as the number of simultaneous false alarms increases. However, the global detector raises fewer false alarms when the local IDS raise more false alarms. For example, for a very poor quality local host IDS (with a 20% *fp*) the dSHT algorithm makes the global detector highly suspicious of alerts received resulting in fewer mistakes.

For the higher quality local host IDS, five simultaneous false alarms will wrongly produce a global worm alert using 15% of the time. While this may not seem particularly small, the chance of getting 5 simultaneous false alarms is highly unlikely to begin with because the IDS quality is set to be high.

Network overhead: The concern that raises the second question listed above is that if the local host IDS quality is too low, during normal operations, dSHT would require an excessive number of queries in each chain before either hypothesis is chosen to be accepted. In essence, the path taken in the decision table would remain in the middle, undecided

portion rather than reaching any decision.

Were this to happen continuously it might adversely affect network operations or allow a sophisticated attacker to trigger minor false alarms to deliberately induce periods of high bandwidth message passing. Fig. 4.2(b) shows the number of messages required to choose either hypothesis for four different environments(indicated by the ambient levels of simultaneous false alarms) and for five different qualities of the local end-host detectors. The numbers are averaged over 20 experiments. The maximum standard deviation observed was 3.2 messages; when 20 false alarms were fired simultaneously from end-node IDSes whose *fp* rates were pegged at 3%.

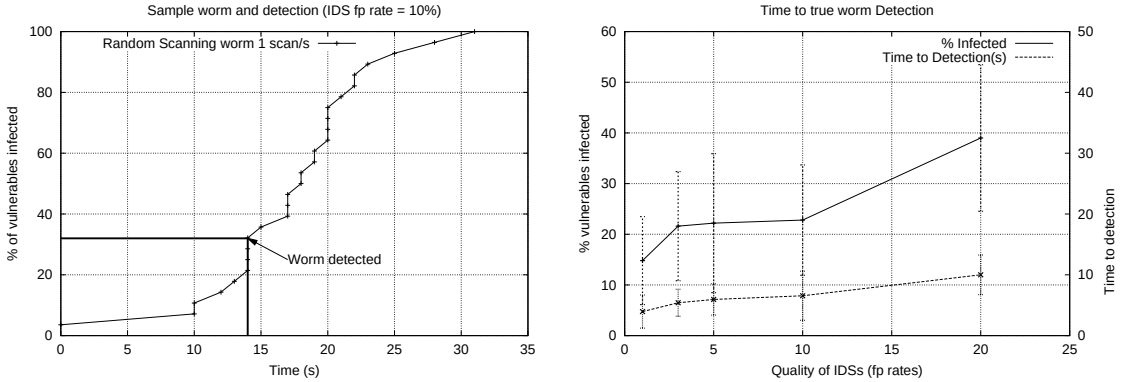
The number of messages increases in proportion to the number of simultaneous false alarms since each false alarm initiates a new query chain. The number of messages, however, depends little on the quality of the local end-host IDS. During periods of false alarms, since the local alerts are independently distributed across end-hosts (next hop neighbors are selected at random), decisions are reached regarding false alarms after querying only four end-hosts on average. There seems to be little danger here in a runaway dSHT causing harm to normal network operations, even when the local end-host detectors are relatively poor.

4.4.2 Performance in Detecting Worm Attacks

The second set of experiments was performed to test the system's response in the presence of self-propagating worm attack. We do not study the effects of false alarms in presence of worm traffic as it would only help to make a "worm" decision sooner. For our worm experiments we set the vulnerability density to be 25%(i. e) one-fourth of the participant are vulnerable; a random process chooses which specific nodes in the test-bed are vulnerable. We configured the worm to send out a random subnet scan every 1 second. Since the entire vulnerable population is on one subnet, this worm is effectively a random scanning worm. The worm scan speed does not have any impact on detection unless it is faster than the detection algorithm. The morphology of the worm is also not of concern as we do not deal with worm semantics. We only exchange much coarser information about anomalies.

We want to determine the effect of various local end-host IDS quality on decision time and infection rates. Thus, we have n experiments to run against this worm; one for

each end-host IDS quality. We again repeat this experiment 20 times to reduce the effects of random fluctuations.



(a) A sample infection sequence and detection instant

(b) Results from all worm experiments showing the percentage of infected nodes at detection time as a function of local end-host IDS quality

Figure 4.3: Worm experiments

The results from a typical worm attack experiment are shown in Figure 4.3(a). The percentage of vulnerable machines infected is plotted as a function of time and exhibits the characteristic s-curve infection profile. In this example, the decision table is constructed using a 10% false alarm rate in the end-node detectors. At this rate, a worm decision is reached at 14 seconds after the launch of the attack with 32% of the vulnerable nodes already infected. Since the local end-host IDS in this case is rather poor, a decision is not reached until relatively late in the infection profile.

Detection times and percentages of infected hosts from all experiments were collected and are shown plotted together in Figure 4.3(b). We notice that the number of infections before worm-detection increases with decreasing quality of end-node detectors. While poorer quality end-host detectors do not necessarily lead to larger problems with respect to false alarms, they have a significant impact on the global dSHT detector's ability to quickly detect worms; before unacceptable numbers of vulnerable nodes have been compromised. Since the global dSHT must be more tolerant to high levels of false alarms, it takes longer to claim a worm with the required high levels of confidence. However, there are no cases of missed worms. Sooner or later, worms are always detected. Only those worms

that carefully avoid all non-vulnerable nodes will not be detected. However, as mentioned earlier in section 4.3.1, IDSes used in practice are much better than the one we used and can detect more sophisticated attacks enabling even the vulnerable nodes to participate in the protocol.

4.5 Future Work

There are quite a few important aspects that we still need to address. A couple of them are listed below.

We need to define the anomaly vector to share amongst the detection agents. Some of the features of this vector could be a flag to indicate presence of machine instructions in traffic to servers, the size of such instruction sequences, the frequency of such connection attempts, the recent CPU usage statistics, etc.

In our current study we have not taken into consideration the effect of the worm traffic from outside our network of interest. To address this, we are developing an Internet scale-down node. This node represents the Internet external to our network and would generate traffic into our emulation network based on the mathematical model of the worm specification. We may be able to make use of the work done by Liljenstam et al. [78] for this. Evaluating dSHT in the presence of traffic from this Internet Scale-down node forms our next step in this direction.

We have also not considered the effects of malicious nodes in the federation in these experiments. To overcome such problems, we could introduce several variations in the protocol. For example, instead of declaring 'worm' immediately after the first such decision, we could wait until a certain number of unique participants make the same decision. It is worth noting that a similar problem has already been formulated and solved by the systems community as the Byzantine Generals problem [12, 72, 89]. Those solutions might help alleviate this problem at the cost of using more network bandwidth and a delayed detection.

Chapter 5

A Dynamic Programming Formulation for Worm Response

5.1 Introduction

Dealing with known worms is a solved problem – signatures to be used by Intrusion Prevention Systems(IPSs) are developed to prevent further infections, and patches are developed to fix vulnerabilities exploited by these worms. Dealing with unknown worms – worms that exploit zero-day vulnerabilities or vulnerabilities for which patches have either not been generated or not applied yet – is still a research question. Several ingenious proposals to detect them automatically exist. Many of them have also proposed sophisticated counter measures such as automatic signature generation and distribution [70, 98, 114] and automatic patch generation to fix vulnerabilities [103].

Often times, even if automated, there is not much time to either generate or distribute signatures or patches. Other times, system administrators are skeptical about applying patches. During those instances when such automatic signature based traffic filtering or patching are not feasible, the only option left is to either completely shut-down the vulnerable service or keep it running risking infection. It is usually preferred to shut-down the service briefly until a mitigating response is engineered to the worm.

However, making this decision becomes hard when one is not completely sure if there is really a worm, and if the service being offered is vulnerable to it. It does not make much sense to shut-down a service and later realize that such an action was not warranted.

Whereas suspending the service in an attempt to prevent infection is not considered bad. Intuitively, it is desired to shut-down the service briefly until it is clear whether there is an attack or not. Balancing the consequences of providing the service risking infection against that of not providing the service is of the essence.

This chapter captures this intuition and devises an algorithm using Dynamic Programming(DP) techniques to minimize the overall cost of response to worms where cost is defined as some mathematical expression of an undesirable outcome.

These algorithms use information about anomalous events that are potentially due to a worm from other co-operating peers to choose optimal actions for local application. Thus the response is completely decentralized.

We surprisingly found that for certain scenarios, to leave oneself open to infection by the worm, might be the least expensive option as demonstrated by our algorithms. We also show that these algorithms do not need a great deal of information to make decisions.

5.2 Dynamic Programming

The basic model of a system consists of two main features: (1) a discrete-time dynamic system and (2) a cost function that is additive over time. The system has the form

$$x_{k+1} = f_k(x_k, u_k, w_k), \qquad k = 0, 1, \ldots, N-1 \tag{5.1}$$

where

- k indexes discrete time,
- x_k is the state of the system and summarizes past information that is relevant for future optimization,
- u_k is the control or decision variable to be selected at time k,
- w_k is a random parameter, also called disturbance or noise depending on the context,
- N is the horizon or the number of times control is applied.

and f_k is the function that describes the system and in particular the mechanism by which the state is updated.

The cost function is additive in the sense that the cost incurred at time k, denoted by $g_k(x_k, u_k, w_k)$, accumulates over time. Thus the total cost is

$$g_N(x_N) + \sum_{k=0}^{N-1} g_k(x_k, u_k, w_k)$$

where $g_N(x_N)$ is a terminal cost incurred at the end of the process. However, because of the presence of a random parameter, w_k, the cost is generally a random variable and cannot be meaningfully optimized. We therefore formulate the problem as an optimization of the *expected cost*

$$E\left\{ g_N(x_N) + \sum_{k=0}^{N-1} g_k(x_k, u_k, w_k) \right\},$$

where the expectation is with respect to the joint distribution of the random variable involved. The optimization is over the controls $u_0, u_1, \ldots, u_{N-1}$, and each control, u_k, is chosen based on the current state of the system, x_k. This is called **closed loop** optimization as opposed to **open loop** optimization when all controls have to be decided at once at time 0 without any knowledge of the state of the system at any time later.

Mathematically, in closed-loop optimization, we want to find a sequence of functions, $\mu_k, k = 0, \ldots, N-1$, mapping the system state x_k into a control u_k which when applied to the system minimizes the total expected cost. Thus $u_k \leftarrow \mu_k(x_k)$. The sequence $\pi = \{\mu_0, \ldots, \mu_{N-1}\}$ is referred to as a *policy* or *control law*.

For each policy, π, the corresponding cost for a fixed initial x_0 is denoted by $J_\pi(x_0)$. We want to minimize this for a given x_0 over all policies that satisfy the constraints of the problem. The policy that does this is denoted by π^* and minimizes the corresponding cost, $J_{\pi^*}(x_0)$. However, it is also possible to find the policy that minimizes the cost for any x_0.

An introduction to a few notations are in order now. We denote by $J_k(x_k)$ the *cost-to-go* from state x_k at time k to the final state at time N. Thus, $J_N(x_N)$ is the terminal cost and $J_0(x_0) = J_\pi(x_0)$ is the total cost.

Dynamic Programming Algorithm: An optimal total cost is given by the last step of the following algorithm, which proceeds backwards in time from period $N-1$ to period 0:

$$J_N(x_N) = g_N(x_N), \tag{5.2}$$

$$J_k(x_k) = \min_{u_k} \underset{w_k}{E}\Big\{ g_k(x_k, u_k, w_k) + J_{k+1}(x_{k+1}) \Big\}, \qquad k = 0, 1, \ldots, N-1, \tag{5.3}$$

where the expectation is taken with respect to the probability distribution of w_k, which depends on x_k and u_k. Furthermore, if u_k^* minimizes the right side of equation (5.3) for each x_k and k, the corresponding policy π^* is optimal.

5.3 DP Problems with imperfect state information

In this section, we first describe DP problems involving imperfect state information. Then, we show how these can be transformed into problems with perfect state information through state augmentation. We then list down the complexities involved in solving such problems. In the next section, we will formulate worm response as a DP problem with imperfect state information. We also explain how and why the complexities involved in such formulations do not affect the worm response problem.

5.3.1 Problem Description

Often, information about the exact state of the system, x_k is not available. Instead, only a certain observation, z_k, about the system state is available. The observation takes the form:

$$z_0 = h_0(x_0, v_0), \qquad z_k = h_k(x_k, u_{k-1}, v_k), \qquad k = 1, 2, \ldots, N-1, \tag{5.4}$$

where v_k is the observation disturbance and characterized by a given probability distribution

$$P_{v_k}(.|x_k, \ldots, x_0, \quad u_{k-1}, \ldots, u_0, \quad w_{k-1}, \ldots, w_0, \quad v_{k-1}, \ldots, v_0).$$

The initial state x_0 is also random and has a probability distribution P_{x_0}. The probability distribution of w_k may depend on the state of the system and the control but not the prior state disturbances, w_{k-1}, or observation disturbances, v_{k-1}. The control u_k is constrained to take values from a given nonempty subset U_k of the control space. It is assumed that this subset does not depend on the x_k.

Let us denote by I_k the information available to the controller at time k and call it the information vector. We have

$$\begin{aligned} I_k &= (z_0, z_1, \ldots, z_k, \quad u_0, u_1, \ldots, u_{k-1}), \quad k = 1, 2, \ldots, N-1 \\ I_0 &= z_0 \end{aligned} \tag{5.5}$$

Analogous to the basic model of a dynamic programming problem in section 5.2, we want to find an admissible policy $\pi = \{\mu_0, \mu_1, \ldots, \mu_{N-1}\}$ that minimizes the cost function

$$J_\pi = \underset{\substack{x_0, w_k, v_k \\ k=0,1,\ldots,N-1}}{E} \left\{ g_N(x_N) + \sum_{k=0}^{N-1} g_k\left(x_k, \mu_k(I_k), w_k\right) \right\}$$

subject to the system evolution

$$x_{k+1} = f_k(x_k, \mu_k(I_k), w_k), \quad k = 0, 1, \ldots, N-1,$$

and the measurement equations (5.4) in which u_{k-1} is replaced by $\mu_{k-1}(I_{k-1})$.

5.3.2 Re-formulation as a Perfect State-information Problem

In the absence of precise information about the state of the system, it is intuitively clear that we need to define a new augmented system whose state at the time k would contain information about all the variables that can help the controller while making the k^{th} decision [22]. The information vector I_k forms an ideal candidate to describe the state of the new system. By definition of I_k in equations (5.5), this new system can be defined to evolve as:

$$I_{k+1} \;=\; (I_k, z_{k+1}, u_k), \qquad k \,=\, 0, 1, \ldots, N \,-\, 2, \qquad I_0 \,=\, z_0, \tag{5.6}$$

where, I_k describes the state of the system, u_k is the control as usual while z_{k+1} can be treated as the random disturbance as it is dependent on a random variable v_k as mentioned in equation (5.4).

The cost incurred during the k^{th} stage is now:

$$\tilde{g}_k(I_k, u_k) \;=\; \underset{x_k, w_k}{E}\Big\{ g_k(x_k, u_k, w_k) | I_k, u_k \Big\} \tag{5.7}$$

Thus the problem with imperfect state-information has now been reformulated as a perfect state-information problem with the augmented system evolution (5.6) and augmented cost per stage (5.7). By writing out the DP algorithm (5.2) and (5.3) for the above system, we get:

$$\begin{aligned} J_{N-1}(I_{N-1}) = \min_{u_{N-1}} \Bigg[\underset{x_{N-1}, w_{N-1}}{E} \Big\{ & g_N\Big(f_{N-1}(x_{N-1}, u_{N-1}, w_{N-1})\Big) \\ & + \; g_{N-1}(x_{N-1}, u_{N-1}, w_{N-1}) | I_{N-1}, u_{N-1} \Big\} \Bigg] \end{aligned} \tag{5.8}$$

and for $k = 0, 1, 2, \ldots, N-2$, we have:

$$J_k(I_k) = \min_{u_k} \left[\underset{x_k, w_k, z_{k+1}}{E} \Big\{ g_k(x_k, u_k, w_k) + J_{k+1}(I_k, z_{k+1}, u_k) | I_k, u_k \Big\} \right], \tag{5.9}$$

These equations form the DP algorithm for the reformulated imperfect state problem. An optimal policy is obtained by first minimizing the right hand side of equation (5.8) for every possible value of the information vector I_{N-1} to obtain $\mu^*_{N-1}(I_{N-1})$. The $J_{N-1}(I_{N-1})$ thus calculated is used in equation (5.9) to obtain $\mu^*_{N-2}(I_{N-2})$ and the corresponding minimizing $J_{N-2}(I_{N-2})$ over all possible I_{N-2}. This is continued all the way until $J_0(I_0) = J_0(z_0)$ is calculated. The optimal cost is then given by

$$J^* = \underset{z_0}{E} \Big\{ J_0(z_0) \Big\} \tag{5.10}$$

Unfortunately, even if the control and observation spaces are simple, the space and dimensions of the information vector may be prohibitively large. This makes the application of the algorithm very difficult or prohibitively expensive in many cases. Such problems are solved analytically or approximately.

5.4 Response Formulation with imperfect State information

In this section will formulate the computer worm response problem as a DP problem with imperfect state information. For this purpose, we state the problem precisely. We assume that there could be only one worm and that the worm is a random scanning worm. We also assume that there is another process, such as an IDS, that tries to detect the presence of this worm albeit not very accurate. This DP formulation only tells us which control should be applied to minimize the costs incurred until the worm detection process is complete.

5.4.1 Problem Statement

System Evolution: Consider a machine that provides some service. This machine needs to be operated for N steps. Each step could be a time interval, occurrence of a discrete event or something else fancy. This machine can be in one of two states, P or $\overline{P}$, corresponding to the machine being in proper(desired state) or improper(infected by a worm) state respectively. During the course of operating the machine, it goes from state P to $\overline{P}$ with a certain probability λ and remains in state P with a probability $\overline{\lambda} = (1 - \lambda)$. If the

machine enters state $\overline{P}$, it remains there with probability 1. The value of λ is an unknown and depends on how much of the Internet is infected with the worm.

Sensor: The machine also has a *sensor* which inspects the machine for worm infections. However, this *sensor* cannot determine the exact state of the machine. Rather, it can only determine the state of a machine with a certain probability. There are two possible observations denoted by G (good, probably not infected) and B(bad, probably worm infected). Alternatively, instead of infections, we can imagine that the *sensor* looks for infection attempts and anomalies. The outcome would then indicate that there is probably a worm on the Internet(B) or not(G) as opposed to whether the host machine is infected or not. For the time being, let us assume that the inspections happen pro-actively and at random intervals.

We also assume that the *sensor*'s integrity is not affected by the worm.

Controller: The machine also includes a *controller* that can continue(C) or stop(S) operating the machine. The machine cannot change states by itself if it is stopped. Thus the *controller* can stop the machine to prevent a worm infection and start it when it deems it is safe to operate the machine. There are certain costs involved with each of these actions under different conditions as described in the next paragraph. The controller takes each action so that the overall cost of operating the machine for N steps is minimized.

Costs: Continuing(C) to operate the machine when it is in state P costs nothing. It is the nominal. We incur a cost of τ_1 for each time step the machine is stopped(S) irrespective of its state, and a cost τ_2 for each step an infected machine is operated. One might argue that τ_1 and τ_2 should be the same because an infected machine is as bad as a stopped machine. In that scenario, the problem becomes trivial and it can be stated right away that the most cost effective strategy is to operate the machine uninterrupted until it is infected. On the other hand, we argue that operating an infected machine indirectly costs more as it can infect other machines also. Hence, we assume that $\tau_2 > \tau_1$.

Alert Sharing Protocol: Since a computer worm is a distributed phenomenon, inspection outcomes at one machine is a valid forecast of the outcome from a later inspection at another identical machine. Hence, a collection of such machines with identical properties

seek to co-operate and share the inspection outcomes. Under this scheme, an inspection outcome at one machine is transmitted to another co-operating peer chosen randomly. The *controller* on the randomly chosen machine uses such received messages to select the optimal control to apply locally. This has the effect of a machine randomly polling several neighbors to know the state of the environment and gives the uninfected machines an opportunity to take appropriate actions to prevent being infected.

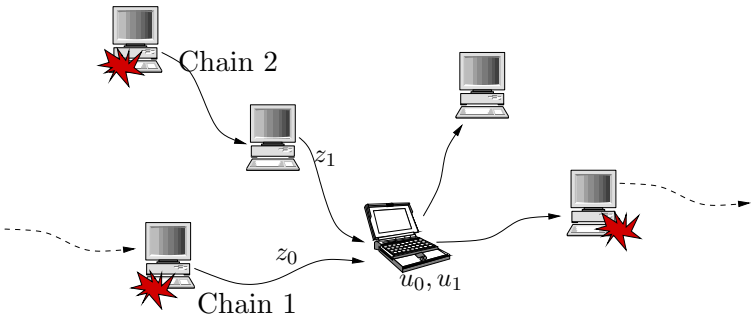


Figure 5.1: Alert Sharing Protocol. The laptop is our machine of interest. It uses information, z_0 and z_1, from different chains to choose, actions, u_0 and u_1. It may or may not have seen an anomaly while the machines shown with a blast have seen an anomaly.

Goal: Now, the problem is to determine the policy that minimizes the total expected cost over N steps, stages or time periods. Since, we solve the formulation offline, N is really not a constraint unless it is too big. Even $N = 10$ could be easily solved even on a current PC if not by hand. However, once we have the formulation, we can also solve it approximately or analytically for larger Ns. The rest of this section shows the formulation of this problem and a solution for $N = 3$ and later present and discuss computer generated results for larger Ns.

5.4.2 Problem Formulation

We can see that the above description of the problem fits the general framework of section 5.3, "Problems with imperfect state information." The state space of the machine consists of the two states P and $\overline{P}$,

$$\text{State Space of the machine} = \{P, \overline{P}\} = \text{Uninfected, Infected,}$$

the control space consists of the two actions C and S,

$$\text{Control Space} = \{C, S\} = \text{Continue, Stop,}$$

and the observation space consists of two elements G and B,

$$\text{Observation Space} = \{G,\, B\}$$

The machine by itself does not transit from one state to another. Left to itself, it remains put. It is transferred from P to $\overline{P}$ only by a worm infection which is purely, a random process; an already infected victim chooses this machine randomly. Referring back to equation (5.1), the evolution of this system depends on the current state of the system, x_k, the random disturbance, w_k, the control, u_k, and λ which is a function of the number of machines infected on the Internet – the infectious force. Rolling the disturbance, w_k, into x_k, the evolution of this system shown in Fig. 5.2 can be described by:

$$\begin{aligned}
&P(x_{k+1} = P \mid x_k = P,\, u_k = C) = (1-\lambda) && P(x_{k+1} = \overline{P} \mid x_k = P,\, u_k = C) = \lambda \\
&P(x_{k+1} = P \mid x_k = \overline{P},\, u_k = C) = 0 && P(x_{k+1} = \overline{P} \mid x_k = \overline{P},\, u_k = C) = 1 \\
&P(x_{k+1} = P \mid x_k = P,\, u_k = S) = 1 && P(x_{k+1} = \overline{P} \mid x_k = P,\, u_k = S) = 0 \\
&P(x_{k+1} = P \mid x_k = \overline{P},\, u_k = S) = 0 && P(x_{k+1} = \overline{P} \mid x_k = \overline{P},\, u_k = S) = 1
\end{aligned} \tag{5.11}$$

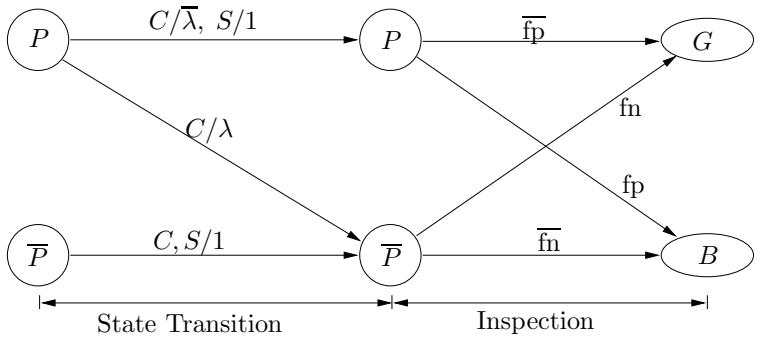


Figure 5.2: State Transition probabilities for each action and observation probabilities for each state.

We denote by $x_0, x_1, \ldots, x_N$, the states of the machine when the first, second and the N^{th} messages are received respectively. $u_0, \ldots, u_N$ denote the actions taken by the *controller* upon receipt of the first $\ldots N^{\text{th}}$ messages. Assuming the machine initially starts in state P, the probability distribution of x_0 is

$$P(x_0 = P) = \overline{\lambda}, \qquad P(x_0 = \overline{P}) = \lambda. \tag{5.12}$$

We do not have to know the initial state the machine starts as mentioned in Sec. 5.2. This assumption is for exposition only. Note that the outcome of each inspection of the

machine is an imperfect observation about the state of the system. Here again, we roll in the observation disturbance, v_k, into the observation, z_k. Referring back to equation (5.4), we can view each measurement of the system state as a random variable with the probability distribution:

$$\begin{aligned} P(z_k = G \mid x_k = \overline{P}) &= \text{fn} & P(z_k = B \mid x_k = \overline{P}) &= (1 - \text{fn}) \\ P(z_k = G \mid x_k = P) &= (1 - \text{fp}) & P(z_k = B \mid x_k = P) &= \text{fp} \end{aligned} \tag{5.13}$$

where fp and fn are properties of the *sensor*s denoting the false positive and false negative (miss) rates.

The costs resulting from a sequence of states $x_0, x_1, \ldots, x_N$ and controls $u_0, u_1, \ldots, u_N$ is

$$g_0(x_0, u_0) + g_1(x_1, u_1) + \cdots + g_{N-1}(x_{n-1}, u_{N-1}) + g_N(x_N)$$

where

$$g(P, C) = 0, \qquad g(P, S) = g(\overline{P}, S) = \tau_1, \qquad g(\overline{P}, C) = \tau_2, \qquad g(x_N) = 0. \tag{5.14}$$

Assuming the cost function remains the same regardless of the cardinality of the message being processed, the sub-script k can be dropped from g. Also, $g_N(x_N) = 0$ because u_N is chosen with accurate knowledge of the environment, (i.e) whether there is a worm or not. If there is a worm, $u_N = S$, and $u_N = C$ otherwise. The information vectors at the receipt of each message is the same as eq.(5.5).

Note that the progression, $x_0, \ldots, x_k$ appears on a sequence of machines and $u_0, \ldots, u_k$ appears on one machine. We remind readers that z_k is the observed state of the last machine in the k^{th} chain that runs through the machine in question(the laptop in Fig.5.1). Whereas u_k is the control applied in response to z_k in this machine. Our problem now is to find functions $\mu_k(I_k)$ that minimize the total expected cost

$$\underset{x_k, z_k}{E} \left\{ g(x_N) + \sum_{k=0}^{N-1} g\big(x_k, \mu_k(I_k)\big) \right\}$$

We now apply the DP algorithm from equation (5.9). It involves finding the minimum cost

over the two possible actions, C and S, and it has the form

$$\begin{aligned} J_k(I_k) = \min_{\{C,S\}} \Bigg[& \Big(P(x_k = P \,|\, I_k, C) \cdot g(P, C) + P(x_k = \overline{P} \,|\, I_k, C) \cdot g(\overline{P}, C) \Big) \\ & \qquad + \underset{z_{k+1}}{E} \Big\{ J_{k+1}(I_k, C, z_{k+1}) \,|\, I_k, C \Big\}, \\ & \Big(P(x_k = P \,|\, I_k, S) \cdot g(P, S) + P(x_k = \overline{P} \,|\, I_k, S) \cdot g(\overline{P}, S) \Big) \\ & \qquad + \underset{z_{k+1}}{E} \Big\{ J_{k+1}(I_k, S, z_{k+1}) \,|\, I_k, S \Big\} \Bigg], \end{aligned} \tag{5.15}$$

where $k = 0, 1, \ldots N-1$ and the terminal condition is $J_N(I_N) = 0$. Applying the costs given above in equations (5.14), and noticing that $P(x_k = P \,|\, I_k, S) + P(x_k = \overline{P} \,|\, I_k, S)$ is the sum of probabilities of all elements in a set of exhaustive events which is 1, we get

$$\begin{aligned} J_k(I_k) = \min \Bigg[& \tau_2 \cdot P(x_k = \overline{P} \,|\, I_k, C) \; + \underset{z_{k+1}}{E} \Big\{ J_{k+1}(I_k, C, z_{k+1}) \,|\, I_k, C \Big\}, \\ & \qquad \tau_1 \; + \underset{z_{k+1}}{E} \Big\{ J_{k+1}(I_k, S, z_{k+1}) \,|\, I_k, S \Big\} \Bigg], \end{aligned} \tag{5.16}$$

which is the required DP formulation of response to worms. Next, we demonstrate a solution derivation to this formulation assuming $N = 3$.

5.4.3 Solution

Here we show a solution assuming that we expect to know with certainty about the presence of a worm at the receipt of the third message, that is, $N = 3$. As mentioned before, the same procedure can be followed for larger Ns without loss of generality.

With that assumption, control u_2 can be determined precisely. If the third message says there is a worm, we set $u_2 = S$, and we set it to C otherwise. This also means that the cost to go at that stage is

$$J_2(I_2) = 0. \qquad \text{(Terminal Condition)}$$

Penultimate Stage: In this stage we want to determine the cost $J_1(I_1)$. We use equation (5.16) to compute this cost for each of the eight possible values of $I_1 = (z_0, z_1, u_0)$ under each possible control, $u_1 = \{C,\ S\}$. Then, the control with the smallest cost is chosen as the optimal one to apply for each z_1. Applying the terminal condition to the DP formulation

(5.16), we get

$$\begin{aligned}
J_1(I_1) = \min\Big[&\tau_2 \cdot P(x_1 = \overline{P} \mid I_1, C) \; + \underset{z_2}{E}\Big\{ J_2(I_1, C, z_2) \mid I_1, C \Big\} \,, \\
&\qquad\qquad \tau_1 + \underset{z_2}{E}\Big\{ J_2(I_1, S, z_2) \mid I_1, S \Big\}\Big], \\
= \min\Big[&\tau_2 \cdot P(x_1 = \overline{P} \mid I_1, C) \; + \underset{z_2}{E}\Big\{ J_2(I_2) \mid I_1, C \Big\} \,,\; \tau_1 + \underset{z_2}{E}\Big\{ J_2(I_2) \mid I_1, S \Big\}\Big] \\
&\qquad\qquad\qquad\qquad \ldots \text{From eq (5.6)} \\
= \min\Big[&\tau_2 \cdot P(x_1 = \overline{P} \mid I_1, C) \; + \underset{z_2}{E}\{0\} \,,\; \tau_1 + \underset{z_2}{E}\{0\}\Big] \qquad \ldots \text{Terminal Condition} \\
= \min\Big[&\tau_2 \cdot P(x_1 = \overline{P} \mid I_1, C) \,,\; \tau_1 \,\Big]
\end{aligned}$$

The probabilities $P(x_1 = \overline{P} \mid I_1, C)$ can be computed using Bayes' rule and eqs.(5.11–5.13) assuming the machine starts in state P. We show the calculations for a couple of them here. See Tables 5.1 & 5.2 for complete sample solutions.

(1) $P(x_1 = \overline{P} \mid G,\, G,\, S)$

$$\begin{aligned}
&= \frac{P(x_1 = \overline{P},\, G,\, G,\, \mid S)}{P(G,\, G,\, \mid S)} \\
&= \frac{\sum\limits_{i=\{P,\overline{P}\}} P(G|x_0 = i) \cdot P(x_0 = i) \cdot P(G|x_1 = \overline{P}) \cdot P(x_1 = \overline{P}|x_0 = i, u_0 = S)}{\sum\limits_{i=\{P,\overline{P}\}} \sum\limits_{j=\{P,\overline{P}\}} P(G|x_0 = i) \cdot P(x_0 = i) \cdot P(G|x_1 = j) \cdot P(x_1 = j|x_0 = i, u_0 = S)} \\
&= \frac{(\overline{\text{fp}} \cdot \overline{\lambda} \cdot \text{fn} \cdot 0) + (\text{fn} \cdot \lambda \cdot \text{fn} \cdot 1)}{(\overline{\text{fp}} \cdot \overline{\lambda} \cdot \overline{\text{fp}} \cdot 1) + (\overline{\text{fp}} \cdot \overline{\lambda} \cdot \text{fn} \cdot 0) + (\text{fn} \cdot \lambda \cdot \overline{\text{fp}} \cdot 0) + (\text{fn} \cdot \lambda \cdot \text{fn} \cdot 1)}
\end{aligned}$$

(2) $P(x_1 = \overline{P} \mid G,\, G,\, C)$

$$\begin{aligned}
&= \frac{P(x_1 = \overline{P},\, G,\, G,\, \mid C)}{P(G,\, G,\, \mid C)} \\
&= \frac{\sum\limits_{i=\{P,\overline{P}\}} P(G|x_0 = i) \cdot P(x_0 = i) \cdot P(G|x_1 = \overline{P}) \cdot P(x_1 = \overline{P}|x_0 = i, u_0 = C)}{\sum\limits_{i=\{P,\overline{P}\}} \sum\limits_{j=\{P,\overline{P}\}} P(G|x_0 = i) \cdot P(x_0 = i) \cdot P(G|x_1 = j) \cdot P(x_1 = j|x_0 = i, u_0 = C)} \\
&= \frac{(\overline{\text{fp}} \cdot \overline{\lambda} \cdot \text{fn} \cdot \lambda) + (\text{fn} \cdot \lambda \cdot \text{fn} \cdot 1)}{(\overline{\text{fp}} \cdot \overline{\lambda} \cdot \overline{\lambda} \cdot 1) + (\overline{\text{fp}} \cdot \overline{\lambda} \cdot \text{fn} \cdot \lambda) + (\text{fn} \cdot \lambda \cdot \overline{\text{fp}} \cdot 0) + (\text{fn} \cdot \lambda \cdot \text{fn} \cdot 1)}
\end{aligned}$$

In general, we have

$$\begin{aligned} P(x_k|I_k) &= \frac{P(x_k \cdot I_k)}{P(I_k)} \\ P(I_k) &= \sum_{x_0=\{P,\overline{P}\}} \cdots \sum_{x_k=\{P,\overline{P}\}} P(z_0|x_0)P(x_0) \cdot \prod_{m=1}^{k} P(z_m|x_m)P(x_m|x_{m-1},\, u_{m-1}) \\ P(x_k \cdot I_k) &= P(I_{k-1}) \cdot P(z_k|x_k)P(x_k|x_{k-1},\, u_{k-1}) \end{aligned}$$

The *cost-to-go*, $J_1(I_1)$, thus calculated are used for the zeroth stage.

Stage 0**:** In this stage we want to determine the cost $J_0(I_0)$. We use equation (5.16) and values of $J_1(I_1)$ calculated during the previous stage to compute this cost. As before this cost is computed for each of the two possible values of $I_0 = (z_0) = \{G, B\}$, under each possible control, $u_1 = \{C,\, S\}$. Then, the control with the smallest cost is chosen as the optimal action to perform for the observed state of the machine. Thus we have,

$$J_0(I_0) = \min\left[\tau_2 \cdot P(x_0 = \overline{P} \mid I_0, C) + \underset{z_1}{E}\Big\{J_1(I_1) \mid I_0, C\Big\},\ \tau_1 + \underset{z_1}{E}\Big\{J_1(I_1) \mid I_0, S\Big\}\right]$$

The optimal cost for the entire operation is finally given by

$$J^* = P(G)J_0(G) + P(B)J_0(B)$$

We implemented a program that can solve the above formulation for various values of $\lambda, \mathrm{fp}, \&\ \mathrm{fn}$. We ran the program and tabulated the resulting rule-set in tables 5.1 & 5.2. The next section gives a brief discussion on choosing realistic values for the various parameters, presents and discusses the results from our program runs.

5.5 Alternate Re-formulation using Sufficient Statistics

In section 5.3.2, we presented a re-formulation of the imperfect state information problem in which the information vector, I_k, assumed the state of the system and included all the observations made and controls applied so far. This increases the dimension of I_k by two for each transition of the system after the first one, exploding the state space that needs to be explored.

In this section, we will present the essence of an alternative re-formulation where the state of the system is probabilistically represented conditioned only on the latest observation and control applied. In other words, we reduce I_k to smaller dimensions containing

only the *Sufficient Statistics* yet summarizing all essential contents of I_k as far as control is concerned. We first explain these two terms before presenting the re-formulation itself.

5.5.1 Sufficient Statistic

Refer back to eqs. (5.8) and (5.9). Suppose we can find some function $S_k(I_k)$ such that the minimizing control in those two equations depends on I_k through $S_k(I_k)$. Then, the right hand side of those two equations can be written as:

$$\min_{u_k} H_k\big(S_k(I_k), u_k\big).$$

Such a function S_k is called a *Sufficient Statistic*. An optimal policy obtained by the above minimization can be written as

$$\mu_k^*(I_k) = \overline{\mu}_k\big(S_k(I_k)\big),$$

where $\overline{\mu}_k$ is an appropriate function. Thus, if $S_k(I_k)$ is characterized by a set of fewer numbers than I_k, it may be easier to implement the policy in the form $u_k = \overline{\mu}_k\big(S_k(I_k)\big)$ and take advantage of the data reduction.

5.5.2 Conditional State Distribution

A Couple of candidates for S_k are:

1. The identity function, $S_k(I_k) = I_k$
2. The conditional probability distribution, $P_{x_k|I_k}$, of the state given the information vector. This is also known as the *belief state* of the system.

It is assumed here that v_{k+1} depends explicitly only on the immediately preceding state, control and the system disturbance and not on any of the earlier ones. Under this assumption, we state without proof that

$$J(I_k) = \overline{J}_k(P_{x_k|I_k}), \tag{5.17}$$

$$P_{x_{k+1}|I_{k+1}} = \Phi_k(P_{x_k|I_k}, u_k, z_{k+1}) \tag{5.18}$$

where $\overline{J}_k$ is an appropriate function, and Φ_k is a function that can be determined from the problem. We refer the readers to Bertsekas [22] for the proof and justification of eqs. (5.17) and (5.18) respectively.

Given that $P_{x_k|I_k}$ is a *sufficient statistic* function, we have,

$$\mu_k(I_k) = \overline{\mu}_k(P_{x_k|I_k}), \qquad k = 0, 1, \ldots, N-1,$$

Regardless of the computational reduction, this representation of the optimal policy as a sequence of functions of $P_{x_k|I_k}$, is conceptually useful. It provides a decomposition of the optimal controller into two parts:

(a) An *estimator*, which generates $P_{x_k|I_k}$ using only the most recent observation and control, z_k and u_{k-1}

(b) An *actuator*, which generates u_k based on $P_{x_k|I_k}$

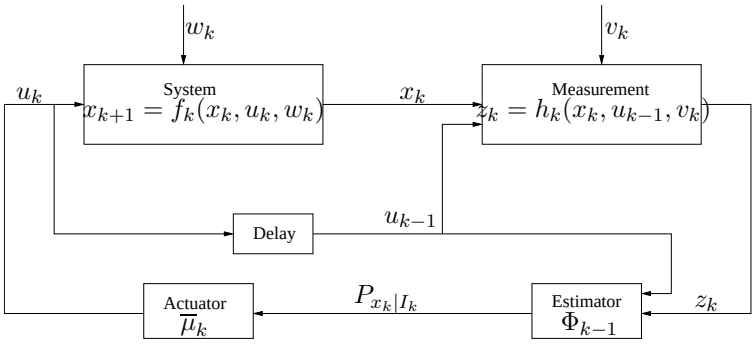


Figure 5.3: The controller split into an *Estimator* and an *Actuator*

Fig. 5.3 explains this concept. We also learn from the figure that, the imperfect state information problem has now been reduced to a perfect belief state information problem. Here, the system state is $P_{x_k|I_k}$ that evolves according to Φ_k while the controller controls the probabilistic state $P_{x_k|I_k}$ so as to minimize the expected *cost-to-go* conditioned on the information I_k available. This split gives a better handle on the design of these two distinct aspects of the *controller*.

5.5.3 Reduction using Sufficient Statistics

Armed with the above eqs. (5.17) and (5.18), we can now re-state the DP algorithm (5.8) & (5.9) as:

$$\begin{aligned}\overline{J}_{N-1}(P_{x_{N-1}|I_{N-1}}) = \min_{u_{N-1}} \Bigg[\underset{x_{N-1}, w_{N-1}}{E} \Big\{ g_N\Big(f_{N-1}(x_{N-1}, u_{N-1}, w_{N-1})\Big) \\ + \; g_{N-1}(x_{N-1}, u_{N-1}, w_{N-1}) | I_{N-1}, u_{N-1} \Big\} \Bigg]\end{aligned} \tag{5.19}$$

for $k = N-1$ and for $k < N-1$,

$$\overline{J}_k(P_{x_k|I_k}) = \min_{u_k}\left[\underset{x_k,w_k,z_{k+1}}{E}\left\{g_k(x_k,u_k,w_k)+\overline{J}_{k+1}\big(\Phi_k(P_{x_k|I_k},u_k,z_{k+1})\big)|I_k,u_k\right\}\right], \quad (5.20)$$

Finite State Systems. Suppose that the system under study is a finite state system such that $x_k = \{1,2,\ldots,n\}$ and that when a control u is applied the system goes from state i to state j with a probability of $p_{ij}(u)$. For each state x_k the system assumes (which is hidden), and a control u_k applied, a cost of $g_k(x_k,u_k)$ is incurred. The terminal cost for being in state x_N at the end of N stages is denoted by $G_N(x_N)$. We want to minimize the expected sum of costs incurred over the N stages. This problem can be reformulated into a perfect state information problem where the objective is to control the column vector of conditional probabilities:

$$p_k = \begin{pmatrix} p_k^1 \\ p_k^2 \\ \vdots \\ p_k^n \end{pmatrix}, \qquad \text{where} \qquad p_k^i = P(x_k = i|I_k), \qquad i = 1,\ldots,n$$

p_k is called the *belief state* and evolves according to eq. (5.18), where Φ represents an *estimator*. p_0 is given or can be calculated from the problem data. The corresponding DP algorithm (eqs.(5.20) & (5.19)) has the form:

$$\overline{J}_k(p_k) = \min_{u_k}\left[p_k' g(u_k) + \underset{z_{k+1}}{E}\left\{\overline{J}_{k+1}\big(\Phi_k(P_{x_k|I_k},u_k,z_{k+1})\big)|p_k,u_k\right\}\right], \quad (5.21)$$

$$\overline{J}_N(p_N) = p_N' G, \quad (5.22)$$

where $g(u_k)$ is the column vector with components $g(1,u_k),\ldots,g(n,u_k)$. $p_k' g(u_k)$, the expected stage cost, is the inner product of the vectors p_k and $g(u_k)$.

5.5.4 Response Formulation using Sufficient Statistics

The worm response problem as we have described in section 5.4.1 is a finite state system and can be solved using the last DP algorithm, (5.21) & (5.22), mentioned above with appropriate re-formulation. The only parameters that we need to define are the conditional probability distribution of the state, $P_{x_k|I_k}$, and the corresponding evolution function Φ_k. Once these parameters are defined, it is straightforward to compute the minimizing costs and corresponding actions.

We show one such solution assuming, again, that $N = 2$. We define the conditional state distribution and their evolution as:

$$p_1 = \big[P(x_1 = \overline{P}|I_1)\big], \qquad p_0 = \big[P(x_0 = \overline{P}|I_0)\big]$$

$$\text{and} \qquad p_1 = \Phi_0(p_0, u_0, z_1) = \begin{cases} \frac{p_0\,\mathrm{fn}}{p_0\,\mathrm{fn}+(1-p_0)\overline{\mathrm{fp}}} & \text{if } u_0 = S, \quad z_1 = G, \\ \frac{p_0\,\overline{\mathrm{fn}}}{p_0\,\overline{\mathrm{fn}}+(1-p_0)\mathrm{fp}} & \text{if } u_0 = S, \quad z_1 = B, \\ \frac{p_0\,\mathrm{fn}+(1-p_0)\lambda\,\mathrm{fn}}{p_0\,\mathrm{fn}+(1-p_0)(\overline{\lambda}\,\overline{\mathrm{fp}}+\lambda\,\mathrm{fn})} & \text{if } u_0 = C, \quad z_1 = G, \\ \frac{p_0\,\overline{\mathrm{fn}}+(1-p_0)\lambda\,\overline{\mathrm{fn}}}{p_0\,\overline{\mathrm{fn}}+(1-p_0)(\overline{\lambda}\,\mathrm{fp}+\lambda\,\overline{\mathrm{fn}})} & \text{if } u_0 = C, \quad z_1 = B \end{cases} \tag{5.23}$$

based on the problem data and Fig. 5.2. We define only the probability of the machine being infected because the state space of the system is binary. $P(x_0 = \overline{P}|I_0)$ automatically implies $P(x_0 = P|I_0)$. This makes the presentation simpler. Note that the *belief state*, p_k, is a column vector with only one element. This makes the cost vectors also column vectors with only one element.

$$g(C) = \big[g(\overline{P}, C)\big] = \tau_2 \qquad g(S) = \big[g(\overline{P}, S)\big] = \tau_1$$

We will show how one of these p_1 is derived. The rest are derived similarly. For example,

$$\begin{aligned} p_1 &= P(x_1 = \overline{P}|u_0 = C, z_1 = G) = \frac{P(x_1 = \overline{P}, z_1 = G|u_0 = C)}{P(z_1 = G|u_0 = C)} \\ &= \frac{p_0\,\mathrm{fn} + (1-p_0)\lambda\,\mathrm{fn}}{p_0(1\cdot\mathrm{fn} + 0\cdot\overline{\mathrm{fp}}) + (1-p_0)(\overline{\lambda}\cdot\overline{\mathrm{fp}} + \lambda\cdot\mathrm{fn})} \end{aligned}$$

Substituting these definitions into the DP re-formulation above, (eqs. 5.21 & 5.22), the solution we need is:

$$\begin{aligned} \overline{J}_2(p_2) &= 0, \\ \overline{J}_1(p_1) &= \min[\tau_2 \cdot p_1,\ \tau_1], \end{aligned}$$

$$\begin{aligned} &\overline{J}_0(p_0) \\ &= \min\Big[\tau_2 \cdot p_0 + P(z_1 = G|p_0, C)\overline{J}_1\big(\Phi_0(p_0, C, G)\big) + P(z_1 = B|p_0, C)\overline{J}_1\big(\Phi_0(p_0, C, B)\big)\ , \\ &\qquad \tau_1 + P(z_1 = G|p_0, S)\overline{J}_1\big(\Phi_0(p_0, S, G)\big) + P(z_1 = B|p_0, S)\overline{J}_1\big(\Phi_0(p_0, S, B)\big)\Big]. \end{aligned}$$

We spare the reader of tedious calculations but mention that the numerical solution to this set of equations, though same, is much easier to compute than that presented for the previous (sec. 5.4.3) re-formulation.

5.6 A Practical Application

5.6.1 Optimal Policy

Table 5.1 shows the optimal policies for a few different values of λ. In the first two scenarios for high λ, the policy chooses S for a B observation and C for a G observation.[1] An interesting policy arises in the last scenario. It says, with a low λ the best policy is S only when there are two consecutive B observations. This table only demonstrates a sanity check of the algorithm as the machine will not know the current value of λ and hence cannot meaningfully choose the policy to implement.

However, we do know the costs payable in the event of infection. Table 5.2 shows the optimal policies for a few different costs of infection, τ_2. In the first scenario where the cost of operating a infected is not much higher than stopping the machine, the optimal policy is S when you get a B observation and C otherwise. This enables us to back-off from the response when we see a G. In the second scenario, where $\tau_2 = 10 \cdot \tau_1$, the optimal policy is to S upon a B and remain there. The policy for the last scenario is quite drastic in keeping with the huge τ_2. It chooses S the first time we get any message. Even if that message is a G because the fact that an inspection was triggered means that something abnormal has happened and the outcome could be a false negative. This policy chooses C only when we see two G messages consecutively.

5.6.2 Choosing λ

Choosing realistic values for the various parameters is of great importance if the solution needs to be of any practical value. Here we discuss some factors that need to be considered while choosing the parameters' values for building the rule-sets.

The value of λ varies with the extent of infection in the Internet. Given that we are still uncertain whether there is a worm or not in the Internet, λ can not be determined with any accuracy or certainty. Rather, only estimates can be made.

So, we again use the distributed Sequential Hypothesis Testing developed earlier to estimate λ [34]. Given a sequence of observations $\vec{y} = \{y_0, y_1, \ldots, y_n\}$, made by the other participating nodes and two contradicting hypotheses that there is a worm on the

[1] Notice that some of the I_1 such as (B, B, C) may not be reachable because of the control policy applied in stage 0.

Internet(H_1) and not(H_0), the former is chosen when the likelihood ratio of these hypotheses is greater than a certain threshold η [34]. This threshold η is determined by the performance conditions required of the algorithm. Assuming the observations are independent, the likelihood ratio of these two hypotheses and η are defined as follows:

$$L(\vec{y}) = \prod_{i=1}^{n} \frac{P(y_i|H_1)}{P(y_i|H_0)}, \quad \eta = \frac{DD}{DF} \tag{5.24}$$

where DD is the minimum desired detection rate and DF is the maximum tolerable false positive rate of the distributed Sequential Hypothesis Testing(dSHT) algorithm. We define each of the above probabilities as follows:

$$\begin{aligned} P(y_k = B \mid H_1) &= [\lambda\,(1 - \text{fn}) + (1 - \lambda)\,\text{fp}] & P(y_k = G \mid H_1) &= [(\lambda\,\text{fn}) + (1 - \lambda)(1 - \text{fp})] \\ P(y_k = B \mid H_0) &= \text{fp} & P(y_k = G \mid H_0) &= (1 - \text{fp}) \end{aligned} \tag{5.25}$$

The first one of those above is the probability of a B observation is the sum of probability of getting infected (λ) times the probability of detection and the probability of not getting infected($(1 - \lambda)$) times the probability of false positives. The others are defined similarly.

For any given sequence of observations, we calculate $L(\vec{y})$ for several λ values – say for ten different values in steps of 0.1 starting at 0.1. The minimum λ for which the $L(\vec{y})$ exceeds η will be taken as the current levels of infection and used appropriately in calculating the optimal responses.

Given equations (5.24) and (5.25), all observations over a sequence of nodes can be expressed as one number, the $L(\vec{y})$. A node receiving this number from a neighbor, can update it using its own observations and eq. (5.24) and the corresponding λ picked for applying the DP algorithms to choose response.

In practice however, a table of rule-sets would be calculated offline for each value of λ. Then, the table corresponding to the λ chosen as above will be consulted for the optimal action to take given the observation vector received and the sequence of local observations and actions taken so far locally.

Thus, each node only receives a likelihood ratio of the worm's presence from its peers. Each node also has to only remember its own past observations and corresponding actions.

5.6.3 Larger Ns

Using the *Sufficient Statistics* re-formulation developed in section 5.5, it becomes easy to apply the model for larger Ns. We implement this model and evaluate it in a simulation. This evaluation and the results are discussed in the next section.

5.7 Evaluation

The sufficient statistics formulation discussed in the previous section was implemented and evaluated with a discrete event simulation. The simulation consisted of 1000 participants with 10% of the machines being vulnerable. We set the number of stages to operate the machine, $N = 4$ to calculate the rule-sets. Note that $N = 4$ is used only to calculate the rule-sets but the machines can be operated for any number of steps. N is essentially the number of past observations and actions that each machine remembers. The local IDSes were set to have a false positive and false negative rates of 0.1. These characteristics of the local IDS is used to calculate the probability of infection, λ with a desired worm detection rate of 0.9 and failure rate of 0.1. In all the following experiments, we used a random scanning worm which scans for vulnerable machines once every unit-time.

5.7.1 Experiments

Parameters of Evaluation: We conducted experiments to evaluate the effectiveness of the response model discussed here. We designed a set of experiments to verify the efficacy of the model and to understand the effect of various parameters on the effectiveness of the model in controlling the spread of the worm. The only free variable we have here is the ratio of the costs of stopping the service to that of getting infected. There is no one particular parameter that can measure or describe the effectiveness of the response model. Rather, the effectiveness is described by a pair of parameters. These parameters are:

- Number of machines that are not infected.
- Number of machines that provide service, i. e. in state C.

So, in this evaluation, we will measure the effect of various τ_2/τ_1 ratios on above two parameters.

Algorithm: The evaluation was conducted as a discrete-event simulation. The algorithm for the simulation is as follows. At each time cycle,

- all infected machines attempt one infection,
- all machines that had a alert to share, share the likelihood ratio that there is a worm on the Internet with one another randomly chosen vulnerable node,
- and all vulnerable machines that received an alert earlier take a response action based on the information received and the current local observations.

Results: In the first experiment, we want to make sure that we have a worm that behaves as normal random scanning worm and validate the response model for degenerate cases. We verify this by providing no response. This response can be achieved by setting the cost ratio to 1. This means that the cost of stopping the service is the same as getting infected. In this scenario, we expect the response model not to take any defensive measures against suspected infection attempts. As expected, we see in Fig. 5.4, that none of the machines are stopped (S state). The worm spreads as it would spread when there is no response model in place. This validates our worm and also our response model.

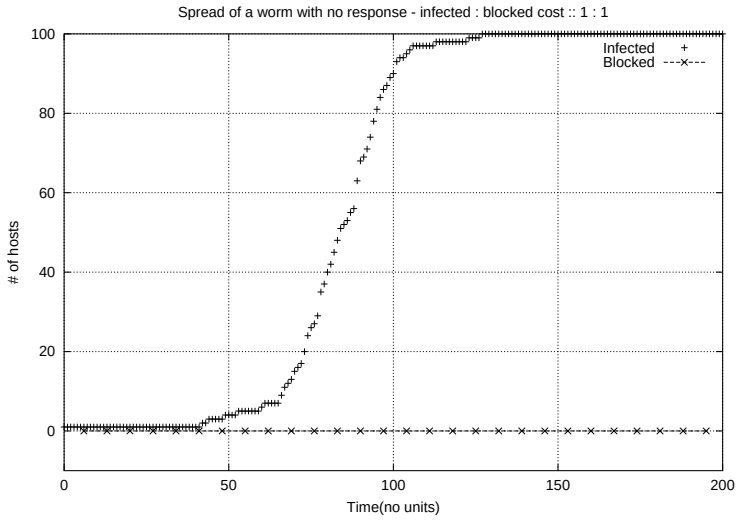


Figure 5.4: No machines are stopped when the cost of being infected is the same as cost of shutting down the machine.

As another sanity check we set the machines to remember infection attempts forever. Under this policy, once a machine enters the S state, it remains in that state forever.

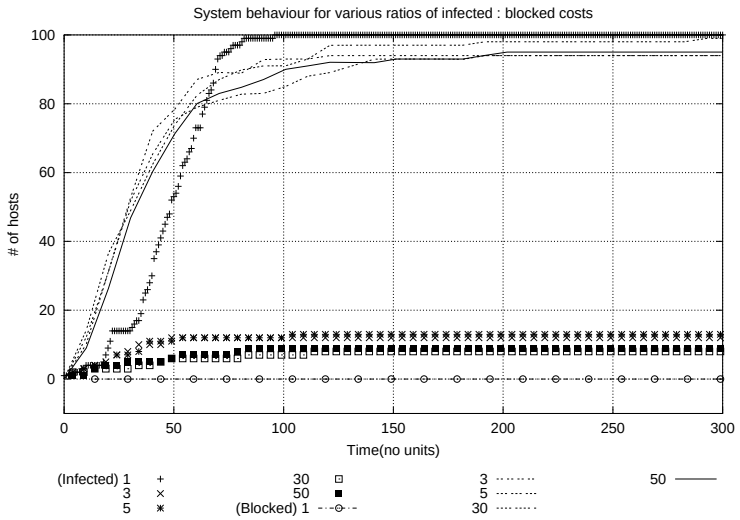


Figure 5.5: Once entered the S state, a machine stays there.

We see that in this case (Fig. 5.5) the number of machines infected are very low except when $\tau_2/\tau_1 = 1$.

In the next experiment, we try to understand the behavior of our response model in various situations. Since the only free variable is the ratio τ_2/τ_1, we repeat the previous experiment with various values for that ratio. The results for this set of experiments is shown in Fig. 5.6. This graph shows behavior of our response model in five different tests. There are two different curves for each test indicating the number of vulnerable machines being infected and the number in S state against time. We can see that when the ratio is 1, the number machines that are in S state is 0. As the ratio τ_2/τ_1 rises, the response becomes stricter. We see that the number of machines in the stopped(S) state is higher when the cost of being infected is higher and correspondingly the worms spreads significantly slower than without any response in place.

5.7.2 Effects of increasing N

The experiments shown earlier in this section were all conducted with $N = 4$. An interesting question to ask here, "What happens if we increase the value of N?". Fig. 5.7 shows the performance of the system for various values of N while holding the ratio of τ_2/τ_1 constant at 30. The set of sigmoidal curves trace the growth of the worm, while the other set of curves trace the number of nodes that are shut-down at any given instance of

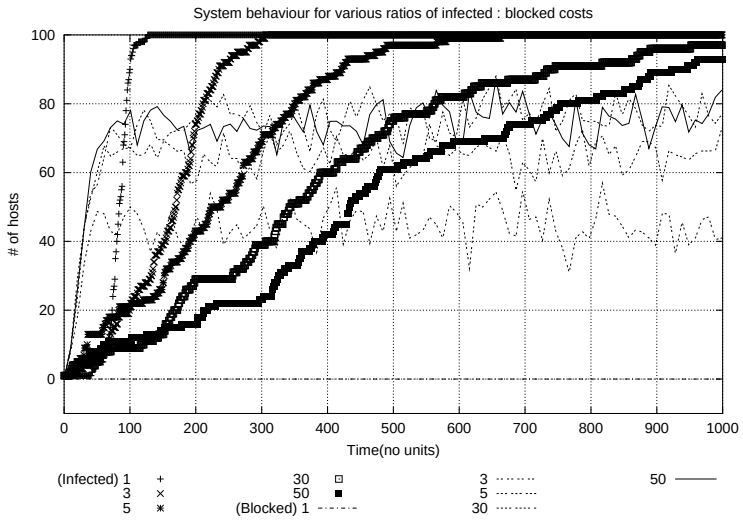


Figure 5.6: Higher costs of being infection invoke stricter responses.

time. We notice that there is no appreciable slowing of the worm with increased values of N – all the worm growth curves are bunched up together. This is due to the small number of dimensions to the state – $x_k \in \{P, \overline{P}\}$ – a larger observation space does not contribute much to improve the performance of the system. Note that the x-axis is in log-scale in this figure.

5.8 Limitations and Future Work

There are several topics in this chapter left to be addressed in the future. There are issues to be addressed at three different levels – in the model itself, in the evaluation of the model and problem that would arise during the practical implementation of this model.

This is a collaborative response model. As with any collaborative effort, there is a host of issues such as privacy, confidentiality, non-repudiation, etc, that will need to be addressed during practical adoption. Thankfully, these are issues for which there are solutions available already through cryptography and IPSEC. Still, co-operation amongst various entities on the Internet such as amongst corporate networks pose more legal and economic problems than technical. In such cases where sharing anomaly information with networks outside of the corporation is not feasible, applying this response model within the corporate network itself can provide valuable protection.

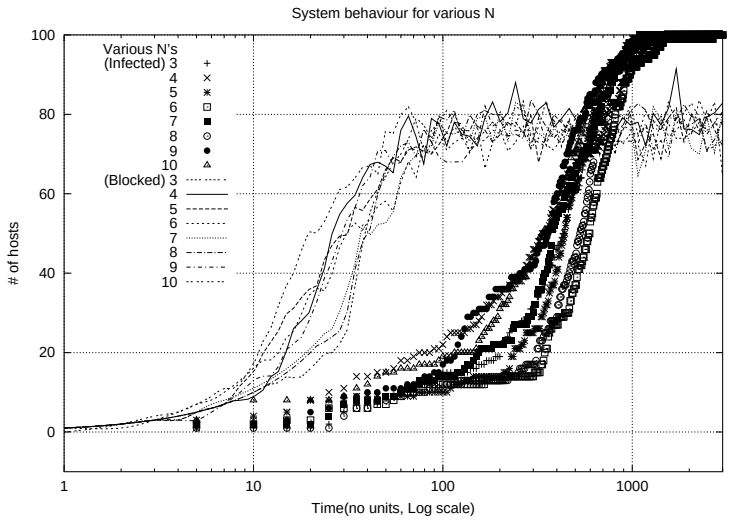


Figure 5.7: Larger Ns do not contribute much to improve performance.

When there is a cost to sampling packets, this model can be extended to optimally stop the sampling process and declare either that there is a worm or that there is no worm. Interestingly, this extension would lead us to the distributed Sequential Hypothesis Testing that we discussed in the previous chapter. Actions such as C and S if applied frequently could lead to a very unstable system. We need to evaluate this factor in light of ambient anomaly levels in different environments. This is a problem that arises during adoption of this technology. However, this can be addressed in various ways. For example, the set of response options can be made slightly larger with options to have several levels of reduced functionality instead completely shutting down the service.

One of the major problems that needs to be addressed while implementing this model in reality is the assignment of realistic values to the costs τ_1 and τ_2. However, there is some prior work that attempts to assign costs to various responses that can used [18, 76].

As already argued at length in chapter 3, evaluating worm defenses is a difficult problem. At one extreme we have realistic evaluation possible only on the Internet but is infeasible. At the other extreme, we have mathematical models only. In between these two extremes, we have simulations such as the one used in this chapter and emulations such as the one used in the previous chapter 4.

With the availability of data about Internet traffic during worm outbreaks, it may be possible to evaluate the defense model on a network testbed such as Emulab by replaying

the traffic for a scaled down version of the Internet. Such an experiment would need the available data to be carefully replayed with tools such as TCP Replay,TCP Opera, etc. This is a task that can explored in the future to evaluate worm defenses. Scaling down the Internet is another problem in itself [117].

An issue still left to be explored is the behaviour of this model in face of false alarms and isolated intrusions. For eg., consider one and only participant raising an alarm for an isolated event and several other participants choosing the S control. We would like to know when these participants would apply the C control. Trivially, we can set a time-out for the defense to be turned-off. However, the time-out should be chosen carefully and probably be dynamic to guard against exposing oneself to slow worm attacks.

	$\lambda = 0.50$, fp $= 0.20$, fn $= 0.10$, $\tau_1 = 1$, $\tau_2 = 2$		
	Information vector I_k	Optimal Cost-to-go J_k	Optimal Action u_k
Stage 1	(G, G, S)	0.031	C
	(B, G, S)	0.720	C
	(G, B, S)	0.720	C
	(B, B, S)	1.000	S
	(G, G, C)	0.270	C
	(B, G, C)	1.000	S
	(G, B, C)	1.000	S
	(B, B, C)	1.000	S
Stage 0	(G)	0.922	C
	(B)	1.936	S
Start		1.480	C
	$\lambda = 0.30$, fp $= 0.20$, fn $= 0.10$, $\tau_1 = 1$, $\tau_2 = 2$		
	Information vector I_k	Optimal Cost-to-go J_k	Optimal Action u_k
Stage 1	(G, G, S)	0.013	C
	(B, G, S)	0.388	C
	(G, B, S)	0.388	C
	(B, B, S)	1.000	S
	(G, G, C)	0.119	C
	(B, G, C)	0.569	C
	(G, B, C)	1.000	S
	(B, B, C)	1.000	S
Stage 0	(G)	0.604	C
	(B)	1.793	S
Start		1.091	C
	$\lambda = 0.10$, fp $= 0.20$, fn $= 0.10$, $\tau_1 = 1$, $\tau_2 = 2$		
	Information vector I_k	Optimal Cost-to-go J_k	Optimal Action u_k
Stage 1	(G, G, S)	0.003	C
	(B, G, S)	0.118	C
	(G, B, S)	0.118	C
	(B, B, S)	1.000	S
	(G, G, C)	0.031	C
	(B, G, C)	0.154	C
	(G, B, C)	0.726	C
	(B, B, C)	1.000	S
Stage 0	(G)	0.252	C
	(B)	1.227	C
Start		0.515	C

Table 5.1: An optimal policy table - varying λ

	$\lambda = 0.30$, fp $= 0.20$, fn $= 0.10$, $\tau_1 = 1$, $\tau_2 = 2$		
	Information vector I_k	Optimal Cost-to-go J_k	Optimal Action u_k
Stage 1	(G, G, S)	0.013	C
	(B, G, S)	0.388	C
	(G, B, S)	0.388	C
	(B, B, S)	1.000	S
	(G, G, C)	0.119	C
	(B, G, C)	0.569	C
	(G, B, C)	1.000	S
	(B, B, C)	1.000	S
Stage 0	(G)	0.604	C
	(B)	1.793	S
Start		1.091	C
	$\lambda = 0.30$, fp $= 0.20$, fn $= 0.10$, $\tau_1 = 1$, $\tau_2 = 10$		
	Information vector I_k	Optimal Cost-to-go J_k	Optimal Action u_k
Stage 1	(G, G, S)	0.067	C
	(B, G, S)	1.000	S
	(G, B, S)	1.000	S
	(B, B, S)	1.000	S
	(G, G, C)	0.594	C
	(B, G, C)	1.000	S
	(G, B, C)	1.000	S
	(B, B, C)	1.000	S
Stage 0	(G)	1.279	C
	(B)	2.000	S
Start		1.575	C
	$\lambda = 0.30$, fp $= 0.20$, fn $= 0.10$, $\tau_1 = 1$, $\tau_2 = 100$		
	Information vector I_k	Optimal Cost-to-go J_k	Optimal Action u_k
Stage 1	(G, G, S)	0.665	C
	(B, G, S)	1.000	S
	(G, B, S)	1.000	S
	(B, B, S)	1.000	S
	(G, G, C)	1.000	S
	(B, G, C)	1.000	S
	(G, B, C)	1.000	S
	(B, B, C)	1.000	S
Stage 0	(G)	1.744	S
	(B)	2.000	S
Start		1.849	C

Table 5.2: An optimal policy table for various costs of infection, τ_2

Chapter 6

Conclusion

This chapter recollects what has been detailed in the previous chapters and elicits a holistic view of worm defense from what has been presented. It also identifies some of the critical problems still unsolved that are significant impediments to progress in the field and suggests future directions for research in the field.

6.1 Summary

This dissertation gave a thorough overview of the history of worms and worm research, examples of worms seen in the wild, and of the hypothetical variety. It also identified the various problems involved in defending against worms, and paradigms used in addressing them.

As already observed in chapter 2, detection and response form two of the three fundamental blocks of a strong worm defense program, prevention being the third one. The first two are reactive measures (i. e.) those aspects of defense that need to work while a worm has already been launched and is spreading currently. The third one is a proactive measure . This dissertation addressed the two most important components – detection and response – the reactive aspects of worm defense.

Deviating from the currently popular paradigm of handling worms by automatic signature generation and pattern matching, the techniques developed in this dissertation are independent of worm signatures. This deviation helps to counter polymorphic and zero-day worms effectively.

Worms, by definition, are a distributed phenomenon. Hence, the detection tech-

nique developed here uses observations and evidence from various sites instead of focusing on one particular machine or network. It is a distributed and decentralized detection technique, and hence does not suffer from single point failures as some of the other popular techniques do.

This detection technique used dSHT to build a strong worm detector using weak or imperfect anomaly detectors as components. The performance characteristics of this strong worm detector thus built can be tuned to the desired rates of successful detection and misses.

The distributed nature of this technique and its ability to build strong detectors out of weak components helps tap the vast amounts of anomaly information available at end-user systems – home and office users primarily. These are users who cannot or usually do not run sophisticated intrusion detectors but are still targets of worm attacks. The poor anomaly or intrusion detectors that they run cannot make authoritative detections of worms but by co-operating with each other, they can detect worms in unison with high degree of accuracy.

Response techniques developed hitherto by the research community address the worm problem after detecting the worm. Hence, they primarily deal with automatic patch and signature generation, distribution, and application. However, it is clear that this strategy of catching up is not very effective. Much damage can be done by the worm before the patches are disseminated to all susceptible machines. In contrast, the strategy developed here deals with responding to events that are possibly due to a worm but cannot be verified yet.

This technique is applicable while the detection process is still in progress – during the time when reasons for the observed anomalies are unknown. During such instances, drastic responses such as shutting down services need to considered carefully before being applied. While such response during a real worm attack is desired even if it results in loss of service, they are costly actions to undertake in response to false alarms or when there is no danger of a worm attack. On the other hand, not responding to suspicious events can be very expensive when those events were really due to a worm. The response model developed here considers these various alternatives, evaluates the costs of each action and inaction, and chooses the option that would result in an optimal long-term cost. If and when evidence suggests that the observed anomalies are not due to a worm, the system automatically backs-off from the response actions activated. Hence, the response system is

dynamic, adjusting to the current environment. The response technique here uses a novel control-theoretic approach using Dynamic-Programming tools.

Though the response system is itself dynamic, the dynamic programming algorithm does not have to be solved in real-time. The algorithm is pre-computed off-line and a control rule-set is generated that can be easily looked up for appropriate responses to implement for each observation of the environment. Moreover, individual nodes are free to choose appropriate response actions and are not constrained by a central leader or controller. Thus the response is completely localized.

No assumptions are made about the topology of the network to which these co-operating peers are attached for either of the above algorithms to work. All that is required is network connectivity and an ability to reach the peers. Thus, these algorithms work regardless of the scanning algorithm employed by a worm. However, detection could be delayed and responses may be ineffective if the worm is a sub-net scanning worm whereas the co-operating peers are assumed to be distributed randomly all over the Internet and the algorithms choose their peers at random from a given set to exchange information.

In addition to these two important techniques, this dissertation also developed an evaluation framework to evaluate such new technologies. As an example it showed how a *Hierarchical Model of Defense* that was developed earlier can by evaluated by this framework.

Thus, by addressing detection, response and mitigation aspects of worm defense and by developing an evaluation framework, this dissertation provides an end-to-end solution to the worm problem.

6.2 Future Directions

There are several aspects to the proposed solutions that still need to be addressed. For example, the evaluation framework presented in chapter 3 still suffers from scale-down[1] issues. Coming up with a solution to this problem will unlock a great deal of understanding about the dynamics of Internet-wide, large scale phenomenon such as computer worms, distributed denial-of-service, etc. This situation arises from a more fundamental problem – the complete topology of the Internet is unknown. So, a study mapping the topology of the

[1]Scale-down is a problem of too small a statistical sample involved in the experimental setup compared to the real Internet.

Internet will be very useful; this can be then scaled-down with scaling hypothesis proposed by Psounis et al. [91].

The experiments conducted and described in this dissertation were done on the Emulab testbed without any background traffic. Replicating the huge volumes of traffic seen on the Internet is infeasible and in fact, not even required. One possible approach is to have a few nodes of the testbed generate the subset of traffic from the Internet that would be pertinent to the experiment being conducted. The volume of such traffic would be more manageable. For example, imagine an experiment modeling an enterprise network. There is no need to generate the ambient Internet traffic associated with a military domain or even the traffic within another network that is not visible to this enterprise network. It is sufficient to generate traffic that would normally be seen by the enterprise domain that is being modeled.

A faithful means of reproducing ambient traffic as would be seen on the Internet would be a great help in conducting controlled experiments that reflect the reality. So far, we do not have any solution to fill this gap. There are tools such as `tcpreplay` and `tcpopera`, etc, that can play back recorded traffic. However, there is no clear understanding on how to model the traffic such that it can be generated from a specification rather than just by replaying pre-recorded traffic.

We do not yet know what are necessary and sufficient descriptions of an anomaly. This is a huge gray-area. Anomaly detection has always been plagued by huge amounts of false-positives. A sizable reduction in the false positive rates is highly desired. Specification-based anomaly detection is one way to go about it.

The next concern in these distributed algorithms is the privacy concern about sharing anomaly information with other peers. A provably secure data sanitization process will be a great selling point for these systems. Also there is a need for security and authentication in the communication amongst the co-operating peers. IPSec might provide a suitable solution. There are also certain initiatives such as CIDF [37], IDIAN [55] and IDMEF [61] but none of them is being used currently.

A leading cause for the prevalence of worms is the homogeneity of computer systems, particularly computer with pre-installed commercial applications and operating systems. These systems invariably ship operating systems compiled with the same configurations. An attacker who can remotely exploit a vulnerability in one such machine, immediately gains the power to attack millions of other similar machines Internet-wide.

So, some heterogeneity in the way commercial systems are shipped can go a long way in frustrating the spread of worms. One means of achieving this is Address Space Layout Randomization.

In this technique, dynamically loadable libraries are loaded on to random locations based on a certain key on each machine rather than one preferred location across machines. This helps to stop worms that make assumptions about the location of certain functions in the system's image in memory. However, smarter worms can be built to locate the required functions by first locating the key. Stronger cryptographic solutions might help here.

6.3 Final Observations

Regardless of the various sophisticated techniques being developed for countering worms, going by the history of the past worm attacks, simply applying patches in a timely fashion will alleviate the problem to a great extent. The next best defense is to shut-down unnecessary network services that are turned on by default. It is even better if these service are shut-down by default.

The days of extremely fast worms that just create havoc without any particular benefits to the attackers are believed to be gone. Such attackers' population has dwindled. The current and future attackers are in the trade after particular benefits. These benefits include identity thefts, financial fraud and computers that can be hooked to botnets. The final motive is financial gain. Such activities require the panning of large numbers of computers without raising any suspicions. Slow spreading worms are a perfect tool to carry out such an operation will dominate the future worm scene.

After all, computer security is not all about worms. Worms are just one small part of the huge taxonomy of malware and other issues afflicting the reliability of computing systems. In general, the techniques developed here can be extended to be used in other scenarios that involve distributed phenomenon; not only worms. The detection technique developed here can also be used to trouble-shoot network defects. Identifying problems that can be solved using these approaches form one of the future directions of research.

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