Simulating Cyber Attacks, Defenses, and Consequences

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Abstract

Many fields use modeling and simulation to provide analysis and insight into building better systems, but the field of information protection has not produced significant research results in this area to date. Perhaps this is due to the extreme complexity of the cyber attack and defense problem, the enormous size of the search space, the lack of good data on attacks and defenses, the inability to derive consequences in a systematic way, or the lack of a coherent view of information protection. Despite these sometimes seemingly unscalable barriers, this paper is about simulations of attacks, defenses, and consequences in complex cyber systems such as computer networks; and more specifically about one attempt to create simulations capable of providing meaningful results in this field.

We begin by discussing limitations on modeling and simulation that are relatively unique to information protection, discuss the model we chose, and how simulation works. Next we show results of individual simulations and runs of a few thousand simulations that characterize small portions of the design space for attacks alone and then attacks in the presence of defenses. We continue with issues of parallel simulation and demonstrate results from large-scale simulation runs involving scores of parallel processors covering

millions of runs and varying several parameters of interest. Results are given for the effects of detection and reaction time on success rates, the effects of defender strength on success rate, non-linearities between strength and time and the effectiveness of a defense, and differences between results for varying threat profiles. We then add issues of costs and produce expected loss and cost results, discuss and demonstrate the effects of strategies on results, review limitations of metrics and sensitivity to variations in parameters, and briefly discuss validation of results.

Modeling, Simulation, and Data Limitations in Information Protection

Modeling and simulation have been used in many fields for a variety of purposes, but the ultimate purpose of all such activity is, in one form or another, to gain experimental knowledge of events without performing experiments. Models are used to portray some specific issues in the systems under consideration and simulation is used to repeatedly exercise those models under different conditions. The limits of the value of modeling and simulation come from three things; (1) limits on accuracy of the models, (2) limits on the accuracy of the data upon which the simulation is based, and (3) the ability to explore the simulation space through the use of multiple *runs* of the simulator through the space.

In information protection, these three issues are often more complex than in many other fields. For example:

- In a physics simulation, we pretty much know the nature of the physical phenomena under consideration and can model it at any desired level of granularity at the expense of increased computing power and decreased spatial size. Thus any number of reasonable models allows a particular granularity to be run with known accuracy in a given amount of time. While there may be factors that we are unaware of and therefore fail to include in our model, the model itself can be very close to perfect. In information protection, we are modeling very complex phenomena involving mixes of human behavior and interactions of complex interdependent systems with time bases ranging from nanoseconds to years. There is no widely published or accepted information physics which would allow us to make an accurate model, and the sizes of the things we are modeling are so large and complex that we cannot describe them with any reasonable degree of accuracy.

- In most fields of science and engineering, we have measurable phenomena and we measure that phenomena as a preface to simulation. For example, in simulating a bridge, we know how large all the parts are, the properties of the materials, and so on. In information protection, we have no consensus on how to describe a protection system, and no set of commonly accepted metrics upon which to base a set of measurements to be used for simulation.

- Runs through the information protection space are sequences of events that a number of different actors and automated systems may take. Depending on the precise order of events, dramatically different outcomes may result. There is no sense of localization or convergence. A small change in input may produce a large change in output. The most minor change in ordering could make the difference between an attack aborted almost as it begins and an attack which devastates an organization. This in turn means that a single missed run through the space may miss a major result - while the number of possible runs through the space is a power set of a large set of possibilities. The space it too large to explore and yet we cannot know how important a particular run will be to the outcome.

While this would seem to make the effort of developing simulations futile, it actually provides much of the best justification for actively pursuing it. Consider that a typical exercise of some set of minimal attacks against an information protection system costs tens of thousands of dollars. An attack that reflects what real people might actually do costs tens of thousands of dollars. In addition, these experimental attacks only provide one run through the space of possible scenarios. If the attack succeeds, it only indicates one path to the end, while if an attack fails, it only indicates that one attempt was thwarted. Furthermore, the cost associated with protection failure can be quite large. For many organizations, even a single attack can be devastating. The high cost of running real-world attacks, the limited extent to which they exercise the space of actual attacks, and the high potential for harm from a successful attack conspire to make some other means of analysis an imperative. The question is: What means do we use?

Available Models and Our Selection

Many techniques have been used for trying to analyze information protection, from probabilistic risk analysis to a wide range of experience-based system analysis methods. While we don't universally dispute the value of these other techniques, they are limited in (1) their applicability, (2) their historical effectiveness, (3) their ability to help understand tradeoff issues encountered in real situations, and (4) their ability to model the effects of time and the sequential nature of attack and defense.

- The limits of applicability are not known for the most part because of the lack of metrics and the lack of an overarching theory of information protection. The most experienced experts in this field have participated in in-depth analysis of at most several hundred organizations. Even the best experts cannot do a thorough analysis of a substantial organization in less than a few weeks of effort, which means that 20 organizations per year is the practical maximum experience of an individual. After 30 years in the field, this comes to less than 1,000 samples from which to judge by experience. Furthermore, the data from these analyses is not in a standard form and is not shared because of the contractual and legal limitations on revealing such information. Limits on probabilistic risk analysis and other similar methods comes from the disconnect between the underlying theory and the reality of the behavior of malicious actors in a rapidly evolving technology. There are something like a thousand new attack scripts published per year, and the probability of use changes on the scale of weeks to months. The actual loss often cannot be computed even after a loss has occurred, and the range of expected losses vary by several orders of magnitude depending on the specifics of what takes place. It has been described as an estimate multiplied by a guess computed to 3 digits of accuracy, and used to make multi-million dollar decisions. [Cohen97-03]

- Data on the historical effectiveness of analysis techniques is not available, and it is not likely to becom available in the foreseeable future. One reason for this is that there is no repeatable experiment in real-world information protection. Each company that makes a decision simply lives with the result with no real way to measure the value of that decision. Analytical techniques such as probabilistic risk analysis can be applied, but the results are not of real value since the real events that transpire don't usually reflect the statistics upon which the analysis was based. Other less numerical methods are based on organizational or behavioral characteristics that reflect the practices of the most successful organizations, but they don't allow the analysis of tradeoffs. It is widely understood that the effectiveness of successful preventive defenses cannot be measured because you cannot tell what would have happened had they not been there. How can you measure what does not occur?

- The ability to understand tradeoffs is severely limited in most methods of information protection analysis. For example, when we look at how an organization works in a qualitative way, we cannot analyze the effect of reducing our testing process in exchange for improving our training process. All we really know is that if you don't do both, you are asking for trouble, and if you do both, you can always do them better. We can tell you that you seem to be doing it better or worse, and if you have specific training and testing goals, we may be able to measure whether you meet them, but this is of no real value in determining how much to invest where or what the return on investment will be. In quantitative risk assessment, we can try to trade off different values for parameters, but the lack of measurement combined with the sensitivity of the results to minor changes in data values makes the value of the analysis highly dubious.

- The real death blow to previous techniques is their inability to deal with the effects of time and the sequential nature of attack and defense in a meaningful manner. It is simply incongruous to try to understand the effectiveness of prevention of, detection of, and reaction to intentional acts of malicious, motivated, goal-directed actors without taking time into consideration. For example, what does the probability of success of an attack mean without a notion of how many times an attack can be attempted or the time taken per attempt? How can we hope to effectively model sequential attacks as parallel statistical events? How can we hope to determine how quickly we need to respond or the effect of response time when we don't include time in our models? But if we include the notion of time into these models, how can we evaluate the effects of time without analytical methods that model time? We cannot.

For the purposes of simulation, none of the previous models will do because they do not model anything that we can simulate. Furthermore, the previous models ignore the issue of time, which is fundamental to simulation. For this reason, we searched for other types of models.

The models we examined were essentially schemes for classifying threats, attack mechanisms, protective mechanisms, and consequences. A reasonably good survey of these techniques is provided by John Howard in chapter 6 of his Ph.D. dissertation. [Howard97] The goal of our modeling process was to generate a set of cause-effect chains that would allow us to simulate the processes of attack and defense.

In the end, we designed our model with the notion of balancing complexity with the quality of the results. The complexity issue bears its head in two ways, (1) a simple model allows for very rapid simulation and a minimal number of parameters, but in exchange it collapses the problem into one that may be too simple to be meaningful, while (2) a fully detailed model of every specific threat, attack mechanism, and defense mechanism may be very accurate, but it requires massive amounts of data that are likely to change before any real system can be characterized and it will require enormous amounts of time in order to produce a meaningful characterization of the space. It is the tradeoff between specificity and performance that drove us to the model we use. To make this point a bit clearer, let's quickly look at two other extremes in modeling:

Suppose we take a very simple model such as the one used by Howard in his dissertation. While we don't intend to imply that the model is not useful for the purpose it was intended to be used for, its use in a simulation would leave us with severe limitations. Here is the scheme proposed by Dr. Howard:

Table 1 - Howard's Model of Cyber Attack

Attackers		**Tools**				**Access**	
Hackers		User Command		Implementation Vulnerability		Unauthorized Access	
Spies	=>	Script or Program	=>	Design Vulnerability	=>	Unauthorized Use	=>
Terrorists		Autonomous Agent		Configuration Vulnerability			
Corporate Raiders		Toolkit					
Professional Criminals		Distributed Tool					
Vandals		Data Tap					

The first problem we see in Table 1 is that all paths lead through one of two classes of vulnerability, three steps of unauthorized access, and corruption, denial, theft, or access. If we use this model, it brings almost no information about what protective measures might be effective, allows no differentiation between methods of attack and the time or effort they require, and leaves out the details that might lead to better design decisions. The tools in this model are strictly technical in nature, and thus the model misses the broad range of issues in information protection. Similarly, the number of threats are so few that a meaningful association of the threats with their methods is not attainable. This model was never intended to be used for the purpose of simulation, and as a result, it is not very useful in that application.

In Table 2, we have another example in which actors of different sorts use mechanisms of different sorts. Again we see too little complexity, but we do see an association between actors and actions that was missing in Howard's effort and this allows us to differentiate causes based on effects and effects based on causes to some extent. [Am094] For example, if we have a case of physical destruction, the only possible causes are operators, and data entry clerks can only cause data diddling.

Table 2 - Amoroso's Model of Cyber Attack

	Operators	**Programmers**	**Data Entry**	**Internal**	**Outside**
Physical Destruction	*Bombing Short circuits*				
Information Destruction	*Erasing Disks*	*Malicious software*			*Malicious software*
Data Diddling		*Malicious software*	*False data entry*		
Theft of Services		*Theft as user*		*Unauthorized action*	*Via modem*
Browsing	*Theft of media*			*Unauthorized access*	*Via modem*

Theft of Information				*Unauthorized access*	*Via modem*	

Another still different taxonomy (Table 3) exemplifies the use of a classification scheme to differentiate attack methods. While this scheme is not nearly filled out, it provides interesting detail that would be useful if it was fully described. [Landwehr94] While the resolution here is a bit better, this model lacks cause and effect relationships, notions of time, and so forth.

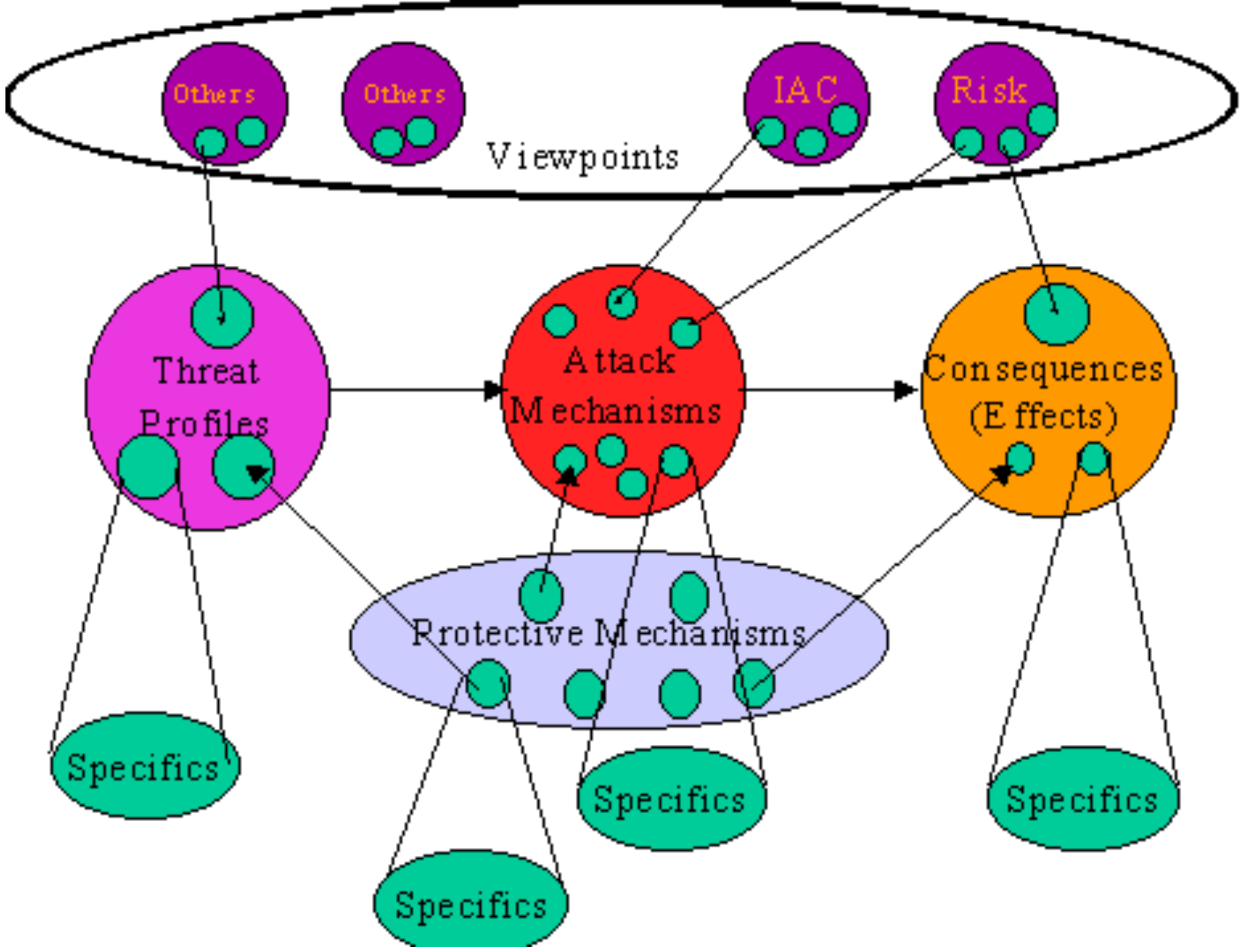
Table 3 - Landwehr's Model of Cyber Attack

				Non-Replicating
			Trojan Horse	Replicating (virus)
		Malicious	Trapdoor	
	Intentional		Logic/Time Bomb	
				Storage
		Non-Malicious	Covert Channel	Timing
Genesis			Other	
		Validation Error (Incomplete/Inconsistent)		
		Domain Error (Including Object Re-use, Residuals, and Exposed Representation Errors)		
	Inadvertent	Serialization/aliasing		
		Identification/Authentication Inadequate		
		Boundary Condition Violation (Including Resource Exhaustion and Violable Constraint Errors)		
		Other Exploitable Logic Error		

At the other extreme, we have the notion of characterizing every known vulnerability in every system based on its configuration, every known attack method, and every configuration of prevention, detection, and reaction. To give a sense of this, there are more than 15,000 known computer viruses, scores of virus detection products, and it takes a substantial amount of effort to test any one version of any one product against the set of viruses. Simply analyzing the number of runs of 10 virus infections in the presence of a known scanner would lead to more than 10^40 possible runs, and the information gained would be of almost no value in determining, for example, how quickly to react to a virus attack, and much less valuable in assessing the potential for actual harm, which is largely unrelated to these details.

In the end, we chose a model of our own devising. (see Plate 1) The key issue underlying this decision was the notion that we need a basis for a cause-effect analysis of chains of events that can be overlaid on the architecture of an information environment. Once we have a model of cause and effect, we can begin to try to simulate, with the notion of time naturally falling out of the delay between cause and effect. The model we developed [Cohen98] was designed for the purpose of simulation and analysis and has been the subject of considerable research. It is based on a set of 37 classes of threats, 94 classes of attack mechanisms, and about 140 classes of protective mechanisms. These are interlinked by a database which associates threats with attacks and attacks with defenses. In addition, the database associates threats, attack methods and defense methods with other characteristics such as their impact on integrity, availability, access, and leakage; the sophistication level of the attackers; and their use in prevention, detection, and reaction.

Plate 1 - A Cause Effect Model of Cyber Attack and Defense



This set of cross reference data provides a great deal of information which can be used in simulation, and is something that other models available today largely lack. This set of cross references comprises about 15,000 pieces of relational data. In addition to the pre-existing data, for the purposes of simulation we had to add about 20,000 new pieces of data to provide metrics which permit simulation to proceed in a meaningful manner. In particular, we needed to characterize the time required for each attack and each defense to operate and the effectiveness of each defense against each attack. These are also affected by attacker and defender skill levels. All of this is modeled by a set of statistical functions that provide results with the proper statistical characteristics whenever a value is called for by the simulator.

A large portion of these values are identical or similar to each other because they are a result of the way in which an organization operates. For example, reaction time for most detected security events is dominated by the incident response capability of the organization. It may take hours or even days before a detected attack generates a reaction that would result in defeating the attacker, regardless of the specific mechanisms, and with a few exceptions where automation has been chosen.

Values that are not tied to common phenomena tend to remain the same across many similar systems. For example, the likelihood that a virus scanner will detect a virus doesn't have to be experimentally derived for each system, and published results are available for most commercial products. Similarly, the prevention, detection, and reaction capabilities of a particular operating environment tend to be fixed by the system's design and augmented by add-on products. Once these have been characterized the first time, simply determining the system configuration yields most of the numerical values required for simulation. Some of these characteristics are described in a recent related paper. [Cohen9903]

Financial values are necessarily tied to the organization under study, as are network topologies, but again these can be greatly simplified by effective modeling to dramatically reduce data requirements. For example, most networks consisting of a firewall and a few hundred computers can be modeled effectively by five or six nodes for the purposes of understanding the process of attack and defense. A LAN consisting of 40 Windows computers, a Novel file server, and a Unix-based firewall might be modeled with only 4 nodes. Adding more nodes doesn't alter the result significantly, it only adds more complexity and data to the simulation.

To quickly summarize, we decided to model systems at a level that we felt would be meaningful in terms of the decisions that have to be made. This means that the model is limited in accuracy, but that it is feasible to explore the space and look at variations in parameters. More detailed models can be built, but the expense of doing so and the time required for such an activity is rarely justified. Even with the model we have selected, the specifics must be modified for each analysis done and there are significant data and computational requirements.

The Simulation Engine Operation

The simulation is driven by a model of the network under analysis, a cause and effect model of threats, attacks, and defenses, a set of characteristic functions that produce numerical values, and a pseudo-random number generator.

- **The network model** consists of a set of *nodes* and *links* that describe the systems under attack.
- **The cause and effect model** is the one described earlier and shown in Plat 1..
- **The characteristic functions that produce numerical values** are generated by a team of analysts for each network under consideration. This is also called, in the parlance of war gaming, a firing table.
- **The pseudo-random number generator** is, essentially, a linear feedback shift register. The results of this generation process is referred to in this paper, as in the parlance of war gaming, as dice rolls.

Simulation proceeds as follows:

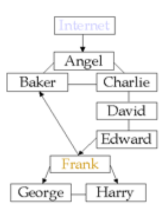
- The analysts program in the characteristic functions and model.
- The user specifies a defender strength, strategy, and a number of simulation runs to be made involving a threat attempting to launch an attack starting at one node in the model and aimed at gaining access to another node in the model. Additional parameters may be added to reflect the form of the output and other related information.
- The system computes a list of relevant attack methods and a set of feasible attack paths. The attack methods are chosen based on the capabilities of the selected threat(s) and any strategic information provided to guide the attack selection process. The feasible attack paths are generated by taking calculating all sequences of nodes that form non-looping paths from the source to the destination.

- For each simulation run, pseudo-random values are used to select a specific attack path out of the feasible attack paths, to select each attack in turn based on the specified strategy, and to evaluate the performance of each attack, prevention, detection, and reaction. Each event that occurs is placed in an event queue in time order, with events capable of generating further events depending on the specifics of the outcomes. The next pending event is analyzed, the event queue is updated, and this continues until the attacker wins, the defender wins, or a maximum simulation time is exceeded.

- Results are stored and may be presented at the request of the user.

Sample Runs and Results

For the purposes of the simulation runs we describe throughout this paper, the following diagram characterises the network. In this diagram, arrows indicate uni-directional information flow. Named nodes are linked with lines and defenses in each node are as specified in the listing.



Internet has no defenses

Angel has anomaly detection, path diversity, sensors, waste data destruction reintegration, improved morality, fine-grained access control, perception management, integration principle, time, location, function, and other similar access limitations, security marking and/or labeling, auditing, and testing.

Baker has fine-grained access control and perception management.

Charlie has background checks, feeding false information, effective mandatory access control, automated protection checkers and setters, and trusted applications.

David has time, location, function, and other similar access limitations, auditing, and uninterruptable power supplies and motor generators.

Edward has program change logs, trusted applications, and effective mandatory access control.

Frank has properly prioritized resource usage, trusted system

	technologies, and uninterruptable power supplies and motor generators. **George and Harry** have no defenses.

The run in table 4 demonstrates the simulation process. The attacker is of type 10 (i.e., a hacker) who starts by trying to get into the Internet somewhere, and from there tries to attack Frank. The defender in this case acts correctly 90 percent of the time. Comments have also been added to this output for reader clarity.

In this table, *What* indicates attack, defense, or comment; *Node* indicates the node involved; *Time* indicates the time from the beginning of the attack in years, months, days, hours, minutes, and seconds; *What* indicates the technique used and whether it succeeds or fails; and *Details* indicate the specifics of what happened. Specifics include [attacker luck vs. defender quality] and, optionally, (luck relative to a threshold).

Table 4 - A single run of a hacker attacking Frank from the Internet with defender strength at 90%

```
(simulate '(10) "Internet" "Frank" 90)
```

COMMENT Test comment

What	Node	Time	What	details
ATTACK	Internet		below-threshold attacks->Internet	[743 !< 0](14 < 20) =======> Prevention will fail
COMMENT				The attacker stays below detection thresholds to get access to the Internet - This will succeed and take about 12 hours for this quality of attacker.
ATTACK	Angel	12h	process bypassing->Angel prevented	[527 < 900] by ((improved morality) (testing) (time, location, function, and other similar access limitations))

ATTACK	Angel	13h	imperfect daemon exploits->Angel prevented	[227 < 895] by ((testing) (time, location, function, and other similar access limitations))
ATTACK	Angel	13h 1m	breaking key management systems->Angel prevented	[471 < 883] by ((security marking and/or labeling) (time, location, function, and other similar access limitations) (waste data destruction))
COMMENT				Angel's prevention defeated the above attempts at entry
ATTACK	Angel	2d 13h 1m	race conditions->Angel	[964 !< 855](48 > 20) -> bad luck
COMMENT				Angel was not able to prevent this attack, but the attacker was unlucky and what they tried failed
ATTACK	Angel	2d 13h 2m	below-threshold attacks->Angel prevented	[232 < 855] by ((perception management) (time, location, function, and other similar access limitations))
ATTACK	Angel	3d 1h 2m	Trojan horses->Angel prevented	[627 < 900] by ((fine-grained access control) (improved morality) (testing) (time, location, function, and other similar access limitations))
ATTACK	Angel	3d 1h 2m 30s	privileged program misuse->Angel prevented	[683 < 855] by ((perception management) (time, location, function, and other similar access limitations))
ATTACK	Angel	3d 1h 3m 30s	false updates->Angel prevented	[514 < 900] by ((path diversity) (security marking and/or labeling) (testing) (time, location, function, and other similar access limitations))
				False updates take a long time

COMMENT				to get to work, whether they succeed or not.
ATTACK	Angel	33d 1h 3m 30s	shoulder surfing->Angel prevented	[36 < 895] by ((testing) (time, location, function, and other similar access limitations))
ATTACK	Angel	33d 1h 13m 30s	shoulder surfing->Angel prevented	[101 < 895] by ((testing) (time, location, function, and other similar access limitations))
ATTACK	Angel	33d 1h 23m 30s	infrastructure observation->Angel	[907 !< 866](21 > 20) -> bad luck
ATTACK	Angel	33d 1h 23m 40s	input overflow->Angel prevented	[40 < 895] by ((testing) (time, location, function, and other similar access limitations))
ATTACK	Angel	33d 1h 23m 50s	error-induced mis-operation->Angel prevented	[513 < 855] by ((integration principle (GASSP)) (time, location, function, and other similar access limitations))
ATTACK	Angel	33d 1h 43m 50s	call forwarding fakery->Angel prevented	[630 < 895] by ((testing) (time, location, function, and other similar access limitations))
ATTACK	Angel	33d 1h 44m 50s	hardware failure - system flaw exploitation->Angel	[776 !< 765](55 > 20) -> bad luck
COMMENT				Hardware failures only happen so often, again a long time is required.
ATTACK	Angel	63d 1h 44m 50s	illegal value insertion->Angel prevented	[457 < 889] by ((fine-grained access control) (testing))
ATTACK	Angel	63d 1h	shoulder surfing->Angel	[554 < 895] by ((testing) (time, location, function, and other similar access

		45m	prevented	limitations))
ATTACK	Angel	63d 1h 55m	shoulder surfing->Angel prevented	[560 < 895] by ((testing) (time, location, function, and other similar access limitations))
ATTACK	Angel	63d 2h 5m	perception management a.k.a. human engineering->Angel prevented	[450 < 898] by ((perception management) (testing) (time, location, function, and other similar access limitations))
ATTACK	Angel	73d 2h 5m	implied trust exploitation->Angel prevented	[190 < 855] by ((testing))
ATTACK	Angel	73d 2h 6m	replay attacks->Angel prevented	[272 < 810] by ((time, location, function, and other similar access limitations))
ATTACK	Angel	73d 2h 16m	below-threshold attacks->Angel prevented	[99 < 855] by ((perception management) (time, location, function, and other similar access limitations))
ATTACK	Angel	73d 14h 16m	cryptanalysis->Angel prevented	[23 < 810] by ((time, location, function, and other similar access limitations))
ATTACK	Angel	73d 15h 16m	dumpster diving->Angel	[868 !< 675](2 < 20) =======> Prevention will fail
COMMENT				Angel will be defeated by information gained in dumpster diving. It has taken 73 days to get through
ATTACK	Charlie	73d 19h 16m	cryptanalysis->Charlie	[404 !< 0](19 < 20) =======> Prevention will fail
COMMENT				Charlie falls right away.
			undocumented or unknown	

ATTACK	David	73d 20h 16m	function exploitation->David prevented	[771 < 810] by ((time, location, function, and other similar access limitations))
ATTACK	David	73d 20h 16m 10s	viruses->David	[155 !< 0](85 > 20) -> bad luck
ATTACK	David	73d 20h 46m 10s	strategic or tactical deceptions->David	[413 !< 0](63 > 20) -> bad luck
ATTACK	David	74d 20h 46m 10s	shoulder surfing->David	[844 !< 810](50 > 20) -> bad luck
ATTACK	David	74d 20h 56m 10s	error-induced mis-operation->David prevented	[510 < 810] by ((time, location, function, and other similar access limitations))
ATTACK	David	74d 21h 16m 10s	illegal value insertion->David	[583 !< 0](18 < 20) =======> Prevention will fail
COMMENT				David has some successful prevention and the attacker had some bad luck, but it didn't take long to get through.
ATTACK	Edward	74d 21h 16m 20s	invalid values on calls->Edward	[398 !< 0](89 > 20) -> bad luck
ATTACK	Edward	74d 21h 16m 30s	infrastructure observation->Edward	[704 !< 0](67 > 20) -> bad luck
ATTACK	Edward	74d 21h 16m	viruses->Edward prevented	[664 < 898] by ((effective mandatory access control)(trusted applications))

		40s		
ATTACK	Edward	74d 21h 46m 40s	process bypassing->Edward prevented	[819 < 855] by ((trusted applications))
ATTACK	Edward	74d 22h 46m 40s	imperfect daemon exploits->Edward prevented	[848 < 898] by ((effective mandatory access control)(trusted applications))
ATTACK	Edward	74d 22h 47m 40s	Trojan horses->Edward	[964 !< 898](24 > 20) -> bad luck
ATTACK	Edward	74d 22h 48m 10s	hardware failure - system flaw exploitation->Edward	[987 !< 0](78 > 20) -> bad luck
ATTACK	Edward	104d 22h 48m 10s	strategic or tactical deceptions->Edward	[983 !< 0](25 > 20) -> bad luck
ATTACK	Edward	105d 22h 48m 10s	shoulder surfing->Edward	[468 !< 0](51 > 20) -> bad luck
ATTACK	Edward	105d 22h 58m 10s	cryptanalysis->Edward	[639 !< 0](94 > 20) -> bad luck
ATTACK	Edward	105d 23h 58m 10s	implied trust exploitation->Edward prevented	[117 < 855] by ((trusted applications))
ATTACK	Edward	105d 23h 59m 10s	collaborative misuse->Edward	[426 !< 0](17 < 20) =======> Prevention will fail
				Edward had better defenses

COMMENT				for this threat profile and luck was not with the attacker.
ATTACK	Frank	106d 59m 10s	hardware failure - system flaw exploitation->Frank	[575 !< 0](18 < 20) =======> Prevention will fail
COMMENT				Frank, however, fell after one very well directed and time consuming attack.
A WINS	Frank	136d 59m 10s	=======>	Defeated Frank

Large numbers of simulation runs may be made with the same parameter values to generate statistics. This result of running the same attacker / defender pairing is demonstrated in the detailed run through 1,000 attack sequences given in table 5.

Table 5 - 1000 runs of a hacker attacking Frank from the Internet with defender strength at 90%

```
(simset '(10) "Internet" "Frank" 90 1000)
```

```
Run time: 1065.85 sec.
```

1000 total attacks, of which 1000 were successful (100%)

From	To	Samples	Mean	St. Dev.
1d 17h 12m 10s	2yr 77d 15h 52m 40s	1000	210d 7h 25m 50s	7d 16h 59m 28s

From	To	Samples	Mean	St. Dev.
1d 17h 12m 10s	81d 17h 35m	101	54d 14h 53m 8s	5d 20h 5m 38s
82d 12h 15m 40s	162d 17h 30m 20s	309	123d 13h 52m 56s	7d 3h 39m 18s

163d 19m 30s	243d 11h 43m 30s	273	199d 7h 40m 10s	12d 3h 24m 8s
243d 13h 17m	321d 21h 57m 20s	153	277d 12h 42m 7s	22d 12h 16m 59s
324d 11h 25m 10s	1yr 39d 15h 19m 40s	93	357d 17h 42m 24s	37d 4h 5m 23s
1yr 40d 10h 25m 50s	1yr 117d 20h 38m	34	1yr 75d 5h 41m 50s	75d 14h 31m 12s
1yr 122d 17h 43m 10s	1yr 195d 11h 53m 30s	20	1yr 153d 18h 53m 44s	116d 2h 34m 23s
1yr 201d 8h 48m 20s	1yr 278d 5h 38m 50s	10	1yr 232d 23h 49m 32s	189d 7h 21m 26s
1yr 291d 8h 44m 50s	1yr 340d 50m 10s	4	1yr 317d 22h 5m 25s	341d 14h 1m 48s
2yr 63d 5h 50m 40s	2yr 77d 15h 52m 40s	3	2yr 71d 23h 48m 53s	1yr 98d 1h 4m 16s

From	To	Samples	16	32	48	64	80	96	112	128	144	160
1d 17h 12m 10s	81d 17h 35m	101	XX	XX	XX	XX	XX	XX				
82d 12h 15m 40s	162d 17h 30m 20s	309	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX
163d 19m 30s	243d 11h 43m 30s	273	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX
243d 13h 17m	321d 21h 57m 20s	153	XX	XX	XX	XX	XX	XX	XX	XX	XX	
324d 11h 25m 10s	1yr 39d 15h 19m 40s	93	XX	XX	XX	XX	XX					

1yr 40d 10h 25m 50s	1yr 117d 20h 38m	34	XX	XX
1yr 122d 17h 43m 10s	1yr 195d 11h 53m 30s	20	XX	
1yr 201d 8h 48m 20s	1yr 278d 5h 38m 50s	10		
1yr 291d 8h 44m 50s	1yr 340d 50m 10s	4		
2yr 63d 5h 50m 40s	2yr 77d 15h 52m 40s	3		

The runs in table 5 show statistical characteristics that look like a Bell-curve, but, this is not generally the case for attack and defense simulations. This particular example is unlikely to produce high variance because the set of attack capabilities and defender strength are balanced in a particular way. It is also common to have curves like the one in table 6:

Table 6 - 1000 runs of a paramilitary group attacking Frank from the Internet with defender strength at 20%

```
(simset '(34) "Internet" "Frank" 20 1000)
```

```
Run time: 143.99 sec.
```

1000 total attacks, of which 1000 were successful (100%)

From	To	Samples	Mean	St. Dev.
1h	70d 10h 55m	1000	13d 17h 31m 54s	13h 39m 41s

From	To	Samples	Mean	St. Dev.
1h	23h 35m	264	7h 38m 55s	32m 17s
Empty Interval				
10d 1h	10d 14h 25m	327	10d 6h 40m 10s	13h 38m 32s
10d 14h 30m	10d 23h 20m	18	10d 18h 15m 33s	2d 12h 52m 31s
Empty Interval				
20d 40m	21d 3h 20m	240	20d 7h 29m 46s	1d 7h 28m 9s
Empty Interval				
Empty Interval				
30d 30m	31d 45m	103	30d 7h 29m 10s	2d 23h 40m 57s
Empty Interval				
Empty Interval				
40d 50m	40d 17h 45m	37	40d 7h 23m 30s	6d 15h 2m 22s
Empty Interval				
Empty Interval				
50d 5m	50d 14h 20m	7	50d 7h 19m 17s	19d 19m 42s
Empty Interval				
Empty Interval				
60d 40m	60d 9h 10m	3	60d 5h 40m	34d 18h 39m 31s
Empty Interval				
70d 10h 55m	70d 10h 55m	1	70d 10h 55m	70d 10h 55m

From	To	Samples	17	34	51	68	85	102	119	136	153
1h	23h 35m	264	XX	XX	XX	XX	XX	XX	XX	XX	XX
Empty	Interval	0									
10d 1h	10d 14h	327	XX	XX	XX	XX	XX	XX	XX	XX	XX

	25m											
10d 14h 30m	10d 23h 20m	18	XX									
Empty	Interval	0										
20d 40m	21d 3h 20m	240	XX	XX	XX	XX	XX	XX	XX	XX	XX	
Empty	Interval	0										
Empty	Interval	0										
30d 30m	31d 45m	103	XX	XX	XX	XX	XX	XX				
Empty	Interval	0										
Empty	Interval	0										
40d 50m	40d 17h 45m	37	XX	XX								
Empty	Interval	0										
Empty	Interval	0										
50d 5m	50d 14h 20m	7										
Empty	Interval	0										
Empty	Interval	0										
60d 40m	60d 9h 10m	3										
Empty	Interval	0										
70d 10h 55m	70d 10h 55m	1										

The example in table 6 has clusters of samples surrounding substantially different times and large areas (labeled Empty Interval) with no samples. We have used 20 intervals to make this clearer for this data set, but the same phenomena happens for most data sets at an appropriate level of granularity.

At first this was a great surprise. In fact, the authors' initial reaction was to disbelieve the simulation, so the details of the runs were examined to see what was wrong with the simulator. It turned out that the simulator was working properly and that simulation had revealed a new property of attacks.

This result turns out to be a side effect of the large time differential between different attack techniques. For example, getting a job in order to break into a site is something that a spy would commonly do while a hacker probably would not. For cases where a job is used as an entree, the time scale is on the order of weeks to months, and sometimes years, while most of the technical attacks operate in time scales of seconds to hours. Thus the distribution is very different when human and computer time scales are mixed. If a purely technical attack is going to work, it will usually work quickly. If a series of technical attacks fail and the attacker decides to use human effort, there is a relatively large gap. So the gaps in times reflect the numbers and sorts of human activities within the attack process as well as differentials associated with slower and faster technical attacks.

This example also has a very low-grade defender (only 20 percent of what they do is done right) and a relatively non-technical threat (a paramilitary group). While the curve in table 6 is generally similar to the one from table 5 in that it rises to a peak and then trails off slowly, the clustering has a substantial impact.

Table 6 covers 1,000 samples and 12 out of 20 equal-sized regions have no samples. In a similar run with a very high grade threat (information warriors) only 5 regions had data and, of those; one had 88 percent of results, the next highest had 8 percent, and the third highest had 3 percent. One of the interesting results is that the time clustering of successful attacks is reduced for higher quality defenders, but this tends to happen only as the quality becomes very nearly perfect.

It is also worth noting that the run time for simulation is dramatically affected by the strength of the attacker and defender. This essentially reflects the notion that better defenders force attackers to try more things before success and better attackers have to try fewer things before success. The real-time till success is also far shorter in this case for the same reasons. In the case of the stronger attacker and weaker defender, 14d 13m 44s was the mean time till success, while the stronger defender with the weaker attacker has a mean time to success of 210d 6h 51m 58s - a factor of about 15.

Another key issue that clustering points out is the notion of attack strategies. While these simulations use random selection to decide which attack of those available to the threat is picked next, an actual attacker's strategy might be very different. For example, some attackers may only use methods that they think are hard to detect, while others may go for pure speed, others may try a small number of attacks repeatedly until they succeed, others may tend to try attacks that succeeded well in previous attempts, and still others may choose quicker attacks with increased likelihood. Clearly, this has implications both for attackers and defenders in terms of understanding the issues of attack and defense, but just as clearly, the resources required to do this sort of analysis are considerable. We will address the issues of strategies and resources a bit later.

Another very important consideration in this case is the lack of detection and reaction in the model. In practice, only a very subtle attack will likely use a large number of steps and go undetected by a reasonable defender. Once detected, reaction, even on human time scales, may easily defeat the attack most of the time. Even the fastest success in the hacker runs shown in Table 5 (1d 12h 55m) is within the realm of what human reaction has a chance to stop.

This is not universally true, of course. Stronger attackers tend to gain entry far more quickly. For example, in a subsequent run, a simulated information warrior operating against a fully skilled defender was able to gain access to Frank in 4 minutes, 27 seconds. This is far faster than human defenders are likely to be able to react except in the rarest of circumstances.

This also brings up the issue of attacker and defender quality. We characterize this as a probabilistic measure that affects the *firing tables* and *dice rolls*. On each attack and defense, you can see thresholds for success both for the attacker and defender along with the numbers actually used in the particular move. These thresholds are varied based on the attacker and defender quality provided as input to the simulation. In the case of defenders, the quality is a simulation parameter, while threats have quantitative values in the database used to drive the simulation.

Adding in Detection and Reaction

While these simulations provide interesting results, they ignore detection and reaction to attacks. One way to think of this is in terms of the rating of a physical firewall or a safe. These physical security devices are typically rated in terms of how long they can withstand what sort of assault. A 16-hour safe, for example, is designed to take 16 hours to penetrate given an identified safecracker capability. A 2-hour firewall or firesafe is rated based on the time it takes to bring the protected items up to a particular temperature given a particular temperature fire on the other side of the wall.

Effective protection works because of the combination of prevention, detection, and reaction. Deterrence, arrest and prosecution, and other factors also come into play in a strategic sense, but for the time being, and for the purpose of our current simulations, only tactical issues are considered. Results change rather substantially when we include detection and reaction in the picture. The first and most noticeable change is that all attacks do not eventually succeed. With detection and reaction in place, a key parameter of interest to many people is the probability of successful attack. But this is only the beginning of the issue. Table 7 has an example simulation in which detection and reaction has been included. An industrial espionage expert is trying to get from the Internet to Edward with the defender at 80 percent strength:

Table 7 - A single run of an industrial espionage expert attacking Edward from the Internet with defender strength at 80% where the defender wins

What	Node	Time	What	details
ATTACK	Internet		spoofing and masquerading->Internet	[208 !< 0](12 < 57) =======> Prevention will fail
DETECT	Angel	1s	perception management a.k.a. human engineering->Angel detected	[125 < 768] by ((anomaly detection) (testing) (time, location, function, and other similar access limitations)) in 2h
ATTACK	Angel	1s	perception management a.k.a. human engineering->Angel	[804 !< 798](86 > 57) -> bad luck
ATTACK	Angel	1m 1s	collaborative misuse->Angel prevented	[98 < 794] by ((improved morality) (path diversity))
DETECT	Angel	11m 1s	get a job->Angel detected	[307 < 748] by ((sensors) (testing) (time, location, function, and other similar access limitations)) in 1h 20m 6s
ATTACK	Angel	11m 1s	get a job->Angel prevented	[22 < 800] by ((path diversity) (testing) (time, location, function, and other similar access limitations) (waste data destruction))
REACT-	Angel	1h 31m 7s	get a job@ 11m 1s	[859 !< 584]=>((time, location, function, and other similar access limitations) (waste data destruction))
REACT-	Angel	2h 1s	perception management a.k.a. human engineering@ 1s	[950 !< 728]=>((perception management) (time, location, function, and other similar access limitations))

DETECT	Angel	28d 11m 1s	restoration process corruption or misuse->Angel detected	[111 < 787] by ((security marking and/or labeling) (testing) (time, location, function, and other similar access limitations)) in 2h
ATTACK	Angel	28d 11m 1s	restoration process corruption or misuse->Angel prevented	[382 < 800] by ((path diversity) (security marking and/or labeling) (testing) (time, location, function, and other similar access limitations))
ATTACK	Angel	28d 41m 1s	repair-replace-remove information->Angel prevented	[293 < 790] by ((testing) (waste data destruction))
REACT+	Angel	28d 2h 11m 1s	restoration process corruption or misuse@ 28d 11m 1s	[361 < 560]=> ((time, location, function, and other similar access limitations)) after 2h======> Reaction will succeed in 1d
ATTACK	Angel	29d 41m 1s	collaborative misuse->Angel prevented	[575 < 794] by ((improved morality) (path diversity))
DETECT	Angel	29d 51m 1s	excess privilege exploitation->Angel detected	[34 < 793] by ((anomaly detection) (security marking and/or labeling) (testing) (time, location, function, and other similar access limitations)) in 2h
ATTACK	Angel	29d 51m 1s	excess privilege exploitation->Angel	[887 !< 797](49 < 57) =======> Prevention will fail
ATTACK	Charlie	29d 51m 2s	collaborative misuse->Charlie prevented	[628 < 760] by ((background checks) (feeding false information))
ATTACK	Charlie	29d 1h 1m 2s	inappropriate defaults->Charlie prevented	[699 < 770] by ((automated protection checkers and setters) (effective mandatory access control))
			resource	[673 < 799] by ((automated

ATTACK	Charlie	29d 1h 1m 12s	availability manipulation->Charlie prevented	protection checkers and setters) (effective mandatory access control) (trusted applications))
ATTACK	Charlie	29d 1h 1m 13s	dumpster diving->Charlie	[249 !< 0](96 > 57) -> bad luck
ATTACK	Charlie	29d 2h 1m 13s	protection mis-setting exploitation->Charlie	[816 !< 799](95 > 57) -> bad luck
ATTACK	Charlie	29d 2h 2m 13s	modification in transit->Charlie	[926 !< 760](1 < 57) =======> Prevention will fail
ATTACK	David	29d 2h 2m 14s	repair-replace-remove information->David	[848 !< 0](27 < 57) =======> Prevention will fail
D WINS	Angel	@ 29d 2h 11m 1s		Original Attack@ 28d 11m 1s Detected@ 28d 2h 11m 1s Reacted with:((time, location, function, and other similar access limitations)) after 1d

At 1 second into the attack, the Internet has been breached and a perception management attack against Angel has been detected by a combination of anomaly detection, testing, and time, location, function, and other similar access limitations. It will take 2 hours before this detection reaches a person or system capable of considering a reaction. At 2 hours and 1 second into the attack, the perception management attempted at 1 second into the attack is not reacted to because of defender weakness, so the attack continues.

A restoration process corruption or misuse against Angel is detected at 28 days, 11 minutes and 1 second into the simulation by the combined defenses of security marking and/or labeling, testing, and time, location, function, and other similar access limitations. It will again take 2 hours before an actor capable of responding will get the alert, and at 28d 2h 11m 1s time, location, function, and other similar access limitations is chosen to block further attacks. It will take the organization 1 day to implement this protection, but at that time the attack will be defeated by this method. Sure enough, at 29d 2h 11m 1s into the simulation, the defender wins by this method.

Table 8 has another simulation run under identical initial conditions, but the dice will roll differently this time.

Table 8 - A single run of an industrial espionage expert attacking Edward from the Internet with defender strength at 80% where the attacker wins

What	Node	Time	What	details
ATTACK	Internet		network service and protocol attacks->Internet	[272 !< 0](80 > 57) -> bad luck
ATTACK	Internet	1s	invalid values on calls->Internet	[274 !< 0](89 > 57) -> bad luck
ATTACK	Internet	2s	reflexive control->Internet	[116 !< 0](35 < 57) =======> Prevention will fail
DETECT	Angel	3s	modification in transit->Angel detected	[527 < 768] by ((anomaly detection) (sensors) (time, location, function, and other similar access limitations)) in 1h 20m 6s
ATTACK	Angel	3s	modification in transit->Angel prevented	[444 < 788] by ((path diversity) (time, location, function, and other similar access limitations))
ATTACK	Angel	4s	input overflow->Angel	[841 !< 796](56 < 57) =======> Prevention will fail
			modeling mismatches-	[524 < 720] by ((feeding false

ATTACK	Charlie	5s	>Charlie prevented	information))
ATTACK	Charlie	15s	wire closet attacks->Charlie	[155 !< 0](30 < 57) =======> Prevention will fail
DETECT	David	1m 15s	excess privilege exploitation->David detected	[93 < 720] by ((time, location, function, and other similar access limitations)) in 2h
ATTACK	David	1m 15s	excess privilege exploitation->David prevented	[52 < 720] by ((time, location, function, and other similar access limitations))
DETECT	David	1m 16s	excess privilege exploitation->David detected	[256 < 720] by ((time, location, function, and other similar access limitations)) in 2h
ATTACK	David	1m 16s	excess privilege exploitation->David	[867 !< 720](5 < 57) =======> Prevention will fail
ATTACK	Edward	1m 17s	spoofing and masquerading->Edward	[439 !< 0](42 < 57) =======> Prevention will fail
A WINS	Edward	1m 18s	=======>	Defeated Edward

In this case, the attacker was detected after only 3 seconds when trying to modify data in transit. The detection was accomplished by the combination of anomaly detection, sensors, and time, location, function, and other similar access limitations, and a person or system capable of responding will be alerted in only 1h 20m 6s. Unfortunately, at 1m 18s into the attack, the attacker broke through to the target - long before reaction could even be contemplated. This clearly shows a case where automated reaction might be effective but human reaction would likely fail, even if it were quite rapid.

Detection and reaction times are highly technique and organization dependent and are parameters in the *firing tables*. As we can see, they also have a substantial impact on the effectiveness of defense.

When we look at substantial numbers of simulation runs with detection and reaction included in the process, we get results like those shown in Table 9. This has the same parameters as the runs plotted in Table 6, but with detection and reaction included. We plot successful attacks in red and successful defenses in green.

Table 9 - 1000 runs of a paramilitary group attacking Frank from the Internet with defender strength at 20%

```
(simset '(34) "Internet" "Frank" 20 1000)

Run time: 144.95 sec.
```

1000 total attacks, of which 966 were successful (97%)

From	To	Samples	Mean	St. Dev.
55m	70d 5h 15m	966	13d 23h 38m 48s	14h 9m 56s

From	To	Samples	Mean	St. Dev.
55m	22h 50m	256	7h 45m 1s	33m 21s
10d 50m	11d 2h 25m	330	10d 7h 56m 1s	13h 39m 3s
20d 40m	20d 21h 55m	216	20d 7h 21m 5s	1d 9h 9m 41s
Empty Interval				
30d 35m	30d 22h 40m	111	30d 7h 35m 32s	2d 21h 3m 41s
40d 1h	41d 2h 10m	43	40d 7h 28m 15s	6d 3h 32m 23s
Empty Interval				
50d 1h 35m	50d 14h 40m	8	50d 8h 33m 45s	17d 19h 17m 39s
60d 7h	60d 7h	1	60d 7h	60d 7h
70d 5h 15m	70d 5h 15m	1	70d 5h 15m	70d 5h 15m

From	To	Samples	17	34	51	68	85	102	119	136	153
55m	22h 50m	256	XX	XX	XX	XX	XX	XX	XX	XX	XX
10d 50m	11d 2h 25m	330	XX	XX	XX	XX	XX	XX	XX	XX	XX
20d 40m	20d 21h 55m	216	XX	XX	XX	XX	XX	XX	XX	XX	XX
Empty	Interval	0									
30d 35m	30d 22h 40m	111	XX	XX	XX	XX	XX	XX			
40d 1h	41d 2h 10m	43	XX	XX							
Empty	Interval	0									
50d 1h 35m	50d 14h 40m	8									
60d 7h	60d 7h	1									
70d 5h 15m	70d 5h 15m	1									

1000 total attacks, of which 34 were defeated (3%)

From	To	Samples	Mean	St. Dev.
8h 20m	21d 4h 10m	34	3d 15h 34m	1d 1h 35m 34s

From	To	Samples	Mean	St. Dev.
8h 20m	1d 11h 45m	26	1d 23m 41s	5h 5m 12s
Empty Interval				
Empty Interval				
Empty Interval				

10d 9h 25m	10d 14h 20m	3	10d 12h 35m	6d 1h 50m 5s
11d 2h 30m 6s	11d 7h 15m	4	11d 5h 16m 16s	5d 14h 38m 20s
Empty Interval				
Empty Interval				
Empty Interval				
21d 4h 10m	21d 4h 10m	1	21d 4h 10m	21d 4h 10m

From	To	Samples	2	4	6	8	10	12	14	16	18	20
8h 20m	1d 11h 45m	26	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX
Empty	Interval	0										
Empty	Interval	0										
Empty	Interval	0										
10d 9h 25m	10d 14h 20m	3	XX									
11d 2h 30m 6s	11d 7h 15m	4	XX	XX								
Empty	Interval	0										
Empty	Interval	0										
Empty	Interval	0										
21d 4h 10m	21d 4h 10m	1										

This shows the same phenomena as in the earlier simulation runs wherein the dramatic difference between times associated with different attack methods produces a set of time frames with few if any intervening cases. In this result we also see both the cases where the attacker wins and where the defender wins. The effect of a successful defense on any individual run is to defeat the attacker, and in this example, the presence of a weak defender has almost no effect on the results. If we compare the results in Table 6 with those in Table 9, we also see that the shortest time to attacker success is nearly the same (1h vs 55m), the maximum time to attacker success is about the same (70d 10h 55m vs. 70d 5h 15m), the mean time to attacker success is very close (13d 17h 31m 54s vs. 13d 23h 38m 48s) and the deviation of time till attacker success is nearly identical (13h 39m 41s 1h vs. 14h 9m 56s). But if we provide a much stronger defender, things begin to change substantially.

In Table 10 we show the same simulation parameters except that the defender strength is increased from 20 percent to 90 percent. Because the defender does so well in this circumstance, we have used 5,000 simulation runs to get more meaningful statistics.

Table 10 - 5000 runs of a paramilitary group attacking Frank from the Internet with defender strength at 90%

```
(simset '(34) "Internet" "Frank" 90 5000)
```

```
Run time: 1242.26 sec.
```

5000 total attacks, of which 77 were successful (2%)

From	To	Samples	Mean	St. Dev.
6h 5m	91d 10h 25m	77	14d 14h 16m 14s	2d 16h 54m 12s

From	To	Samples	Mean	St. Dev.
6h 5m	1d 6h 35m	36	17h 56m 6s	3h 12m 25s
10d 6h 30m	11d 12h	14	10d 17h 31m 4s	2d 20h 51m 15s
20d 7h	21d 18h 30m	10	20d 22h 28m	6d 14h 56m 16s
30d 14h 25m	31d 20h 10m	10	30d 23h 11m	9d 19h 1m 54s
41d 4h 10m	41d 4h 10m	1	41d 4h 10m	41d 4h 10m
50d 15h 50m	50d 23h 25m	2	50d 19h 37m 30s	35d 22h 24m 33s
60d 22h 20m	61d 16h 20m	2	61d 7h 20m	43d 8h 24m 33s
70d 18h 55m	70d 18h 55m	1	70d 18h 55m	70d 18h 55m
Empty Interval				

91d 10h 25m	91d 10h 25m	1	91d 10h 25m	91d 10h 25m

From	To	Samples	2	4	6	8	10	12	14	16	18	20
6h 5m	1d 6h 35m	36	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX
10d 6h 30m	11d 12h	14	XX	XX	XX	XX	XX	XX	XX			
20d 7h	21d 18h 30m	10	XX	XX	XX	XX	XX					
30d 14h 25m	31d 20h 10m	10	XX	XX	XX	XX	XX					
41d 4h 10m	41d 4h 10m	1										
50d 15h 50m	50d 23h 25m	2	XX									
60d 22h 20m	61d 16h 20m	2	XX									
70d 18h 55m	70d 18h 55m	1										
Empty	Interval	0										
91d 10h 25m	91d 10h 25m	1										

5000 total attacks, of which 4923 were defeated (98%)

From	To	Samples	Mean	St. Dev.
8h 25m	81d 11h 10m 6s	4923	8d 20h 44m 52s	4h 36m 6s

From	To	Samples	Mean	St. Dev.
8h 25m	2d 11h 45m	2533	1d 4h 23m 34s	34m 26s

10d 9h 5m	12d 4h 10m	1473	11d 5h 31m 40s	7h 1m 27s
20d 8h 20m	22d 9h 20m	613	21d 6h 53m 12s	20h 38m 9s
30d 12h 5m	32d 11h	203	31d 8h 42m 29s	2d 4h 49m 56s
40d 10h 10m	40d 13h 35m	2	40d 11h 52m 30s	28d 15h 13m 13s
40d 22h 50m	42d 5h 15m 5s	66	41d 10h 10m 17s	5d 2h 22m 33s
50d 9h 45m	52d 6h 5s	18	51d 10h 10m 52s	12d 2h 54m 31s
60d 11h 30m	62d 7h 40m 6s	14	61d 16h 3m 35s	16d 11h 34m 18s
Empty Interval				
81d 11h 10m 6s	81d 11h 10m 6s	1	81d 11h 10m 6s	81d 11h 10m 6s

From	To	Samples	127	254	381	508	635	762	889	1016
8h 25m	2d11h 45m	2533	XX	XX	XX	XX	XX	XX	XX	XX
10d 9h 5m	12d 4h 10m	1473	XX	XX	XX	XX	XX	XX	XX	XX
20d 8h 20m	22d 9h 20m	613	XX	XX	XX	XX				
30d 12h 5m	32d 11h	203	XX							
40d 10h 10m	40d 13h 35m	2								
40d 22h 50m	42d 5h 15m 5s	66								
50d 9h 45m	52d 6h 5s	18								
60d 11h 30m	62d 7h 40m 6s	14								
Empty	Interval	0								
81d 11h	81d 11h	1								

10m 6s	10m 6s	

A couple of things come quickly to the fore. For successful attacks, the mean time to success is essentially unchanged from Table 9 to Table 10 (13d 23h 38m 48s vs. 14d 14h 16m 14s). The shortest time to successful attack has gone up substantially (55m vs. 6h 5m) but this may reflect only the total number of successful attacks (966 vs. 77) and perhaps with 50,000 runs we would end up with an attack that took only 55m. The maximum time to successful attack went up by a substantial amount (70d 5h 15m vs. 91d 10h 25m) which would seem to indicate that slower attacks work better. Even more impressive is the spreading of the standard deviation by more than a factor of four (14h 9m 56s vs. 2d 16h 54m 12s). This would seem to show that the uncertainty for the attacker has increased substantially, even for successful attacks.

One conclusion we can clearly see is that stronger defenders do a disproportionately better job of defeating attackers. This defender was only 8 times as good as the one in the previous example, and yet success rates went from 5 percent to 98 percent. At defensive strength 100, only one of a thousand attacks succeeded and it took about 11 days of effort. The mean time to defeat attacks was just a bit over 9 days 8 hours with an 11 hour standard deviation.

Parallel Simulation

While doing a few thousand simulations takes a relatively small amount of computer time, one of the limiting factors in the use of simulation for real systems is the large size of the simulation space, and for making design decisions, the far larger size of the design space. To get a sense of this, consider that we can vary the strength of the attacker, the attacker type, the network architecture, the set of defenses in place at each point in the network, and that in order to get a realistic assessment of a rage of situations, we need to vary the from and to nodes as well.

To get a reasonable characterization of a simple system requires something like 10 different defender strengths and 15 different types of attackers. At 145 seconds per thousands simulations (see the timing information in Table 9), this comes to just over 6 hours and gives a plot that indicates how defender strength impacts probability of success and mean time to penetration across a range of threats.

To make a design decision about which combination of defenses would be best against a set of threats for a given network configuration would require that we look at all combinations of more than 90 defenses - 2^90 6 hour runs. This is clearly not a feasible way to do such an analysis.

Another important set of parameters relate to the question of how we allocate prevention, detection, and reaction resources. For example, is there a great benefit in decreasing reaction time for certain defenses or for the organization as a whole? Even a simplistic variation of this parameter would require a factor of 10 - or 60 hours - to evaluate a single design.

Fortunately, the simulation technique we apply here is inherently parallelizable and just about ideally scalable. We can simply allocate problems to processors in proportion to their processing speed to get near perfect parallelism. For example, with 20 computers available in a computer network we should be able to do the variation of defense strength parameters for all 36 classes of attackers by simply sending each computer a list of simulations to perform. Because this form of simulation is compute bound, communication between processors is only for the purpose of specifying simulations and getting back results. A typical network of personal computers with a standard communications network is perfectly adequate to the task.

In an experimental network configured for this purpose, we assigned the same port on each computer to run the simulation engine and sent simulations to be performed to each processor, taking results back as simulations were completed. The programming effort took about 15 minutes for a rough distribution system for this task and the process was reasonably effective at distributing the computation and returning results. In 140 minutes of real time, 20 400MHz PC processors running Linux performed 1000 simulations each for 35 threat profiles and 10 values of defender strength, or 350,000 simulation runs. This comes to 140 minutes for 350,000 simulations on 20 processors, or about 24 seconds per 1,000 simulation runs. This is not very good parallelism, since it comes to 480 seconds per 1000 runs per processor or about 3.4 times slower than the single processor runs done earlier. We have not spent any time to determine why the performance was so slow, but it is likely related to the shared file system used for communication between processors in this particular network and the manner in which we did program distribution. If this technique is to be used more extensively, performance bottlenecks will be worth removing.

Using the same problem set discussed above, we came up with the results in Table 11 - summarized into defender wins out of 1000 runs - with colors ranging from red (better for the attacker) to green (better for the defender). The results have been sorted (roughly) from best for the attacker to worst for the attacker.

Table 11 - Number (per 1000) of successful defenses by threat type and defensive strength (out of 100%) with 2 hour detection notice time and 2 day response time

Threat	10%	20%	30%	40%	50%	60%	70%	80%	90%	1
infrastructure-warriors	0	0	0	0	0	0	0	0	0	0
vandals	0	0	0	0	0	0	7	48	222	6
hoodlums	0	1	7	30	85	232	463	665	916	1
government-agencies	0	4	18	50	86	153	275	439	623	8
crackers-for-hire	0	5	9	24	60	111	245	399	600	8
consultants	0	8	17	40	102	196	336	500	682	9
vendors	1	1	8	21	55	103	193	289	538	7

information-warriors	1	4	19	28	94	162	246	419	600	8
tiger-teams	1	4	11	52	104	156	289	436	643	8
military-organizations	1	7	24	38	110	173	338	485	704	9
cyber-gangs	1	8	33	76	189	303	552	752	912	9
whistle-blowers	1	8	29	53	124	276	440	660	827	9
foreign-agents-and-spies	1	9	25	47	94	181	293	460	675	8
insiders	1	10	35	88	167	256	438	597	794	9
industrial-espionage-experts	1	10	24	43	105	172	304	376	598	8
economic-rivals	1	14	34	86	165	311	510	692	848	9
nation-states	2	7	27	63	145	232	369	512	722	9
professional-thieves	2	12	39	81	192	346	504	693	868	9
drug-cartels	3	12	54	89	190	309	457	632	774	9
maintenance-people	3	21	71	148	302	508	685	849	952	9
extortionists	4	17	63	103	253	402	619	761	908	9
customers	4	41	104	205	359	554	755	913	950	9
global-coalition	5	6	36	51	102	190	370	521	708	9
activists	5	24	77	163	309	501	666	838	930	9
police	5	36	87	242	367	574	744	880	962	9
crackers	5	50	135	317	478	710	860	951	983	9
competitors	7	62	182	351	548	775	900	968	992	1
paramilitary-groups	9	35	126	251	441	685	823	938	990	1
deranged-people	12	54	164	333	544	745	912	973	995	9

terrorists	13	66	163	356	534	769	880	980	987	9
organized-crime	14	53	162	281	478	702	852	946	986	9
private-investigators	14	66	181	404	641	840	954	990	998	1
reporters	18	87	197	411	657	821	949	985	998	1
club-initiates	22	102	267	490	740	893	964	992	997	1
hackers	23	75	159	345	544	776	931	976	991	9

The *scatter* plot in plate 2 shows the underlying data across all threats with the X-axis indicating defender strength and the Y-axis indicating time. The red indicates cases where attacks succeed and the green indicates cases where the defense defeats the attack. Successful defenses are plotted as negative times so that they can be seen in juxtaposition to the successful attacks. Note that earlier success for an attacker or defender is beneficial, so that points closer to the 0 line are better for either attacker or defender, while a larger volume indicates more wins. This plot clearly shows the clustering described earlier with *dead* bands where no color appears showing periods of time in which no action took place.

Plate 2 - The Distribution of Times Across All Threats

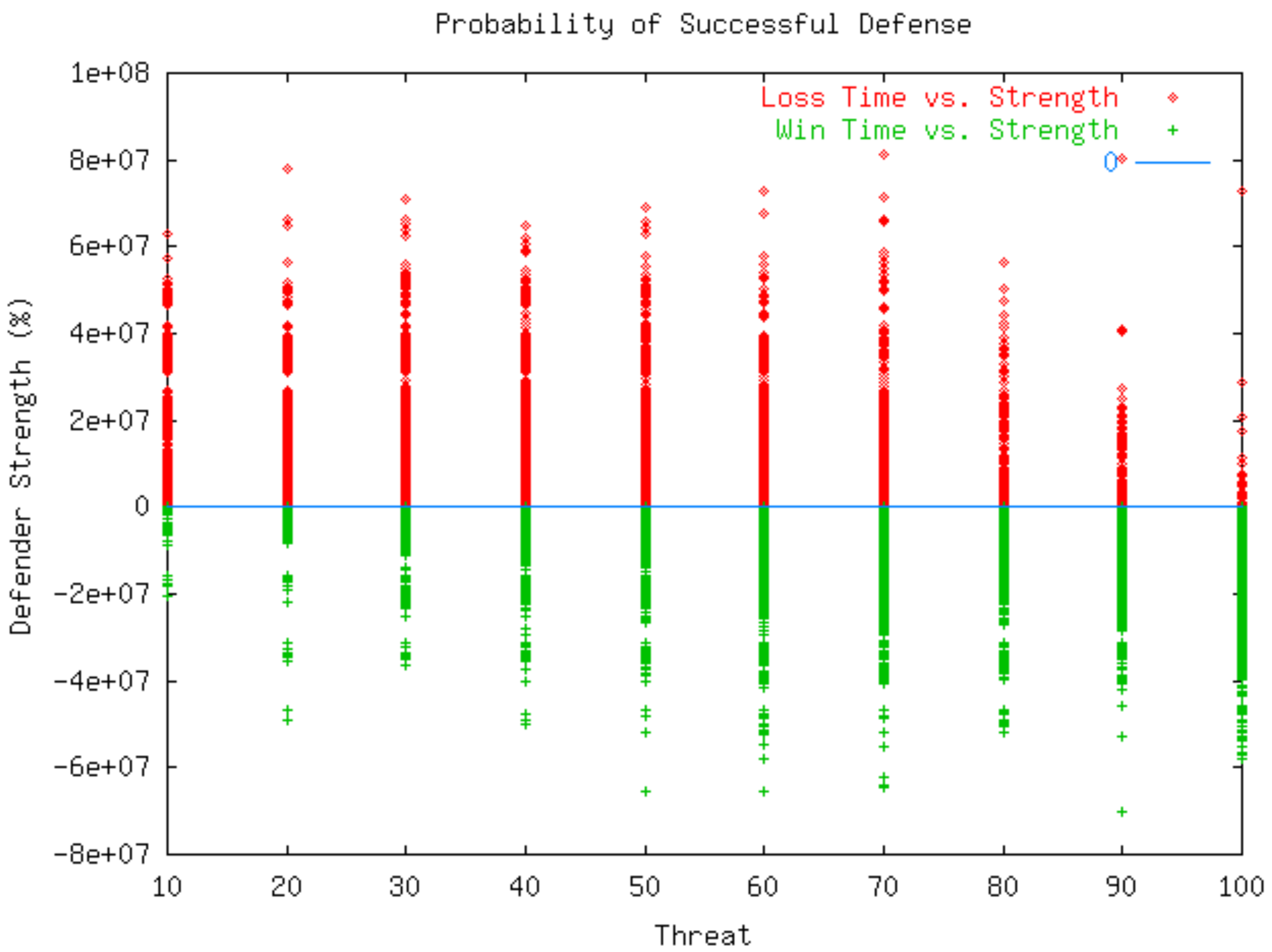
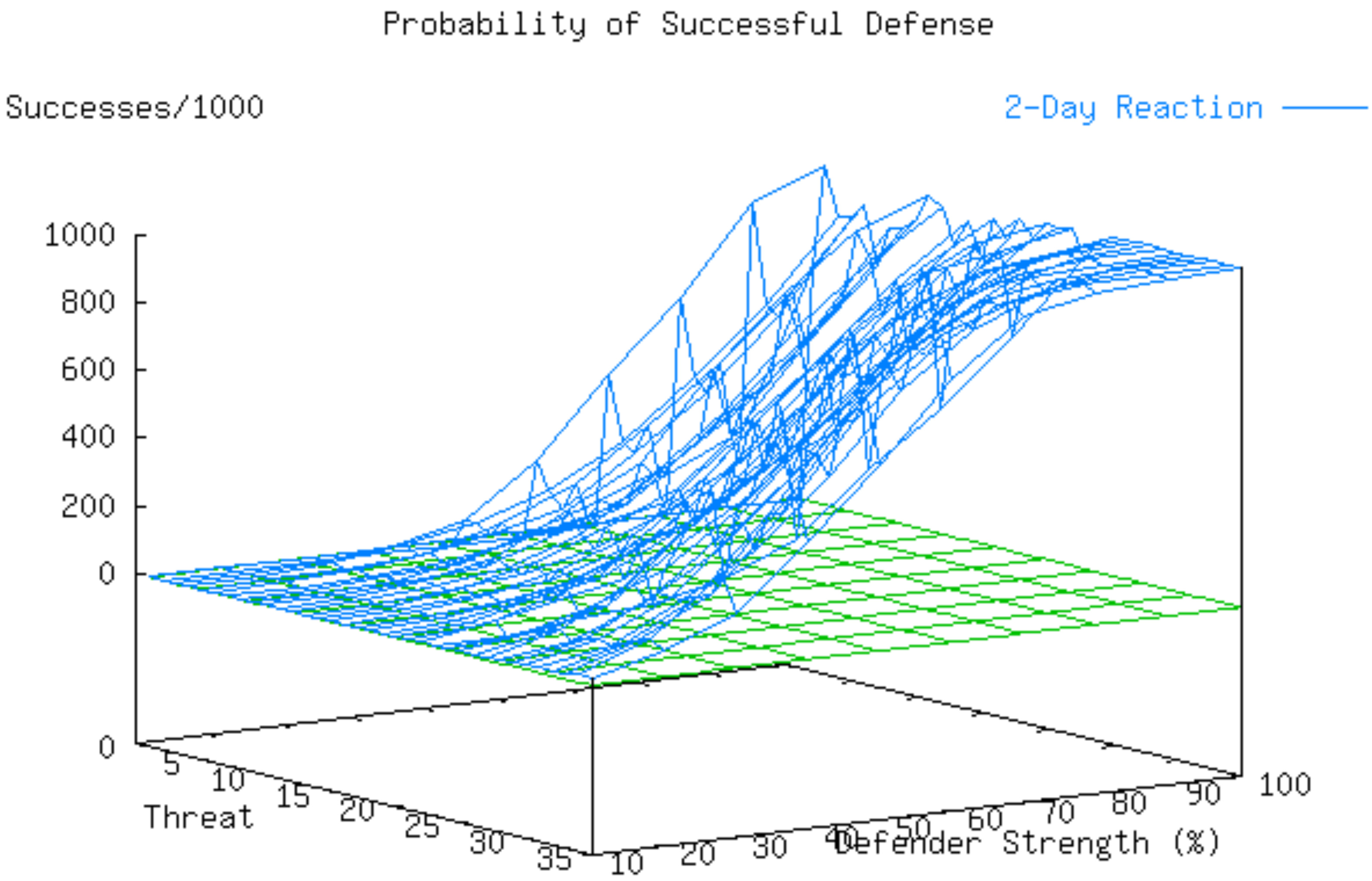


Plate 3 shows the *contour* of the probability of successful defense, and makes it clear that there is a nonlinearity of success with defender strength. It displays different threat types along the X axis, the defender strength along the Y-axis, and the the number of successful defenses per 1000 attacks along the Z-axis. A *zero* grid is also shown (in green) for perspective.

Plate 3 - The Shape of the Successful Defense Probability



This summary information is enlightening in several ways. Perhaps the most interesting is the result indicating that even with a perfect defender, certain threat profiles are never defeated. At first glance, this might seem to indicate that the defender simply had mismatched defenses for the attack mechanisms used by the threat. This notion turns out to be wrong. In fact, the poor performance in this case relates to the effects of detection and response time on the ability to defeat an attacker. The infrastructure warrior threat profile assumes that the attacker only uses techniques that are very fast and that the attacker is highly skilled. Even though large portions of attempted attacks tend to be detected, the defending organization cannot react in time to prevent the harm. As we vary the organization's detection and response time, the overall picture changes dramatically.

More on the Effects of Time

Another similar run, shown in Table 12, Plate 4, and Plate 5, was done with detection and response times of 1 second each and all other parameters identical. The reaults in Table 12 are again sorted most successful for the attacker to least successful for the attacker.

Table 12 Number (per 1000) of successful defenses by threat type and defensive strength (out of 100%) with 1-second detection and response

Threat	10%	20%	30%	40%	50%	60%	70%	80%	90%	10
Information Warriors	4	51	118	264	400	599	757	890	953	99
Hoodlums	7	25	90	212	404	632	838	952	992	10
Whistle Blowers	7	54	112	235	393	581	735	863	964	99
Government Agencies	8	42	137	247	383	582	762	894	955	99
Industrial Espionage Experts	9	42	125	253	425	625	777	911	977	99
Global Coalitions	9	53	134	279	431	651	823	923	972	99
Maintenance People	9	72	193	365	528	755	882	960	995	99
Vendors	10	49	128	263	425	590	761	897	963	98
Military Organizations	11	55	132	264	434	607	799	919	974	99
Customers	11	62	142	319	508	683	847	940	985	99
Extortionists	11	70	192	332	506	744	863	966	988	99
Foreign Agents and Spies	12	42	128	263	413	597	758	904	972	99
Nation States	12	56	147	267	453	667	828	934	985	99
Competitors	12	83	207	380	635	791	933	978	998	99
Tiger Teams	13	42	128	266	435	596	770	903	957	99

Activists	13	53	163	293	490	658	827	917	968	99
Deranged People	13	66	179	356	556	791	917	971	995	10
Police	13	83	212	378	590	796	932	979	996	10
Organized Crime	14	57	139	318	485	699	838	930	980	99
Insiders	14	75	176	350	523	744	882	965	985	99
Crackers for Hire	15	57	126	275	457	647	790	914	974	99
Consultants	16	39	120	260	407	610	755	899	957	99
Professional Thieves	16	57	152	333	529	714	884	948	994	99
Drug Cartels	16	63	129	265	454	643	813	914	983	99
Infrastructure Warriors	16	67	151	301	462	637	815	917	976	98
Hackers	16	85	201	414	661	807	925	976	998	10
Vandals	17	78	212	407	611	802	933	981	994	10
Crackers	17	80	173	354	565	750	900	975	990	10
Reporters	17	88	240	447	688	842	949	992	1000	10
Club Initiates	20	109	298	529	740	884	978	1000	1000	10
Economic Rivals	23	69	166	341	483	684	878	953	986	99
Paramilitary Groups	26	73	197	410	609	774	905	976	994	99
Cyber Gangs	27	66	206	389	621	789	928	971	1000	10
Terrorists	30	98	237	405	633	817	924	975	985	99
Private Investigators	32	103	271	445	693	837	945	991	997	10

Plate 4 - Instant Reaction Distribution Across All Threats

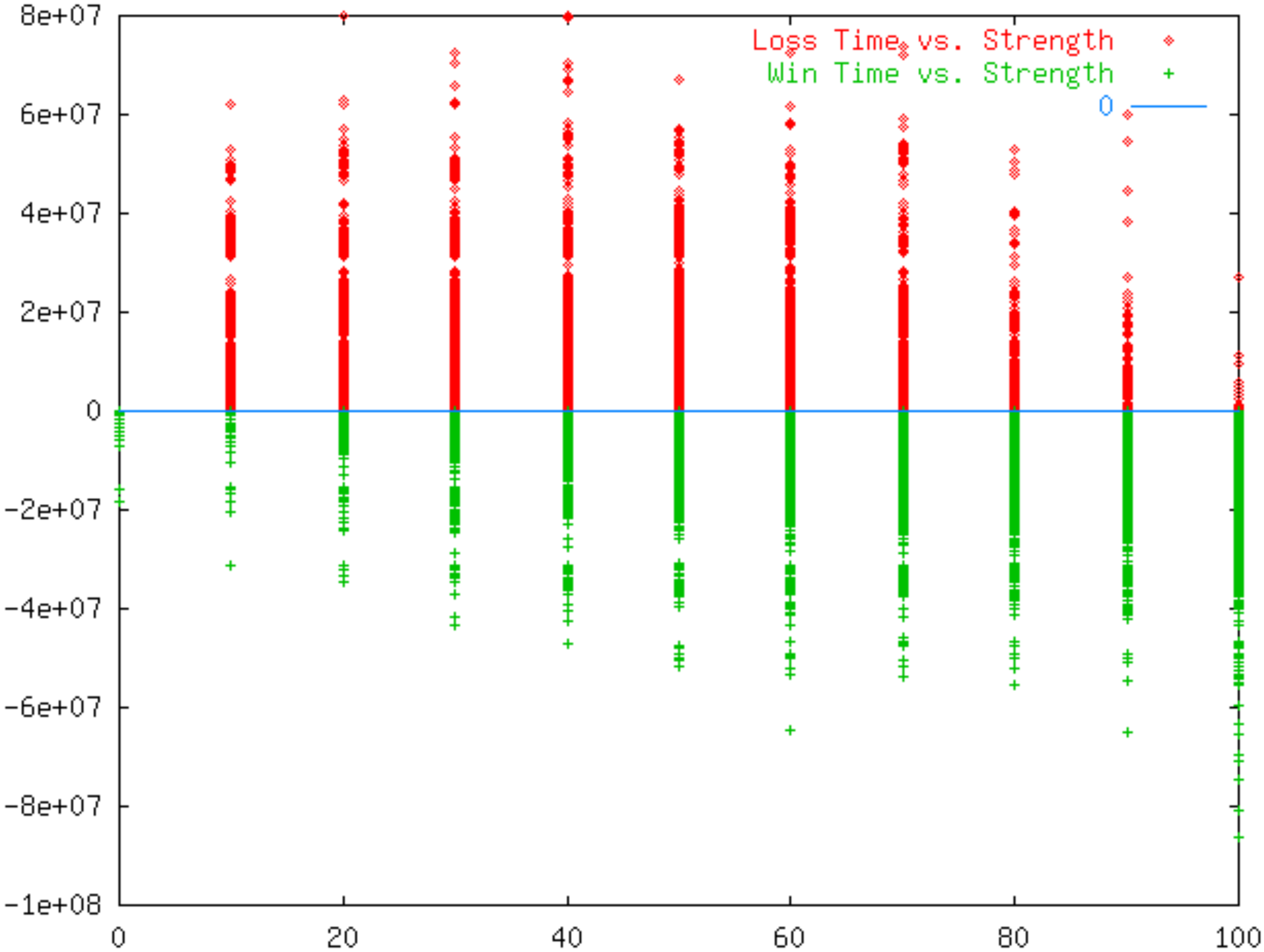
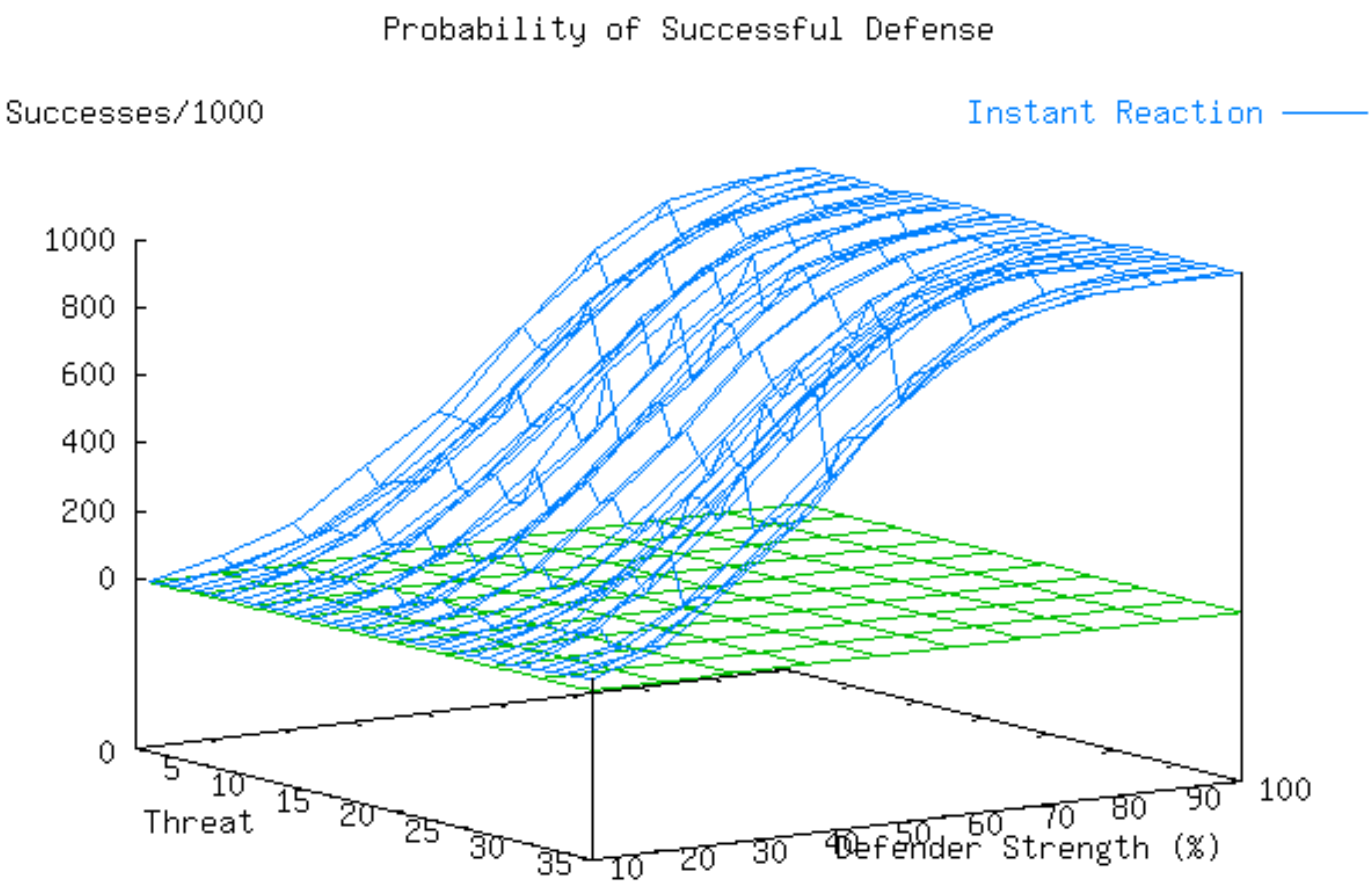


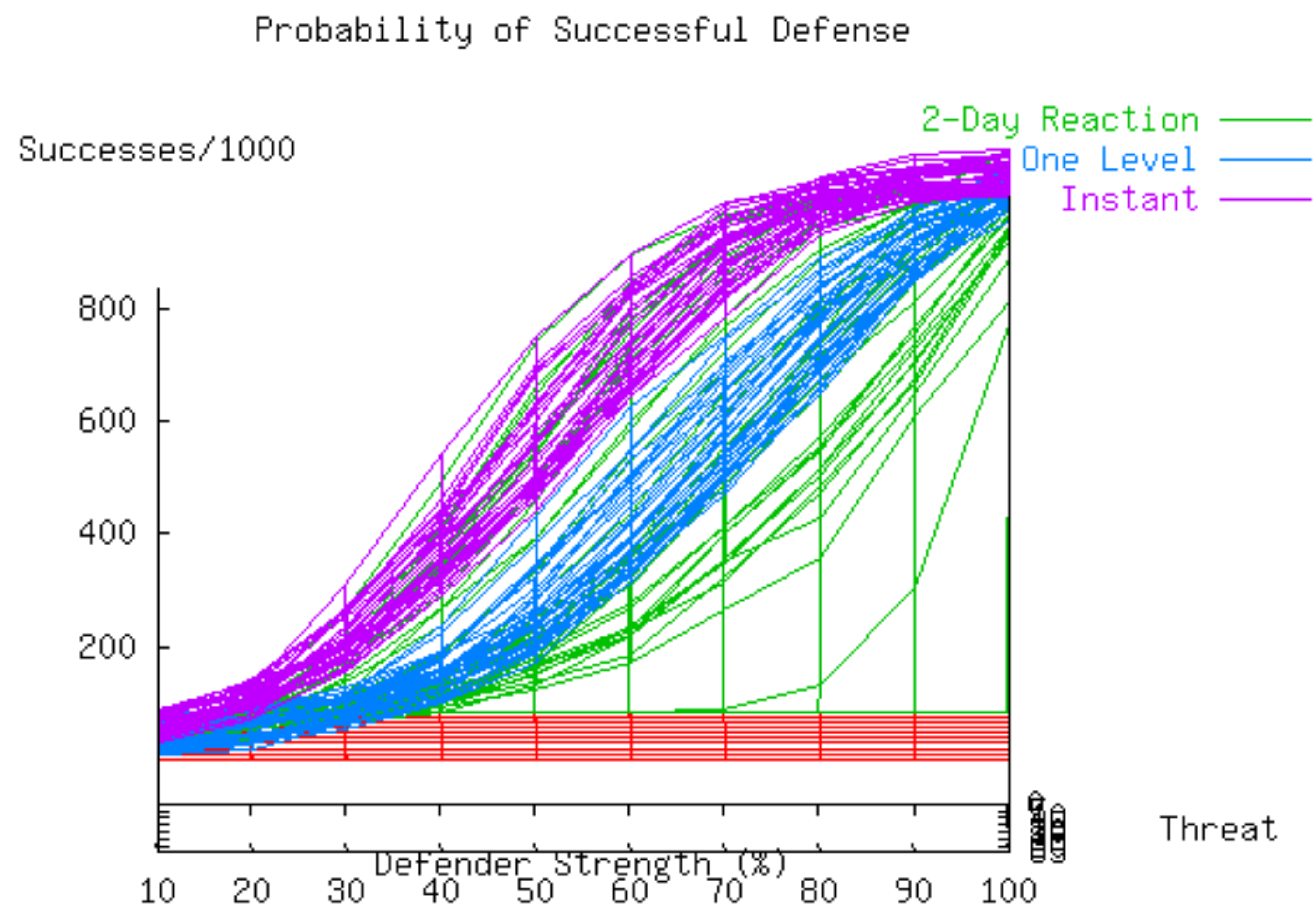
Plate 5 - The Shape of the Successful Defense Probability



Because detection and response were faster, far more of the attacks were mitigated far sooner. This dramatically changes the ordering of which attackers are most successful. For example, infrastructure warriors, who were undefeatable with slow detection and response, move to one of the less effective threats, while information warriors move up 6 places to become the most dangerous threat. The more rapid defense also reduces simulation time considerably, indicating that the total number of events that took place were dramatically reduced. This entire run of 350,000 simulations took only about 40 minutes of real-time on the same computer network used for the previous parallel run, or about a factor of 4 reduction in total moves. The reduction in moves corresponds roughly to a reduction in effort, and the implication would seem to be that faster response means less response and reduced cost. This has not been studied in further depth in this effort, but it is clearly worth looking into.

Another interesting result of these runs is the shape of the curves for each threat as a function of defensive strength. It is clearly non-linear. This would seem to indicate that the return on investment in the quality of a defender is non-linear. In other words, with faster detection and reaction, the skill of the defender becomes less critical to success. Plate 6 contrasts the two cases just discussed and a third case discussed below. It plots all three surfaces from a 'side' view that contrasts the shape of the response functions. The colors labeled *2-Day Reaction*, *One Level*, and *Instant* correspond respectively to the 2-day reaction time example from Plate 3, an example which uses instant reaction but removes defense-in-depth, and the instant reaction with defense-in-depth from Plate 5.. The red surface is the *zero* plane.

Plate 6 - The Nonlinear Functions of the Upcoming and Two Previous Examples



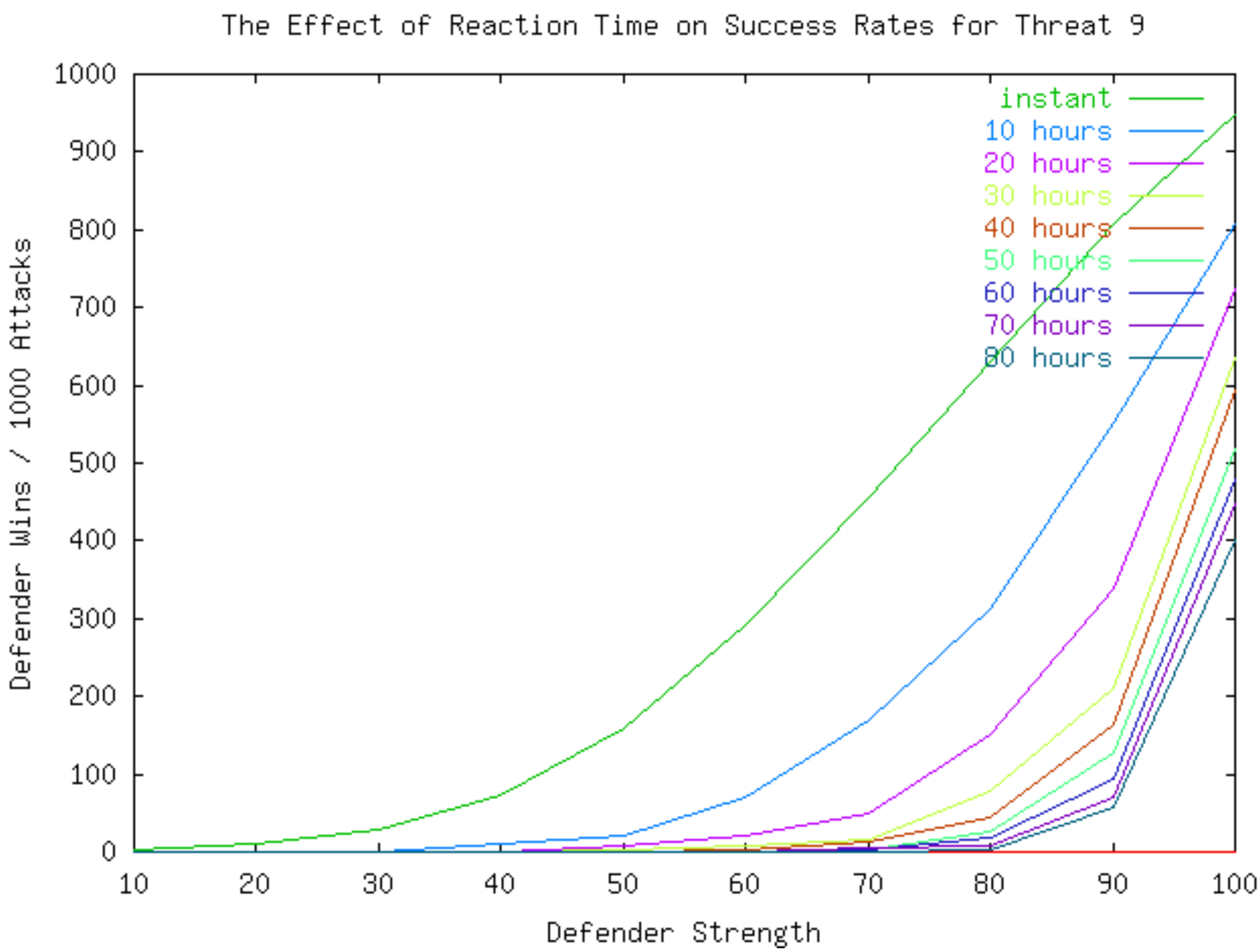
One speculative reason for the non-linearity of the curves is that the attacker must go through several defenses in sequence. Even if each defense is linear in the defender strength, the probabilities for a sequence of linear phenomena add up to a non-linear result because any successful defense causes the attack graph to be severed, and no progress is made toward later defenses. Plate 6 shows the same situation with attacks only going from the Internet to Angel. This requires only one successful attack for success, and it is noteworthy that the resulting set of surfaces are closer to linear than either of the other two. This simulation would seem support this theory, but it is hardly definitive.

As an aside, the fact that the overall curve has moved to the *right* in this simulation where a *firewall* alone was used, (*one-level*) as compared to the simulation in which defense-in-depth was used (*instant-reaction*), might give the notion that defense-in-depth has real value in terms of reducing the requirement for expertise in operational aspects of protection. To get at this more clearly, we need to place the same defenses in each situation. Also note that the one-level defense is better in many cases than the full set of defenses with two-day reaction times. Thus it appears that we may be more successful by being faster in our detection and reaction than by having more defenses that are slower. The precise tradeoff point that optimizes the set and placement of defenses and reaction times for any given situation is too complex to determine for any realistic circumstance, but finite sets of prevention and reaction schemes can clearly be compared and contrasted through this technique.

In Plates 7, 8, and 9, we examine the effects of time in more detail by displaying the strength vs. defender-wins curve for different times ranging from instant to 80 hours (3.33 days). It is noteworthy that the threat dictates the requirement for reaction speed. This is however somewhat simplistic because, as we will see later, it ignores the issue of strategies.

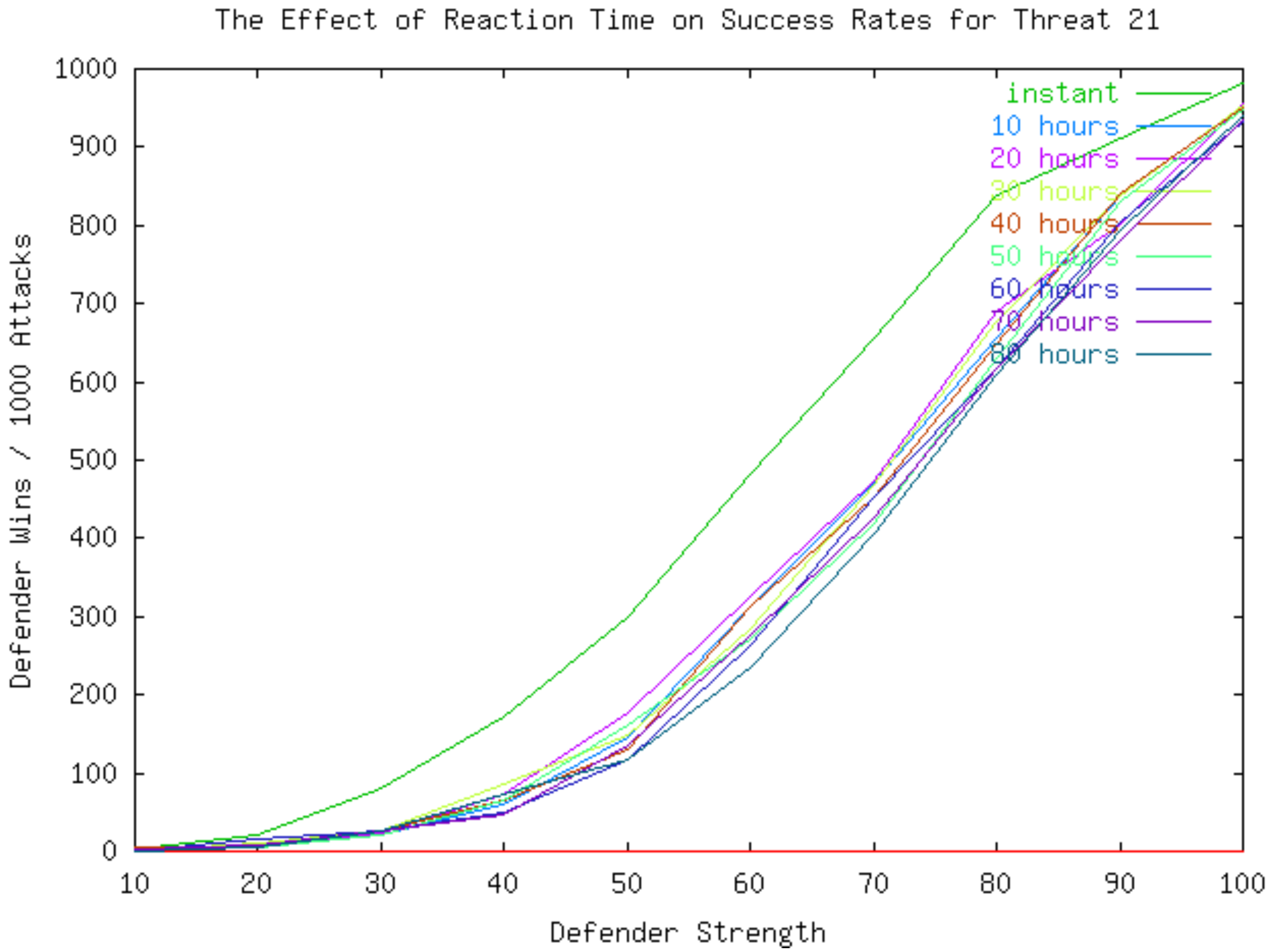
Plate 7 - The Effects of Detection and Reaction Time for Whistle

Blowers



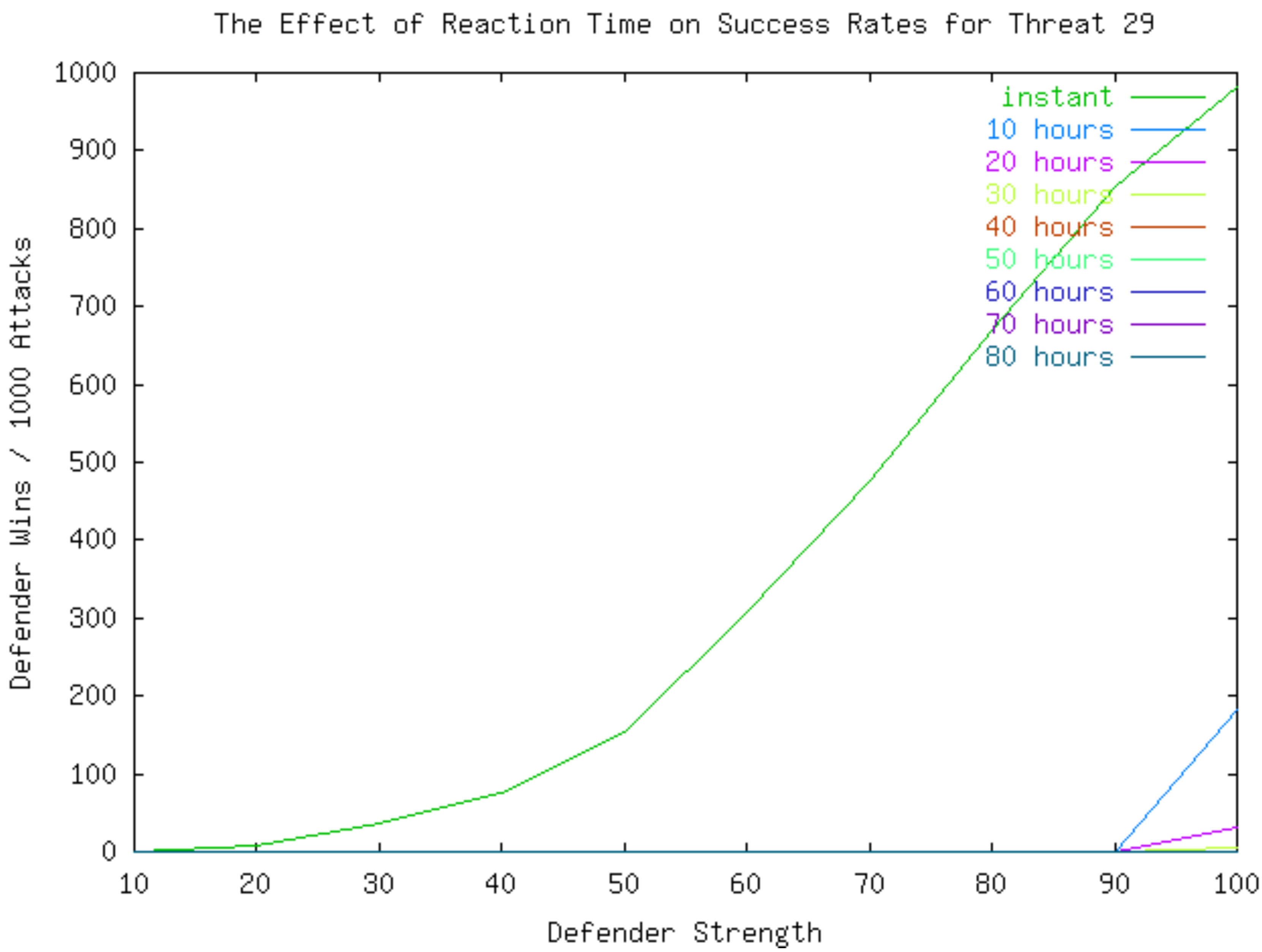
Whistle blowers do things on time scales of hours to days, so a result, the detection and reaction times are about exponential in the range being shown in Plate 7. Revisiting the earlier results from Tables 5, 6, 9, and 10, whose results indicate the time till successful attack, we see that, while they are discontinuous, on the large scale the number of attacks taking longer times go down approximately exponentially with time. Thus the exponential decrease in effectiveness as a function of reaction time seems natural.

Plate 8 - The Effects of Detection and Reaction Time for Deranged People



Deranged people, as shown in Plate 8, typically do something crazy every once in a while, so reaction time is not all that important. The types of attacks they tend to use are not extremely fast and they are relatively easy to defend against. Thus the difference between a three day reaction time and instantaneous reaction is only about 15 percent at its maximum.

Plate 9 - The Effects of Detection and Reaction Time for Infrastructure Warriors



Infrastructure warriors are typically very fast and very harsh. As a result, in Plate 9 we see that rapid reaction is critical to success. In this example, we see that the first 10 hours of delay are very costly, consuming 80 percent of the cases. At 20 hours, we are up to more than 95 percent defeats for the defender, and if we wait 30 hours, the defender almost never wins. For this threat in the situation analyzed, rapid reaction is critical to success. If we want to know how rapid, we must examine the area of the curve between instant reaction and 10 hours in more detail.

A very interesting result that combines these results with the previous results on the distribution of successful attack times, is that the effect of faster reaction time on outcomes is highly non-linear. In fact, effectiveness of defense is not even monotonically improved by decreased reaction time. This is because of the bands of time in which there are no successful attacks. If reaction time is at the end of a one of these *dead* bands, moving it to the other end of the dead band has no effect on the success rates of defenders. Since faster reaction generally costs more, being at the high-speed end of a dead band is typically less cost effective than being at the low-speed end of the same dead band. In fact, since decisions taken over longer times have a tendency to be better thought out, there may be advantages in terms of the quality of the outcomes to taking the extra time to make a decision when time is available. For example, in Table 9 (1000 runs of a paramilitary group attacking Frank from the Internet with defender strength at 20%) there is a large dead band between 21 and 30 days in which speed is of no import.

This discussion has also neglected the notion that defense in depth itself is indicative of a stronger defender, and would seem to lend credence to the notion that having more expertise in the design of a defense makes the quality of the day-to-day defenders less important. Faster detection and response tends to move the curves to the left - in favor of poorer quality defenders, but remember that poorer quality defenders tend to be less responsive and achieving this result may be infeasible.

This brings up yet another limitation of simulation. While we may be able to simulate nearly instantaneous response, we are unlikely to be able to achieve it in many cases.

While these results help to show the power of parallel simulation in this application, this is only the tip of the proverbial iceberg. The full results of these simulations can be used to generate and analyze a wide range of other data such as the clustering phenomena shown in Plate 2 and how clustering is affected by defender strength and strategies, the time spectrum associated with attacks and defenses, and so forth.

While theoretically, you can get the same results sequentially as you can with parallelism, in practice, the time taken in simulation can be a real impediment to progress, and the inability to perform rapid experiments and examine the underlying data inhibits the generation and testing of ideas. Parallelism brings the scientific method closer to real-time, and even the small performance improvements shown in our examples can be quite a substantial advantage.

Adding in Costs

Prevention, detection, reaction, and consequences of attacks, all have costs associated with them, and to here, we have ignored costs as an issue. Costs are easily added to a simulation of this sort by assessing a fixed and per use cost of each attack and defense method and summing the costs from each simulation run. Since fixed costs are based on the defenses placed or attack capabilities available, regardless of the specific simulation run, the simulation need only assess per use costs.

Similarly, we can evaluate costs of consequences by assessing figures to worst case consequence, but this does not fully address the issue from a risk management perspective because all losses are not maximum valued, and no current or anticipated theory addresses the time effect of unmitigated attacks on consequences. As far as anybody seems to be able to tell today, consequences are highly dependent on a wide range of factors including but not limited to, the specifics of the information environment, the interdependencies within the organization, the ability of the systems and people to adapt to adverse circumstances, market conditions, public perceptions, the broader business environment, and on and on. To make matters even worse, in many real-world situations, the costs of consequences vary over several orders of magnitude depending on who you ask about them. The computer virus that spread through the Internet in 1988 [Rochlis89] is a good example in which after-the-fact estimates of loss ranged from hundreds of thousands of dollars to hundreds of millions of dollars.

It is our belief that consequence modeling of the sort required for this sort of analysis is beyond the scope currently attainable by simulation technologies. For that reason, we take the view that consequences are independent of the method by which an attacker gains access to an information system, and revert to a model in which the expert analyst assesses the situation and creates a distribution function that characterizes how much harm can be done in how much time by what sort of an attacker once the target has been defeated. We call this the *characteristic loss function*. Consequences fall out of the final results of the sorts of simulations shown herein. The result is generated by evaluating the characteristic loss function for each threat with a probability given by the simulation results. The probability is derived through simulation based on the strength of the defenders. The loss per unit time is derived by factoring in a rate of attempted attacks by each threat profile based on empirical data.

For the purposes of this example, we will take the results from the simulation runs with instantaneous reaction and assume that the frequency of attack and consequences from threats are taken from Table 13. This table does not reflect an actual organization but that each value used probably applies to some organization. We are also using a constant value for expected loss. A probability distribution is probably more useful in a real situation. Clearly this represents a large multinational organization of some sort.

Table 13 - Sample mean time to attack and expected loss

Threat	Mean Time To Attack	Expected Loss
Information Warriors	10 years	100,000,000
Hoodlums	6 months	100,000
Whistle Blowers	3 years	1,000,000
Government Agencies	3 years	100,000
Industrial Espionage Experts	1 months	10,000,000
Global Coalitions	6 months	10,000,000
Maintenance People	2 months	100,000
Vendors	1 months	100,000
Military Organizations	10 years	10,000,000
Customers	1 months	100,000
Extortionists	1 years	10,000

Foreign Agents and Spies	6 months	10,000,000
Nation States	10 years	100,000,000
Competitors	3 months	10,000,000
Tiger Teams	3 years	1,000,000
Activists	1 years	10,000,000
Deranged People	2 years	10,000
Police	2 months	100,000
Organized Crime	2 months	1,000,000
Insiders	2 weeks	10,000,000
Crackers for Hire	3 months	10,000,000
Consultants	3 months	1,000,000
Professional Thieves	1 years	1,000,000
Drug Cartels	20 years	100,000
Infrastructure Warriors	10 years	10,000,000
Hackers	1 days	2,000
Vandals	1 months	5,000
Crackers	1 hours	10,000
Reporters	3 months	5,000
Club Initiates	3 months	5,000
Economic Rivals	1 months	10,000,000
Paramilitary Groups	3 years	10,000,000
Cyber Gangs	4 years	1,000,000
Terrorists	6 months	1,000,000
Private Investigators	2 months	10,000

We can now compute an annual expected loss chart by multiplying the probability of successful attack by attack frequency and expected loss. The calculation is straight forward. For example, for Information Warriors with the defender at 90 percent strength, 953 of 1000 attacks fail. If the Mean Time to Attack (MTTA) is 10 years and 4.7 percent of the time they succeed, there is a 0.47 percent chance of a 100,000,000 dollar loss in any given year, or an expected loss of 470,000 per year. If we went to 100 percent defender strength this would change to a 90,000 dollar expected loss per year, or a 380,000 dollar change in expected loss. If we sum up the expected loss for each strength level across all threats, we get the total expected loss per year as a function of defender strength, and we can then make a prudent decision based on the tradeoff between quality and cost of defenders. The results are shown in Table 14:

Table 14 - Expected loss vs defensive strength (out of 100%) with 1-second detection and response

Threat	10%	20%	30%	40%	50%
Information-Warriors	9960000	9490000	8820000	7360000	6000000
Hoodlums	201358	197708	184527	159788	120855
Whistle-Blowers	331000	315333	296000	255000	202333
Government-Agencies	33066	31933	28766	25100	20566
Industrial-Espionage-Experts	120571666	116556666	106458333	90885000	69958333
Global-Coalitions	20095277	19203055	17560555	14620277	11538055
Maintenance-People	602858	564533	490925	386291	287133
Vendors	1204500	1157050	1060933	896683	699583
Military-Organizations	989000	945000	868000	736000	566000
Customers	1203283	1141233	1043900	828550	598600
Extortionists	9890	9300	8080	6680	4940
Foreign-Agents-and-Spies	20034444	19426111	17682222	14944722	11903055
Nation-States	9880000	9440000	8530000	7330000	5470000

Competitors	40068888	37189444	32160555	25144444	14802777
Tiger-Teams	329000	319333	290666	244666	188333
Activists	9870000	9470000	8370000	7070000	5100000
Deranged-People	4935	4670	4105	3220	2220
Police	600425	557841	479366	378383	249416
Organized-Crime	5998166	5736583	5237750	4148833	3132916
Insiders	257064285	241160714	214828571	169464285	124360714
Crackers-for-Hire	39947222	38243888	35445555	29402777	22021666
Consultants	3990666	3897388	3568888	3001111	2404944
Professional-Thieves	984000	943000	848000	667000	471000
Drug-Cartels	4920	4685	4355	3675	2730
Infrastructure-Warriors	984000	933000	849000	699000	538000
Hackers	718320	667950	583270	427780	247470
Vandals	59799	56088	47936	36074	23664
Crackers	86110800	80592000	72445200	56589600	38106000
Reporters	19933	18493	15411	11213	6326
Club-Initiates	19872	18067	14235	9550	5272
Economic-Rivals	118868333	113271666	101470000	80178333	62901666
Paramilitary-Groups	3246666	3090000	2676666	1966666	1303333
Cyber-Gangs	243250	233500	198500	152750	94750
Terrorists	1966944	1829055	1547194	1206527	744194
Private-Investigators	58886	54567	44347	33762	18675
TOTALS	756275652	716769854	644161811	519273740	384095519

These results are particularly interesting because the threats that are more important in terms of financial loss change with the defender's strength. At low defender quality, crackers are ranked 4th from the highest consequence, while at high defender strength, crackers are ranked last. On the other hand, insiders dominate throughout the process as the highest expected loss contributor, with their effect on the order of 1/3 of the total expected loss and becoming slightly more dominant as the defender becomes better able to fend of other attacks. The cause of insider dominance is not trivially assessed from these results, and this should not be taken without more detailed examination as indicating a root cause for insiders dominating actual harm in the real world.

As the defenders get to high levels of quality, the expected loss drops down to only about two million dollars per year. While this data is not accurate in the sense of being prescriptive, it is not unrealistic for large organizations. It is easy to believe that different protective schemes would vary in cost by this much and that, if the sensitivity to the quality of defense is as these results would seem to indicate, marginal improvements in protection effectiveness might have large enough financial impacts to warrant in-depth examination. Even at this relatively mildly sloped area of the curve, small improvements in defender quality are worth substantial efforts.

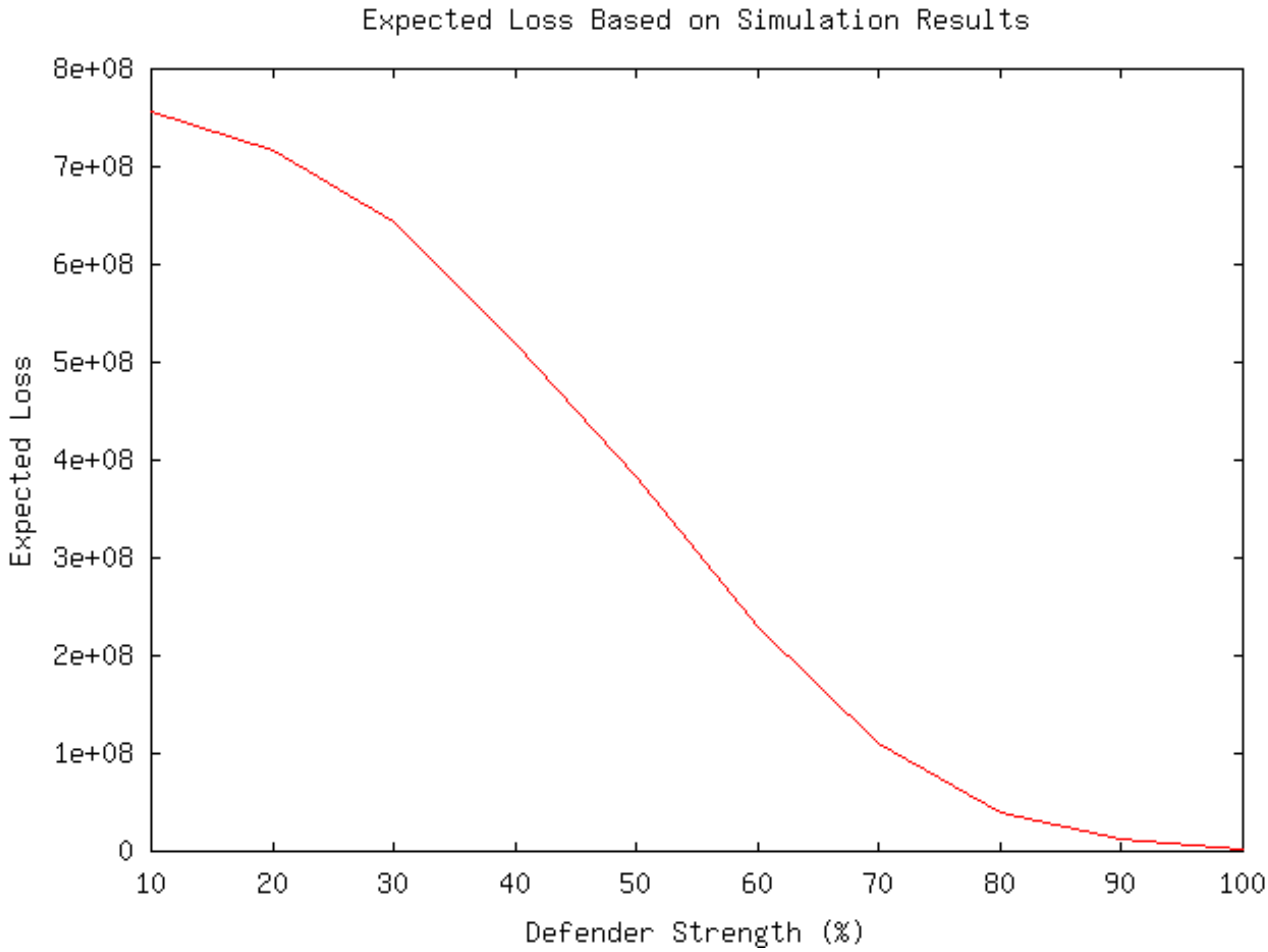
In addition, at this cost level, response costs may become quite important. This example has defenders fielding more than one attack per hour, or almost 9,000 attacks per year. Even if the average reaction only costs one hundred dollars - including the personnel, systems, and infrastructure that have to be there to handle it - this is half of the expected loss at 100% defender strength.

Plate 10 - Instant Reaction By Threat Expected Loss vs. Defender Strength

The dominance of individual threats (Plate 10) is also interesting, but it is important to not pay too much attention to this sort of effect when the data used for these examples is not specific to a particular organization and not validated for any particular use.

Perhaps more important and more enduring is the financial roll-up of expected loss plotted against defender strength as shown in Plate 11. In this case, the knee point for expected loss comes at about 80 percent of maximum defender strength, but again, the specifics of this case are almost certainly not relevant to the reader. What is relevant is the notion that from this data we can compute the cost of talent against the benefit in expected loss reduction and find the proper tradeoff point.

Plate 11 - Instant Reaction Total Expected Loss vs. Defender Strength



If we add in detailed defender costs, this picture changes rather interestingly. It turns out that the cost of increasing the quality of defenders goes up rather steeply as we approach perfection, while going from little expertise to fairly good expertise is far less expensive. With the right education, for ten to twenty thousand dollars per defender, we can go from a defender of strength 10% to a defender of strength 60% to 70%. For another twenty thousand dollars, we may be able to get to strength 80%, but getting to 100% is essentially impossible at any price. For the curve above, this would seem to indicate that we should spend about thirty thousand dollars per year to train security specialists (assuming they are systems administrators and have other expertise already). If we spend much more, it will likely not be worth the cost, while spending less is probably inadequate. Of course this depends heavily on the quality of the training you get for the cost and many other factors. Again, these results are not prescriptive for other cases, but they do seem to demonstrate that the technique is effective in that it is able to produce prescriptive results given reasonably accurate data.

Adding Strategies to Simulations

Up until this point, we have assumed that attackers use random selection to pick attacks out of a set of available attack methods, but realistically, human attackers use non-random strategies to make their selections. For example, some take what they perceive to be the path of least resistance, while others take the path of least detection, and still others select attacks based on speed. The strategic decisions made by attackers substantially changes the manner in which simulations proceed.

In an ideal world, we would analyze all strategies and come up with optimal attacker and defender decisions, but we don't live in such a world, and the nature of the attack and defense situation precludes any fixed optimal strategy. From a game theoretic standpoint, our simulations study a two-person repeated non-zero-sum game with imperfect information. There are no equilibria, the number of possible strategies is the number of combinations of attack methods (about 2^95) for the attacker and the number of combinations of defense methods (about 2^150) for the defender at each node in the sequence from the source of the attack to its destination. Furthermore, this may be a game with uncommon objectives in that the attacker's efforts may not be directly opposed to the defender's efforts, and yet it is not a cooperative game in the sense that the parties do not exchange information in order to gain common objectives.

While we don't propose to analyze strategies in this paper, there are some clear strategic notions that arise out of our results - primarily the notions of stealth and speed for the attacker and speed and skill for the defender. The stealth strategy is one where the attacker tries to use methods that are unlikely to be detected, while the speed strategy exploits high speed attacks in the hopes that the likelihood of success before detection and reaction is higher. The defensive strategy of speed for the defender is addressed by the reaction time analysis above, as is the notion of defender strength.

Our results clearly show that there are advantages to speed for an attacker, but only to the extent that the defender takes time to detect and react. Based on these results, a strong attack strategy would seem to be to attack as quickly as possible for a period of time less than the response time of the defenders, while doing so in a manner that is hard to trace after the fact. When you reach the time to defend, stop, and try from somewhere else. There is also a clear advantage to knowing more about the defender's defenses because the more that attacker knows, the more likely that will be to find a workable stealth strategy. Similarly, intelligence can be used to determine reaction times. One way to do this is by testing the defenses and observing for reactions. For this reason, it might be prudent for defenders to not demonstrate their full reaction capability on every attack. Thus the deception strategy wherein attacks are rerouted to a *honey pot* may be more effective than simply defeating an attacker by forceful termination of sessions. Needless to say, this discussion could go one almost without end. The point to be made in this context, however, is that strategies can be analyzed using simulation and that analysis is revealing.

Clearly strategies are a substantive issue and, at least for now, they will be left for future efforts. Similar efforts in evaluating strategies have been used in a wide range of subject areas including military strategic analysis and in training exercises.

Issues of Measurements, Metrics, and Applicability

For the purposes of simulation, models are both driven and limited in their accuracy by a set of measurements that are used to determine the characteristic functions that set the values used in runs. If these values are ridiculous, the meaning of the simulation is clearly lost and it becomes nothing more than an academic exercise. The pressing questions then are; (1)

How good do these values have to be in order to provide what level of quality in the results of the simulation? and (2) How do we get them to that level of quality?

The theory of measurement posits that there are four *classes* of measurements; (1) *nominal*, (2) *ordinal*, (3) *interval*, and (4) *ratio*.

- Examples of (nearly) nominal measurements are the attack, defense, and threat categories used in our model. They would be nominal except that they are not mutually exclusive and may not be collectively exhaustive, although we try to make them so. The *physical informational*, and *systemic* as well as *theoretical*< *demonstrated*, and *widespread* measurements used in the model do meet the requirements of nominality.

- We do not currently use ordinal measurements (strict ordering by relation) but we do use the closely related partial ordering in our descriptions of the flow of an attack from source to destination.

- Intervals (ordinals with a constant distance and size for ranges) are used in our analysis of results and - to a limited extent as a side effect of limits on granularity. For example, the analysis above used 10%, 20%, ... 100% for defender strength.

- We use integer-valued ratios, such as times and strength measures, which are characterized by their meaningful zero point and meaningful ratios between numbers.

We call the intervals and ratios that we use metrics because they are essentially treated as linear measurements. The question of how good these metrics have to be depends largely on two factors; (1) their intended use, and (2) the sensitivity of results to their quality. The question of how we attain the desired level of quality depends largely on the answers to the first question.

If the intended use were to, for example, predict specifically how a specific system would act under specific attack and defense conditions, the level of detail and accuracy required would be so extreme that we would likely never be able to attain it unless we designed a special purpose simulation for the specific case of interest. This demonstrates the contrast between the simulation of, for example, an electronic component, and the simulation of attacks and defenses on computer systems. Every bit of state in a computer system has the potential of dramatically changing the outcome of an attack, and these bits change so rapidly that we cannot even do a completely accurate *snapshot* backup of a typical computer while it is in operation. Clearly we cannot hope to simulate it at that level of accuracy in a timely enough fashion to be meaningful.

We are limited by what we can realistically hope to achieve, and yet for simulation to be meaningful, we need to be able to gain some predictive value from the effort. Again there seems to be an advantage in looking at two views; (1) the value of absolute results, and (2) the value of relative results. While it would be nice to achieve absolute results in our simulations, there may also be significant value in achieving only relative results. An example is demonstrated in the form of relativistic risk analysis.[Cohen9706] In this technique, we need not know absolute values to be able to compare different system configurations and get relative advantages and disadvantages. While relativistic analysis may not be definitive in terms of the numerical values of results, it can definitely provide results in terms of the advantage of one method over another. Simulation based on relative metrics requires only that the system of measurement be meaningful in a relative sense. The elimination of the requirement for absolute values has many advantages. We see this effect in this paper when, for example, we compare different reaction times and their effect on protection (i.e., Plates 6, 7, 8, and 9). Even if the absolute values of the results are completely wrong, the result appears to be valuable. To the extent that we can get accurate absolute results, this is, of course, all the more helpful, since such results can be used as a rational basis for making design and risk management decisions.

For now, let us then limit our fields of applicability to gaining a deeper understanding of the structure and nature of sequential attacks and defenses, the effects of different design and operational decisions, analysis of strategies for attack and defense, and simulation-based risk management. These all have, as common threads, the notions that (1) the results of individual runs are less important than the aggregate results of many runs that tend to explore the space, and (2) relative results are meaningful while absolute results are even better.

We are then left with the second question of quality; the sensitivity of results to the accuracy of the values of simulation parameters. Clearly, wild parameter values will yield wild results, but without an extreme level of effort, reasonable parametric values can be attained by the solicitation of expert opinions and some examination and testing of the particulars of the organization and systems under analysis. This is the technique we use for generating metrics. The question of sensitivity can be addressed by varying parameters to different degrees and re-simulating to determine the effect on results. For parameters where changes within the tolerance of current measurement have significant impacts, accuracy is more important and measurements can be improved, while parameters that are relatively insensitive need not be so accurately determined. In this case, the simulation capability is itself a useful tool in determining sensitivity and the need for accuracy in parameters.

It turns out, however, that this issue is a bit tricker than this analysis might indicate, because of the scale of the issue. With between 35,000 and 40,000 parameters to consider, and with the statistical requirement of n^2 samples for accuracy of 1/n, even 10 percent accuracy requires 100 simulation runs per parameter value. Exercising 40,000 parameters over a range of 10 values then implies 40 million simulation runs just to determine sensitivity to each parameter varied one at a time. Parameters can conspire synergistically as well, leading to enormous numbers of simulation runs. This of course assumes that simulation results act like random stochastic processes, which they do not, because of the sequential nature of attack and defense. Our initial simulation runs appear to indicate that results do not change by more than a few percent after something like 1,000 runs per parameter set (stochastic analysis would predict a 3.33% deviation at 1,000 samples). If we were to use 1,000 runs, the variation of parameters analysis for each single parameter would take about 400 million runs.

While 400 million simulation runs is not unreasonable given the performance of the present simulator, (with a $500,000 parallel processor this can be done in only a few days) it turns out that we can generate significant sensitivity results for aggregate runs without the need to put forth this effort, and in the process learn a fair amount about the nature of the information protection design space for the particular situation under consideration. Indeed these results may be far more broadly applicable.

It turns out that the nature of the simulation space generated by the binary relation between (1) threat and attack and (2) attack and defense is such that there are only two possible values for these relations. While the simulation may be quite sensitive to these values, they are not subject to variations in parameters except over the values of true and false. Thus two cases exist for these values, which comprise about half of all the values used in the simulation. Furthermore, the vast majority of these values are well known and definitively resolved by the literature and theoretical or practical constraints. For example, we know definitively that locks are effective at preventing some portion of cable cuts, while authentication of packets is most certainly not effective in that role. The elimination of most of these parameters from sensitivity analysis reduces the level of effort by about half.

Perhaps the second most important thing to note in sensitivity analysis is that the times associated with attacks and defenses lead to sets of ordered events. Changes in the absolute values of times are of no import to the final outcome (win or lose) unless they change the ordering of events. Furthermore, many event sequences are only partially order dependent, so that many different orderings may result in equivalent outcomes. It turns out that time represents something like 1/3 of all of the parameters involved in simulation and that many of these times are also fixed against common standards - such as the organization's ability to respond or the limits of performance of current intrusion detection technology. Again, we know or can determine the values of many of these parameters with adequate accuracy so that variations do not have sufficient aggregate affect on the ordering of events so as to cause results to vary significantly for changes in value within our ability to reasonably measure them. This eliminates about another third of the values from the requirement for variation of parameter analysis.

While the results are impacted by changes in the remaining parameters, the impact is essentially linear in the values of those parameters because they are used in a linear fashion to affect outcomes. The net effect is that, except in cases where a win or loss is a close call decided by the value of a parameter, errors aren't magnified significantly by the process. In the case where close calls have an impact, there are two possible impacts; (1) the overall sequence of events is significantly impacted, or (2) the threshold between a win and a loss is changed by the value of the parameter.

In the case of the sequence of events being impacted, the impact can only effect a number of runs proportional to the variation in the parameter. In other words, the value of a metric associated with an attack or defense that works instead of failing in any given run, (or vice versa) impacts the set of all runs where that attack was tried linearly in the value of that metric. So a 10 percent increase in the value of the parameter has at most a 10 percent impact on outcomes of the steps in which it is exercised. Since there are about 100 attack methods and 150 defense methods and only one is selected for the next step at any given moment, in the aggregate, the effect of a 10 percent difference in the value of one parameter is significantly reduced by the likelihood that it will get selected (in the case of attack) or the impact on the attack (in the case of a defense). While variations may have significant impacts on a single run, their impact on a large number of runs is significantly lessened based on their import to the overall situation. In situations where defenses are not very resilient and where attackers are capable of only a few attack methods, the impact of minor changes is greater, because they effect a larger portion of the runs. This is a real-world effect of a lack of redundancy, not just a residual of the simulator, and just as the real world situation will be highly sensitive to minor changes in this circumstance, so will the simulator.

A specific example may be quite helpful here. Suppose that we have a situation where the differences between success and failure are within the bounds of the accuracy of our values. Such an example appears in one of the sample runs shown in Table 4 and is repeated here for the purpose of discussion:

```
What: ATTACK
Node: Angel
Time: 33d 1h 23m 30s
What: infrastructure observation->Angel
Details:  [907 !< 866](21 > 20) -> bad luck
```

In this case, the details indicate that the defense missed preventing the attack by less than a 10 percent difference in the metric associated with its strength in this application (as indicated by the [907 !< 866]). The attack similarly failed because of a very small difference between the random number selected for this run and the overall strength of the attack in the situation (as indicated by the 21>20). If either had a 10 percent difference in values in the proper direction, the results would have been a prevention (in the case of the defense) or a successful attack (in the case of the attack). The net effect of the defensive failure in this simulation run was nothing because the attack failed due to bad luck anyway. The net effect on the attack for this simulation run was that Angel was not defeated until 73d 15h 16m into the run, about a 40 day difference. And yet the overall attack run achieved success at 136d 59m 10s, so that the total effect on attack time was 40 days out of 136 days - or about 30 percent. But this is not the whole story because - from later in that same simulation run we see this:

```
What: ATTACK
Node: Charlie
Time: 73d 19h 16m
What: cryptanalysis->Charlie
Details: [404 !< 0](19 < 20) =======> Prevention will fail
```

After Angel was penetrated, the attacker got lucky in the same type of close call (19<20) and defeated Charlie immediately. Who knows what might have happened next had this attack not succeeded? Again, a small variation in a parameter could have made the difference between immediate success and the attacker trying, for example, a strategic or tactical deception - an attack that would have taken 30 days of effort and may not have succeeded either.

Clearly, we cannot evaluate the results from such runs on a piecemeal basis because of the role that luck may play in attack and defense. Rather, because we cannot accurately measure the situations to the point of being able to be predictive on a case by case basis, we must consider them in the aggregate in order to derive meaningful results. If we think in these terms, it should be clear that a 10 percent difference in the value of the threshold used at any given point in a run will produce a 10 percent change in the number of times there is a success or failure at that point in the simulation. If a particular value is used repeatedly, the effect will accumulate in that run. The net effect will be a time difference in the outcomes of the runs, or in the case where detection and reaction are taken into consideration, an increase or decrease in the wins or losses. Since there are many such events in a typical run, each of which could have an effect in either direction, random errors tend to cancel while correlated errors tend to compliment each other. This is what we see, for example, in the analysis of defender strength and reaction time for the large numbers of sample runs shown in Plates 3 and 6.

The aggregate results provide us with information on the shapes of the curves, but clearly, sensitivity depends on where you are on these curves. For example, in Plate 11 (*Instant Reaction Total Expected Loss vs. Defender Strength*) small errors in defender strength near 100 percent make little difference as will small changes at very low defender strength, but changes between 30 percent and 60 percent cover more than a factor of 3 in expected loss. The ability to measure accurately is far more important if we intend to operate in the middle portion of the curve, while the ability to measure is far less important near the minimums and maximums. If we add an equation for defender strength vs. investment defender strength (i.e., via education and skills development) the place where the sum of the cost of defenders and the expected loss are minimized provides the optimum for costs of training vs. expected loss, and the sensitivity around that point is the issue that has to be settled to better optimize this investment.

The same sort of analysis will apply to other parameters of interest such as reaction time. This would seem to suggest an iterative process wherein initial values that are *reasonably accurate* are used, simulations are done to analyze tradeoffs, and where decisions must be made near highly sensitive areas of curves, more detailed data is measured and more simulations are run in close proximity to the decision point. This notion of variable granularity is not unique to information protection simulation, nor is the idea of using an iterative process for getting the desired accuracy.

Finally, we have the issue of how we obtain data that is appropriately accurate. We begin the iterative process with an initial set of values and an initial model of the network under consideration. We use a gathering process that involves a great deal of expert opinion combined with selective experiments or demonstrations. But if the initial data is not accurate, we may not know whether we are in a sensitive or insensitive portion of the analysis. In other words, without accurate data, we cannot accurately tell whether we need more accurate data or not.

In the end, ground truth can only be measured in the real world. While simulation can help us analyze and improve experimental results, it does not eliminate the need for them both as a basis for simulation and for its validation.

Validation of Results and Limitations

This leads us directly to the question of validation. Let us suppose that our ordinal basis is simply wrong and that our model of threats, attack mechanisms, and defensive measures is not reflective of the reality of attack and defense. In this case, the results of simulation are essentially useless. Similarly, if our model of sequential attacks or strategies is invalid, the results are far less predictive than would be desired. If our metrics of time and strength are not reflective of reality, our results will be far less accurate than desired, and again we will lose predictive power. Validation is needed in order to be able to determine whether or not these issues are being properly addressed and how predictive the results might be.

The scientific method generally uses a process that begins with theory, produces a model, performs experiments based on the model to confirm or refute the theory, and feeds back the results to confirm or refute the theory. As a meta-issue, we will assume that the schema of the scientific method as described here is valid. We then need to perform validation by creating a theory, model, experimental regime, set of experiments, and analysis.

The theory behind our simulation and the specific set of threats, attack mechanisms, and defense mechanisms are those of espoused in "Preliminary Classification Scheme for Information System Threats, Attacks, and Defenses; A Cause and Effect Model; and Some Analysis Based on That Model" [Cohen98] In essence, we posit that causes produce effects through mechanisms. We model this theory with the cause and effect model shown in Plate 1 consisting of threats which use attack mechanisms to cause effects and defenses which mitigate effects by mitigating threats, the links between threats and attack mechanisms, attack mechanisms, the links between attack mechanisms and consequences, and/or consequences.

As was discussed earlier, experiments can be quite expensive and this limits our ability to carry them out. As an alternative, we use a combination of historical data, expert opinion, and limited experiments to try to generate results that are viable for validation.

Historical data, while limited, tends to support the general notions underlying the model in the sense that accounts of attacks as they occur tend to reflect sequences of activities of the sorts produced by our model. This has been validated by examination of the model and select runs of the simulator by many active researchers and practitioners as well as by a substantial review of the literature.

Expert opinion, including the experiences of investigators who have field experience with scores of cases and consultants who regularly work in the field, tend to support the notion that the models are valid and, to a limited extent, that the linkages between threats, attacks mechanisms, and defensive mechanisms are also valid. While there is certainly no consensus of opinion on the particular scheme we use there are also few who dispute that, to the extent that it models the reality of cyber attack and defense, it models it reasonably well.

Limited experiments have also been performed to validate some of the specific numbers and results from published papers and comparisons of products form the basis for many of the numerical values used as metrics. Details of some of the values used in our simulator are provided in the references. [Cohen9903]

Perhaps the least compelling but most important validation of the simulation system is the opinions of people who run individual simulations. In essence, they indicate that the sequences of events and the things that transpire seem reasonable to them. If the results did not seem reasonable, it would be cause for great concern and would be considered a serious refutation. And yet this sort of opinion does little to give us confidence in these results. A further complicaiton comes from the fact that environments differ considerably, so that time-related information, especially in the area of response times, is hard to validate without individual experiments and testing of the specific organization under realistic circumstances.

Perhaps the most compelling results to date are those presented in this paper on issues related to the value of faster reaction, skill levels of defenders, and so forth. When we inspect the specific runs for deeper understanding of why a phenomenon exists, we always seem to find a reasonable explanation that, while sometime surprising, makes sense once we investigate it. This ability of simulation to resolve what would otherwise be rank speculation and to do so in surprising but sensible ways is its greatest validation to date. This indicates not only that the simulations make sense, but that the aggregate results are meaningful in the same way as experiments, even if only at a qualitative level. Indeed, the results appear to have meaning at a quantitative level as well, but this depends heavily on our ability to gather data about the specific circumstance under consideration.

In the long run, widespread use of simulation will produce validation in the form of real-world experience that confirms or refutes the simulation results. For the meanwhile, we are limited in our ability to validate results.

Summary and Conclusions

We have presented a great deal of information on the application of modeling and simulation technologies to information protection, but there is clearly a long way to go.

- We have presented information on modeling approaches and discussed the reasons for our choice of models, briefly described the operation of a simulation engine, and shown sample detailed output runs from simulations to give a sense of what precisely is simulated and what sort of results are derived.

Perhaps the most interesting results here are the shapes of the outcome curves over time and the association of this phenomena with the high degree of time gradation between different attack methods. This result has many implications and, while it may seem almost obvious once it is presented, it was unpublished and not known to the author until simulations revealed it, and it was a surprise until the detailed simulation results were examined. This has all of the hallmarks of a valid experimental basis for scientific inquiry.

- Parallel simulation was described from a technology standpoint and the results of parallel simulations yielded intriguing results. While parallelism attained in our experiments was relatively poor, we believe that almost ideally scalable parallelism is attainable for these simulations. The effect of parallelism in this sort of simulation is most dramatic in that it enables analyses that would otherwise be impractical.

- The curves derived for the effects of defender strength, success rates, and threats and the non-linear shape of those curves were particularly revealing as were the results on the effects of reaction time on success rates. To our knowledge these sorts of results have never been demonstrated before, and they are particularly interesting because of their combination with the results on *dead* zones in attack times.

- By adding costs into the analysis, we were able to demonstrate non-linearities in the tradeoff between skills of defenders and reduction in expected loss, and perhaps the most important result here was that it is not cost effective to have the best computer security experts in an active defense role. For a reasonable cost, we can likely train existing employees to provide the most cost effective reaction capability.

- Finally, we discussed issues of metrics, sensitivity, and validation - a key component of any simulation-based technology. The most important result here is that, for the purposes we are currently applying simulations to address, accuracy does not have to be very good in order to learn a lot more than we know now. At the same time, the data requirements for accurate simulation are substantial and represent a level of effort only well suited today to large organizations with considerable assets at risk.

It appears that these initial results are only the beginning of the sorts of results that simulation technology will provide in the information protection field, and that it is a fruitful area to explore.

References:

- [Cohen97-03] F. Cohen - "Managing Network Security - Risk Management or Risk Analysis?", Network Securityt Magazine, March, 1997.
- [Howard97] John D. Howard, An Analysis Of Security Incidents On The Internet - 1989 - 1995 Engineering and Public Policy dissertation, Carnegie-Mellon University, April 7, 1997. Pittsburgh, Pennsylvania 15213 USA [This research analyzed trends in Internet security through an investigation of 4,299 security-related incidents on the Internet reported to the CERT. Coordination Center (CERT./CC) from 1989 to 1995. Prior to this research, our knowledge of security problems on the Internet was limited and primarily anecdotal. This information could not be effectively used to determine what government policies and programs should be, or to determine the effectiveness of current policies and programs. This research accomplished the following: 1) development of a taxonomy for the classification of Internet attacks and incidents, 2) organization, classification, and analysis of incident records available at the CERT./CC, and 3) development of recommendations to improve Internet security, and to gather and distribute information about Internet security. With the exception of denial-of-service attacks, security incidents were generally found to be decreasing relative to the

size of the Internet. The probability of any severe incident not being reported to the CERT./CC was estimated to be between 0incident would be reported if it was above average in terms of duration and number of sites, was around 1 out of 2.6. Estimates based on this research indicated that a typical Internet domain was involved in no more than around one incident per year, and a typical Internet host in around one incident every 45 years. The taxonomy of computer and network attacks developed for this research was used to present a summary of the relative frequency of various methods of operation and corrective actions. This was followed by an analysis of three subgroups: 1) a case study of one site that reported all incidents, 2) 22 incidents that were identified by various measures as being the most severe in the records, and 3) denial-of-service incidents. Data from all incidents and these three subgroups were used to estimate the total Internet incident activity during the period of the research. This was followed by a critical evaluation of the utility of the taxonomy developed for this research. The analysis concludes with recommendations for Internet users, Internet suppliers, response teams, and the U.S. government.]

- [Amo94] Edward G. Amoroso, Fundamentals of Computer Security Technology, Prentice-Hall PTR, Upper Saddle River, NJ, 1994.
- [Landwehr94] C. E. Landwehr, Alan R. Bull, John P. McDermott, and William S. Choi, A Taxonomy of Computer Security Flaws, ACM Computing Surveys, Vol. 26, No. 3, September, 1994, pp. 211-254.
- [Cohen98] Fred Cohen Cynthia Phillips, Laura Painton Swiler, Timothy Gaylor, Patricia Leary, Fran Rupley, Richard Isler, and Eli Dart A Preliminary Classification Scheme for Information System Threats, Attacks, and Defenses; A Cause and Effect Model; and Some Analysis Based on That Model,[This paper (placed at the end for readability) describes 37 different types of actors that may Cause Information System Failure (Threats), 94 different Mechanisms by Which Information Systems are Caused to Fail (Attacks), and 140 different Mechanisms Which May Prevent, Limit, Reduce, or Mitigate Harm (Defenses). We

describe a cause-effect model of information system attacks and defenses based on the notions that particular threats use particular attacks to cause desired consequences and successful defenders use particular defensive measures to defend successfully against those attacks and thus limit the consequences. Human defenders and attackers also use a variety of different viewpoints to understand and analyze their attacks and defenses, and this notion is also brought to bear. We then describe some analytical methods by which this model may be analyzed to derive useful information from available and uncertain information. This useful information can then be applied to meeting the needs of defenders (or if turned on its head attackers) to find effective and minimal cost defenses (or attacks) on information systems. Next we consider the extension of this method to networks and describe a system that implements some of these notions in an experimental testbed called HEAT.]

- [Cohen9903] F. Cohen, Managing Network Security - The Milisecond Fantasy, Network Security Management, March, 1999, Elsevier [A lot of people have screwy notions about computers that are promoted by and in the media, and many of them get embedded in our psyche without being rationally reviewed. One of the most important ones to understand from a standpoint of managing network security is the fallacy of the time assumptions people commonly make about computers... This paper gives specific times associated with various attack and defense techniques.]
- [Rochlis89] J. Rochlis and M. Eichin, With Microscope and Tweezers: The Worm from MIT's Perspective, CACM 32#6, June, 1989 [This paper describes how one team dissected the Internet Virus of 1988 and what the virus contained.]
- [Cohen97-6] F. Cohen, Relativistic Risk Analysis, Network Security Magazine, June, 1997. [This article examines risk analysis using relativistic rather than absolute measures.]
-